Investigation of Production Planning for Environmental Sustainability Improvement in Polymer LPBF

Han Wang

Doctoral Thesis

Submitted to The University of Nottingham in fulfilment of the requirements for the award of degree of Doctor of Philosophy

August 2023

Abstract

Additive Manufacturing (AM), also known as 3D printing, refers to a family of manufacturing technologies that use a layer-by-layer approach to converting digital models into physical components. The adoption of AM has offered significant sustainability benefits such as improved resource efficiency, extended product life, and reconfigured value chains. However, despite these prospective benefits, the full potential of the sustainable aspects of AM has not been explored, due to a lack of knowledge regarding environmental sustainability improvement in AM.

This thesis documents work on investigating the environmental sustainability improvement in polymer Laser Powder Bed Fusion (LPBF) from a production planning perspective. Three studies were performed to understand how to improve the environmental sustainability of AM: modelling, optimisation, and network effects investigation.

The modelling study revealed environmental sustainability elements in polymer LPBF and their share in the environmental impacts of polymer LPBF. To do this, a layer-based environmental sustainability model was established. In this model, the build time, energy consumption, embedded energy, material consumption, and risk of build failure were considered. It was shown that embedded energy dominated the total energy consumption (approximately 40 to 60%). Meanwhile, the energy relevant to risk of build failure contributed to approximately one third of expected total energy consumption at full capacity utilization.

The study of optimisation demonstrated that integrated optimisation plays a significant role in improving energy efficiency during the additive process. In this study, an exploratory simulation was used to investigate integrated optimisation through the system (or computational tool) development. Building on this, a new framework of integrated optimisation was established. Build volume packing and scheduling were jointly optimized. Specifically, a bottom-left heuristic, capacity

aggregation algorithm and exhaustive search were used to support integrated optimisation. Specific energy consumption was regarded as the optimisation objective. It was found that integrated optimisation approach had a significant effect on improving energy efficiency of polymer LPBF at higher demand profiles. The developed system allowed a lower specific energy consumption during the additive process than the results in extant literature.

The study of network effects revealed the extraordinary potential for environmental sustainability improvement in polymer LPBF by investigating the environmental network effects in the AM platform. Environmental network effects reflect the mutual impact regarding quantity and benefits (i.e., energy efficiency and lead time) between customers and machine operators (or manufacturers) in AM platform. Specifically, machine operators are assumed to care about energy efficiency (i.e., specific energy consumption) and customers are assumed to concern lead time (i.e., schedule attainment). Another computational tool was developed to support this investigation. A build volume-based capacity aggregation algorithm was developed in this system. Specific energy consumption and schedule attainment were considered as the metrics to uncover environmental network effects in the AM platform. It was shown that there were indirect network effects embedded in the AM platform. These powerful effects are likely to help manufacturers improve energy efficiency and help customers reduce waiting time. Based on integrated optimisation, using network effects in the AM platform shows greater performance in improving the environmental sustainability of AM.

Acknowledgements

I would like to thank the Faculty of Engineering for supporting my research at the University of Nottingham (UoN) in the UK.

Additive Manufacturing (AM), one of the advanced technologies, attracts much attention from academia, industry and government around the globe. To this sense, I would like to thank the Centre for Additive Manufacturing (CfAM) for an opportunity to study AM.

It is my fortune, and I am happy to be supervised by Martin Baumers and Ian Ashcroft throughout my PhD journey. I want to thank colleagues at the UoN particularly the Advanced Manufacturing Building (AMB) for their support during my PhD study.

When it comes to my family, I hereby thank my parents and sisters for accompanying me during my PhD life and supporting my research. I am so proud of having such nice family members.

Glossary of terms

3DIP	3D Irregular Packing
AM	Additive Manufacturing
BJ	Binder Jetting
BL	Bottom-Left
CAD	Computer Aided Design
CNC	Computer Numerical Control
C&P	Cutting and Packing
DED	Directed Energy Deposition
DLD	Direct Laser Deposition
DMD	Direct Metal Deposition
FDM	Fused Deposition Modelling
GA	Genetic Algorithm
GHGs	Greenhouse Gases
IPCC	Intergovernmental Panel on Climate Change
LENS	Laser-Engineered Net Shaping
LCA	Life-Cycle Assessment
LPBF	Laser Powder Bed Fusion
ME	Material Extrusion
MTBF	Mean Time Before Failure
MJ	Material Jetting
MIP	Mixed-Integer Programming
OM	Operations Management
OLS	Ordinary Least Squares
P-LPBF	Polymer Laser Powder Bed Fusion
PBF	Powder Bed Fusion
RP	Rapid prototyping
SA	Schedule Attainment
SEC	Specific Energy Consumption
SL	Sheet Lamination
SLA	Stereolithography
WAAM	Wire and Arc Additive Manufacturing

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Chapter 1: Introduction

1.1 Background

Global warming, reaching 1.5°C in the near-term (2021-2040), would create unavoidable increases in multiple climate hazards and pose multiple risks to ecosystems and humans (Figure 1.1). Following the 2018 Intergovernmental Panel on Climate Change (IPCC) report "Global Warming of 1.5 °C", the global CO_2 emission must be reduced by 50% by 2030 to 2040 (IPCC, 2018).

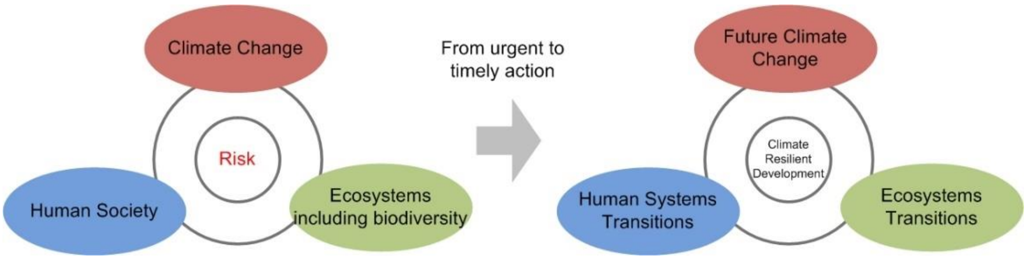


Figure 1.1: The interactions among the coupled systems of climate, ecosystems, and human society

(image source: adapted from IPCC (2022))

The share of fossil fuels in the global energy mix has been stubbornly high, at approximately 80%, for decades. In the Stated Policies Scenario (STEPS), this share decreases below 75% by 2030 and to just above 60% by 2050. A high point for global energy-related CO_2 emissions is reached in the STEPS in 2025 shown in Figure 1.2, at 37 billion tonnes (Gt) per year, and then fall back to 32 Gt by 2050 (IEA, 2022).

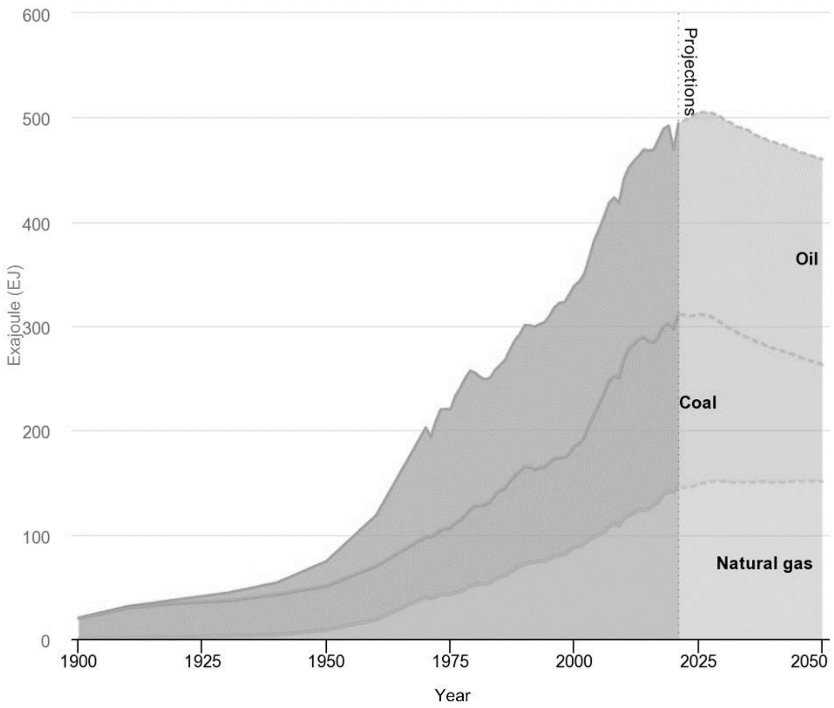


Figure 1.2: Fossil fuel demand in the Stated Policies Scenario, 1900-2050

(image source: adapted from IEA (2022))

In the US, the manufacturing sector accounts for approximately 33.3% of the nation's primary energy usage and 30% of energy-related GHG emissions in 2021 (Nelson et al., 2022). It is expected that global industry's resource demand will double by 2050. An urgent need, cutting 75% of emissions per unit output to realize the target — of 50% of emissions reduction, needs to be addressed (Allwood and Cullen, 2009, Cassettari et al., 2017, Gutowski et al., 2005, Gutowski et al., 2006).

Additive Manufacturing (AM) holds great potential for curbing emissions, improving environmental impacts, costs as well as increasing production flexibility and quality of products by improving resource efficiency, extending the life span of products, and reconfiguring value chains (Baumers et al., 2017a, Efstathiades et al., 2002, Ford and Despeisse, 2016, Huang et al., 2013, Oettmeier and Hofmann, 2017).

Additive manufacturing, which has emerged as a manufacturing technology recently, was originally invented for the manufacture of prototypes automatically. Such technologies were developed in the

1980s and 1990s (Levy et al., 2003). They allow adopters to create objects with minimal technological constraints. In other words, Maruthi and Rashmi (2015) say, "Implementing tools and techniques in production and service makes a better manufacturing sector". A definition embedding the characteristics of AM technology is provided by (ASTM, 2015):

> “A process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies.”

This definition stresses that AM features both an innovation in product creation and development. An example of an available commercial AM system, Figure 1.3 presents a type of Polymer Laser Powder Bed Fusion (P-LPBF) technology (model EOSINT P 100) by the equipment manufacturer EOS GmbH. The standard formulated by American Society for Testing and Materials (ASTM) group “ASTM F42 – Additive Manufacturing” classifies AM processes into seven categories, which include Powder Bed Fusion (PBF) (ASTM, 2009). This research used P-LPBF to describe the specific technology referring to in this category. As one of the most common AM technology variants, the fabrication of parts on this machine occurs in an enclosed internal build volume (Singh et al., 2020). In this chamber, parts are printed layer by layer. However, the physical dimensions of parts are subject to the size of the workspace. In most AM technology variants, the additive process can be observed through a window, which can be seen on the left side of the machine shown in Figure 1.3. A computer is usually contained within the AM system for system control and information exchange.

Figure 1.3: An example of an AM technology

Compared to the conventional manufacturing processes, for example, machining and injection moulding, P-LPBF is embedded with two distinguishing features: (1) P-LPBF is capable of effectively producing complex product geometry and part shapes; (2) P-LPBF is able to print multiple parts contemporaneously in a build (Baumers, 2012, Ruffo et al., 2006).

Based on the mentioned features, P-LPBF technologies are allowed to create novel products and reduce the complexity of supply chains by manufacturing products in a single production step (Tuck et al., 2007). Specifically, P-LPBF adoptions tend to save costs in transportation and inventory, resulting in impacts throughout the supply chain. As stated by Thomas (2016), it is challenging to gather and estimate the supply chain costs for a specific part, and a comprehensive understanding of the impacts of P-LPBF adoption on supply chain cost is required to address these issues. In addition, the overwhelming features of P-LPBF technologies allow the possibility for the mass production of varied products. Hashemi et al. (2020) suggested that a mix of subtractive manufacturing and additive manufacturing (e.g., P-LPBF) techniques would be the most likely scenario for the mass production, for example in the production of electrochemical reactors.

It has been identified that P-LPBF holds four main advantages: (1) printing parts without many geometric constraints; (2) allowing highly customized production in small quantities at a relatively low cost; (3) lower environmental impacts during the use phase with lightweight design; and (4) reducing supply chain costs by localized logistics (Attaran, 2017, Tuck et al., 2008, Van Sice and Faludi, 2021)

While it is occasionally claimed that P-LPBF is able to generate parts without geometric constraints, this does not mean it could remove all manufacturing restrictions. Diegel et al. (2010) suggested four principal design considerations: (1) enclosed voids. Designing a small opening for a part to allow to remove the internal power when hollow structures are required; (2) surface finish. Considering the orientation and angle when designing and printing the component due to the "staircase" effect on horizontally sloping surfaces of the component; (3) strength and flexibility. Parts should be printed to offer the most favourable results based on the orientation; and (4) machine and material costs. Considering the ratio of value and quantity of the product that needs to be manufactured.

Owing to its unique advantages, adopting P-LPBF is likely to enable new business models (Tuck et al., 2007, Holmström et al., 2016). As summarized by Savolainen and Collan (2020), there are two streams of literature on how P-LPBF technologies will form the business of manufacturing: (1) incremental change stream — adopting P-LPBF technologies will help current manufacturers increase their profits and the position on the markets; (2) disruptive change stream — P-LPBF has a significant role to play in the current distribution of economic value in the manufacturing sector. Concerning the role of P-LPBF in future business, they anticipated that LPBF technologies will still be a complementing technology for the selected set of products and found that AM manufacturers will be likely to support spare parts service via OEM-based digital platforms in closed business environments.

However, some limiting factors hinder the application of P-LPBF, for example, dimensional accuracy, quality of surface finish, and repeatability problem (Ruffo and Hague, 2007). In addition, some AM processes (e.g., metal LPBF) may need post-processing, for instance, thermal post-processing, laser peening, laser polishing, machining, and abrasive finishing (Peng et al., 2021a). Considering these factors, LPBF becomes less sustainable than conventional manufacturing technologies, e.g., machining and injection moulding processes (Kellens et al., 2017a).

As with any manufacturing process, the sustainability performance of AM is determined by a multitude of factors. Such factors include all stages in the product life cycle including design, manufacturing, use, maintenance, and end-of-life stages, which could be evaluated from environmental, economic, and social aspects (Mohd Ali et al., 2019, Taddese et al., 2020). Due to the scope of the study, this thesis mainly focuses on the sustainability of environmental aspects in P-LPBF, i.e., environmental impacts in the form of energy consumption and closely related aspects. The factors considered include waste material streams, post-processing energy consumption, process energy consumption, and ancillary energy consumption. As the existing literature has shown, the importance of these factors on the environmental impacts of P-LPBF can be significant (Kellens et al., 2017a, Faludi et al., 2017). Figure 1.4 shows a breakdown of selected environmental impacts for P-LPBF (Kellens et al., 2017a).

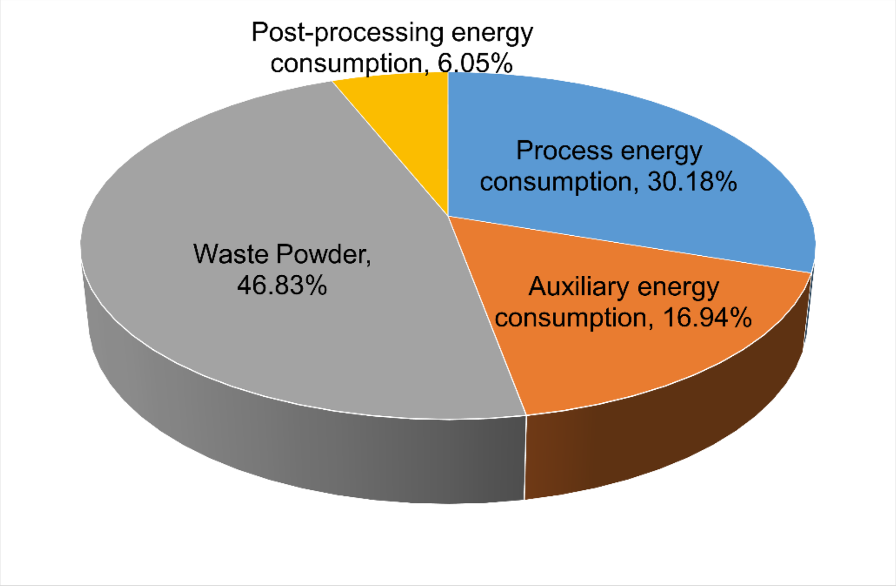


Figure 1.4: Environmental impacts of P-LPBF

(image source: adapted from Kellens et al. (2017a))

Depending on the LPBF technology adopted, energy consumption characteristics can vary significantly in LPBF. Approximately 60% of energy is consumed during the warm up stage in the Powder Bed Fusion (PBF) system (Yoon et al., 2014). In metal LPBF printing, the major environmental contributor is process energy consumption for most scenarios (Faludi et al., 2017). Concerning material consumption, approximately 90% of powder remains in the build volume without being converted into parts and roughly 10-50% of such remaining powder is discarded in P-LPBF (Baumers and Holweg, 2019). In addition, some ill-structured aspects, for example, the risk of build failure has a strong effect on the environmental impacts of metal LPBF (Baumers et al., 2017a).

One particularly interesting facet in the development and spread of technologies, particularly of telecommunication and information technologies, has been the emergence of network effects. In this context, networks represent the collections of points joined together in pairs by lines, which can be found in many systems of interest including the physical, biological, and social sciences (Newman, 2018). In general terms, network effects arise when an increase in the numbers of participants, i.e., the network members, improves the performance of the network (Banton, 2023). This phenomenon is central to the rise and dominance of consumer-facing internet services such as Google and Facebook, but can be applied to other areas as well, such as systems of manufacturing technologies.

One intriguing question is whether such network effects can be harnessed to reduce the environmental burden of manufacturing technologies (Baumers, 2019). In the context of groups, or networks, of AM machines, this relates to the question of whether there is a performance increase when the number of AM manufacturers and customers increases.

In practice, networks of AM technology would rely on a number of different functions. As stated by d'Aveni (2015), this would require systems, referred to as platforms that can:

> "Orchestrate printer operations, quality control, real-time optimization of printer networks, and capacity exchanges."

Building on such a platform, multiple connections can be established between manufacturers and customers through the Internet. This can also be called cloud manufacturing — a service-oriented business model to share manufacturing capabilities and resources in a cloud platform (Velling, 2019).

Adopting cloud platforms, manufacturing companies are likely to gain economic benefits by removing essential elements in traditional IT and enhancing manufacturing business with improved operational efficiency (Xu, 2012). Due to the lower cost of computing and the pervasive broadband networking, cloud manufacturing is potentially cost-effective for manufacturers and provides a technological alignment with the needs of smart manufacturing systems (Knapp and Langill, 2014, Thames and Schaefer, 2016).

As a type of direct digital manufacturing technology, the implications of P-LPBF's digital nature have so far not been understood and appreciated in the operational practice, especially in terms of their sustainability implications. It has been observed that there are three sustainability challenges of in P-LPBF adoption: (1) lacking understanding of the environmental performance of P-LPBF technologies; (2) automation of P-LPBF systems and process planning to improve manufacturing efficiency; (3) improving energy efficiency at higher production volumes (Ford and Despeisse, 2016, Hegab et al., 2023). In consequence, this thesis is motivated by the opportunity to investigate whether innovative production planning approaches can be adopted in P-LPBF operations to reduce its environmental burden.

1.2 Aim and objectives

The main aim of this thesis is to investigate the scope for environmental sustainability improvement in P-LPBF operations. Four specific research objectives that are designed to understand and improve the environmental sustainability of P-LPBF are as follows:

1. Create a new model to increase understanding of the energy consumption and performance of P-LPBF process. Many elements consume energy during the additive process. Understanding each element and its share in the total energy consumption is a prerequisite for the establishment of a precise energy consumption model and, hence, investigation of the performance of AM process (Baumers et al., 2011a, Watson and Taminger, 2018).

2. Quantify the impact of the risk of build failure on the energy consumption of P-LPBF process. The risk of build failure poses a threat to the production cost of metal LPBF, and it is important to investigate such an effect on the energy consumption of polymer LPBF process (Baumers et al., 2017a).

3. Create and apply an exploratory simulation to support sustainability improvements improvement in P-LPBF via workflow optimisation. Exploratory simulation has a significant part to play in realizing the automation of process planning and manufacturing efficiency improvement (Gopalswamy and Uzsoy, 2018, Irdem et al., 2010).

4. Investigate and uncovering network effects in terms of environmental impacts in the AM platform. Network effects have been shown to enhance the performance of technologies and operations (Reddy, 2018) and may have the potential to reduce the environmental impacts of an AM platform (Baumers, 2019).

1.3 Research methodology

Building on the research objectives stated above, this thesis presents a study of how to improve the environmental sustainability of P-LPBF from the development of modelling techniques, application of process optimisation, and an investigation of network effects. An experimental methodology was used to develop models for determining build time and energy consumption. This methodology included part design, printing experiments, data preparation and processing. This allowed for the generation of precise estimating models.

Once the predictive models in terms of build time and energy consumption were established, the exploratory simulations were used to improve the energy efficiency of P-LPBF. In these simulations, a computational tool (or system) was developed to enable the integrated optimisation of build volume packing and scheduling across multiple P-LPBF machines and multiple production days.

Build volume packing was used to optimize the placement of parts within the available build space of AM machines. Scheduling methods were developed to arrange, control and optimize work and workloads in an AM production process. Finally, a system was developed to investigate the environmental network effects in the AM platform. The mutual impact and relationship between manufacturers and customers were studied through an exploratory simulation. This system helped to identify and understand environmental network effects in an AM platform, as well as to investigate its significant potential for environmental sustainability improvement in P-LPBF.

1.4 Structure of the thesis

A description of the content of each chapter is given below.

Chapter 2 provides an overview of background theory relevant to the thesis, consisting of additive manufacturing, sustainability, and operations management. Following this, there is a detailed focal literature review from three aspects: sustainability of AM, workflow optimisation, and environmental network effects.

Chapter 3 outlines the methodology used in this thesis. It describes test part design, printing experimentation, data preparation and processing, theoretical descriptions, and simulation implementation.

Chapter 4 outlines the details of the environmental sustainability investigation and reports the results. An environmental sustainability model is established. In this model, a set of environmental impact-related models were constructed. In addition, predictive models of build time and energy consumption are developed, and the environmental impact results of P-LPBF are presented.

Chapter 5 develops an integrated packing and scheduling optimisation method and present results from its application to P-LPBF. Detailed experimental setting and parameters are provided and it is shown that the developed method can be used to the improve energy efficiency for P-LPBF.

Chapter 6 describes the method developed to study environmental network effects and presents the results obtained. An exploratory simulation was used to investigate network effects in P-LPBF and their effects on improved environmental sustainability demonstrated.

Chapter 7 discusses this study from five aspects: build volume packing, risk of build failure, equilibrium of material consumption, integrated optimisation, and environmental network effects.

Chapter 8 makes conclusions for the work, outlines limitations and makes recommendations for future work.

To aid in understanding the structure of this thesis, Figure 1.7 provides an overview of the content of the chapters.

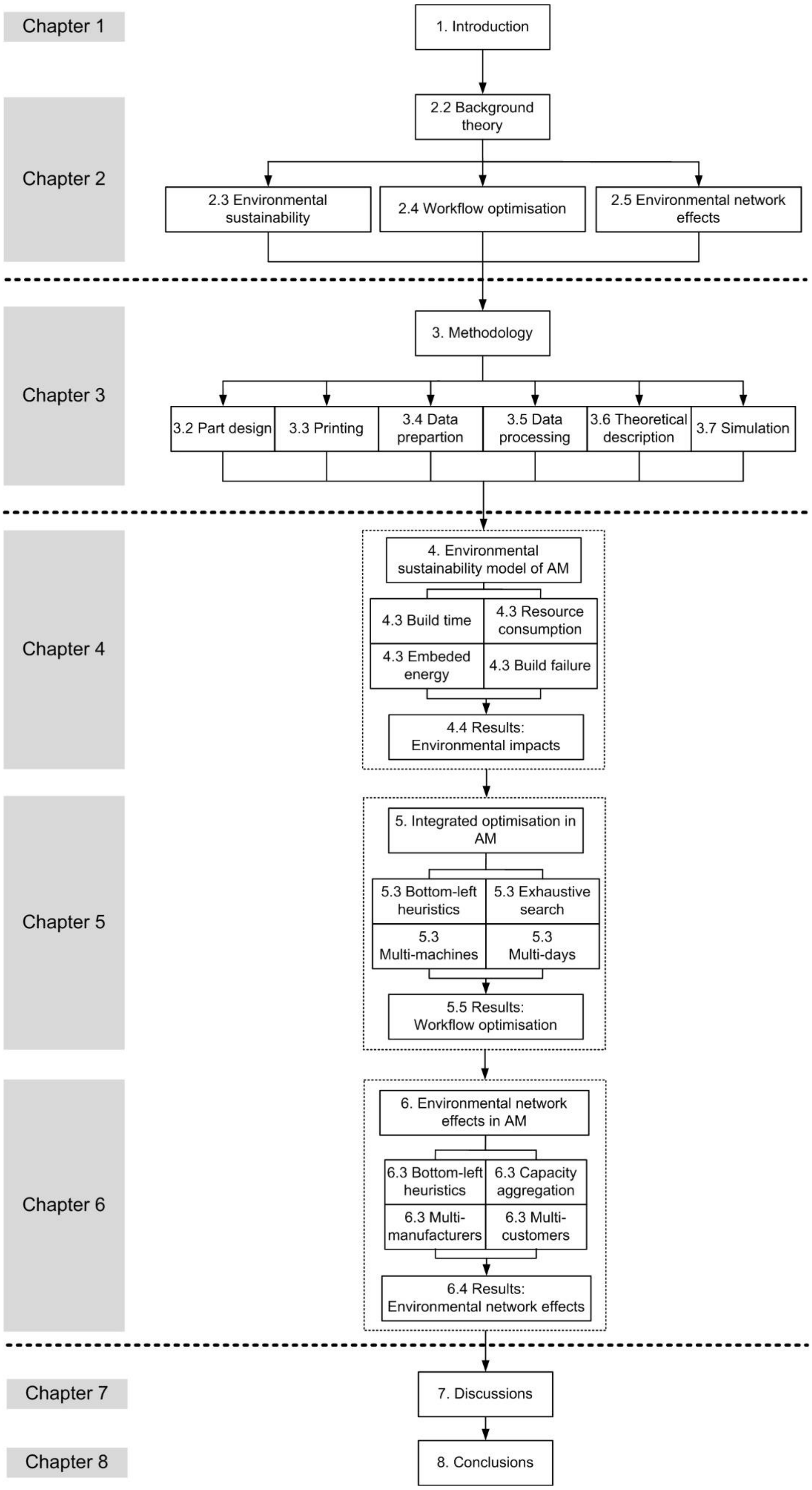


Figure 1.7: Structure of thesis chapters

1.5 Published work

[1] **Wang, H.**, Baumers, M., Basak, S., He, Y., & Ashcroft, I. (2022). The impact of the risk of build failure on energy consumption in additive manufacturing. ***Journal of Industrial Ecology***, 26(5), 1771-1783. https://doi.org/10.1111/jiec.13318

The following additional papers are currently under preparation:

[1] **Wang, H.**, Baumers, M., & Ashcroft, I. Minimizing the energy footprint of Additive Manufacturing: does integrating scheduling and packing optimization make a difference? (Preparing for submission)

[2] Basak, S., Baumers, M., **Wang, H.**, Hague, R., & Tuck, C. Cost Impact of Workflow Optimisation in Laser Sintering. (Preparing for submission)

Chapter 2: Literature review

2.1 Introduction and structure

This literature review aims to identify and evaluate the published work on the environmental sustainability of Additive Manufacturing (AM), the impact of risk of build failure on the energy consumption of AM, how workflow optimisation can be used to improve the energy efficiency of AM, and what are the network effects in the AM platform and how such effects may improve the environmental sustainability of AM.

This research merges interdisciplinary theories and methods from various fields, with AM technologies, environmental sustainability, and operations management, forming the background theory of the thesis, as presented in Section 2.2.

The following sections of this chapter present a summary and analysis of the literature in the areas of the environmental sustainability of AM, workflow optimisation, and environmental network effects. The relationship between the background theory and the focus of this work is shown in Figure 2.1. Specifically, Section 2.3 presents the current status of research on the environmental sustainability of AM; including energy consumption, material consumption, waste and pollution, life cycle analysis, and risk of build failure in AM. Section 2.4 provides an overview of workflow optimisation in AM, consisting of build volume packing, production scheduling, and integrated optimisation. Section 2.5 introduces concepts such as environmental network effects in AM, including industry platforms and network effects. Finally, a summary of this chapter is provided in Section 2.6.

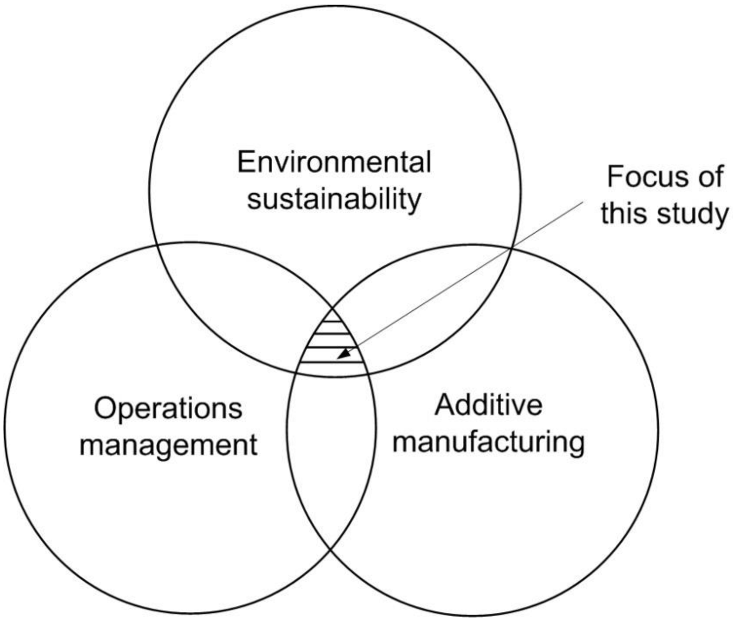


Figure 2.1: Areas of literature reviewed, indicating the focus of this study

2.2 Background theory

2.2.1 Additive manufacturing

Rapid prototyping (RP) technologies were initially developed in the 1980s for creating models and prototype components, however, when these technologies were further developed for end-use manufacture the term Additive Manufacturing (AM) was introduced (Wong and Hernandez, 2012). The basic principle of these technologies is that a digital model, generated through a three-dimensional Computer Aided Design (CAD) software application, can be fabricated directly (Gibson et al., 2021). From this viewpoint, AM is a computer-controlled process of converting the digital CAD model to the physical part as shown in Figure 2.2.

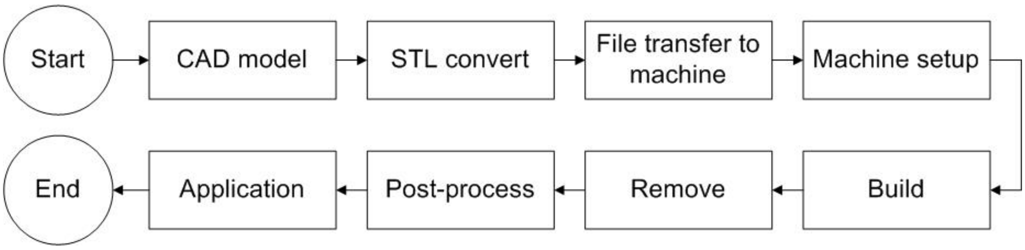


Figure 2.2: Generic process of AM process

(image source: adapted from Gibson et al. (2021))

Specifically, AM parts are designed and represented using CAD software or reverse engineering equipment, for example, laser scanning. Once the CAD model is finished, the following step is to output an STL file format, which can be read by AM machines. The STL contains the external closed surface information of the original CAD model, supporting the calculation of slices. Then, some manipulating operations are implemented to ensure the correct size, position, and orientation for printing when transferring the STL file to the AM machine. Prior to the printing process, the AM machine must be set up properly, for example by the selection of appropriate material, energy source, and layer thickness. The deposition process is then automatically conducted. Once the build is finished, the parts must be removed from the bed. The next step is to clean up the printed parts before they are ready for use, which may require time and experienced manual manipulation because parts may be weak at this stage. Before using printed parts, an additional treatment, e.g., heat treatment, polishing, priming and painting may be carried out. This ensures acceptable properties, surface texture and finish.

Depending on the focus, AM is sometimes called other terms including Automated Fabrication (Autofab), Freeform Fabrication or Solid Freeform Fabrication, Layer-based Manufacturing, or 3D printing.

Compared to conventional manufacturing, adopting AM has two main advantages: first, AM is likely to generate products with fewer geometric constraints. The product could be a complex geometry and multiple functions could be integrated into a single component. Second, AM allows customized production at a relatively low cost (Tuck et al., 2008, Pérez et al., 2020). However, the application of AM is still restricted by a set of limitations (Ruffo and Hague, 2007, Divakaran et al., 2022):

- Limited material availability
- Relatively low productivity
- Dimensional accuracy issues
- Poor surface finish

- Problems with repeatability
- Non-economical production at medium and large volumes

A number of AM technology variants are capable of producing end-use products. In these technologies, Polymer Laser Powder Bed Fusion (P-LPBF) is one of the most widely used techniques (Tuck et al., 2008, Ruffo and Hague, 2007). A schematic diagram of P-LPBF is presented to introduce the main components of this system as shown in Figure 2.3.

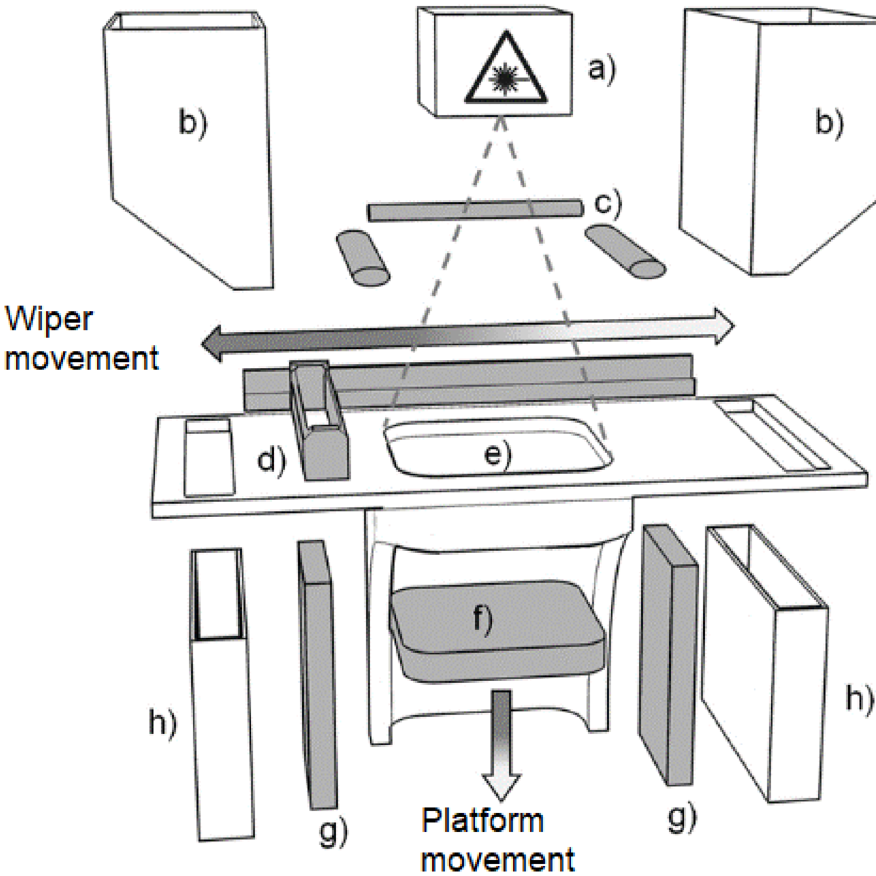


Figure 2.3: A schematic diagram of P-LPBF

(image source: Baumers et al. (2011a))

(a) Laser system; (b) powder feeding system; (c) infrared heaters; (d) powder deposition wiper; (e) build volume; (f) platform; (g) resistance heating elements; (h) overflow containers

This system is equipped with (a) a laser system, used to control a CO_2 laser beam to selectively sinter the preheated surface of the powder bed. This is situated at the top of the build volume (e). Polymer powder, for example, PA2200, is heated to a below-melting point in the build volume. Once the chamber temperature reaches the target level, a layer of 0.1 mm powder is spread on the bed. Consequently, a laser fuses the powder layer-by-layer based on the corresponding cross-section area of the part. The platform (f) is then dropped by the layer height and a wiper movement is implemented to deliver a new layer of powder. During this process, the unused powder is removed to an overflow container (h) for reuse. Layer by layer, the same procedures take place repeatedly until parts are finished in the build volume.

Due to its layer-upon-layer feature, AM allows the possibility of producing a variety of parts in a build and having a higher level of freedom of geometry for designers (Yang et al., 2015). This leads to wide industrial applications, for example, aerospace, automotive, jewelry, and pharmacy (Ben-Ner and Siemsen, 2017).

2.2.2 Sustainability

Sustainability is defined by the World Commission on Environment and Development (WCED, 1987) as "the economic-development activity that meets the needs of the present without compromising the ability of future generations to meet their own needs".

Attention should be paid to the environment not just due to its intrinsic value, but to save resources for future generations (Kuhlman and Farrington, 2010). To be a meaningful concept, Wilkinson et al. (2001) indicated that sustainability must involve maintaining, renewing, or restoring something specific. In addition, sustainability should also include ethical considerations, for example, the fairness of trade-off between current economic pressures and the future needs of the environment (Wilkinson et al., 2001).

Since then, the concept of sustainability has developed further (Kuhlman and Farrington, 2010) with the interpretation of sustainability from three aspects: economy, society, and environment, which is shown in Figure 2.4 (Helming et al., 2008, Robert et al., 2005, Tracey and Anne, 2008).

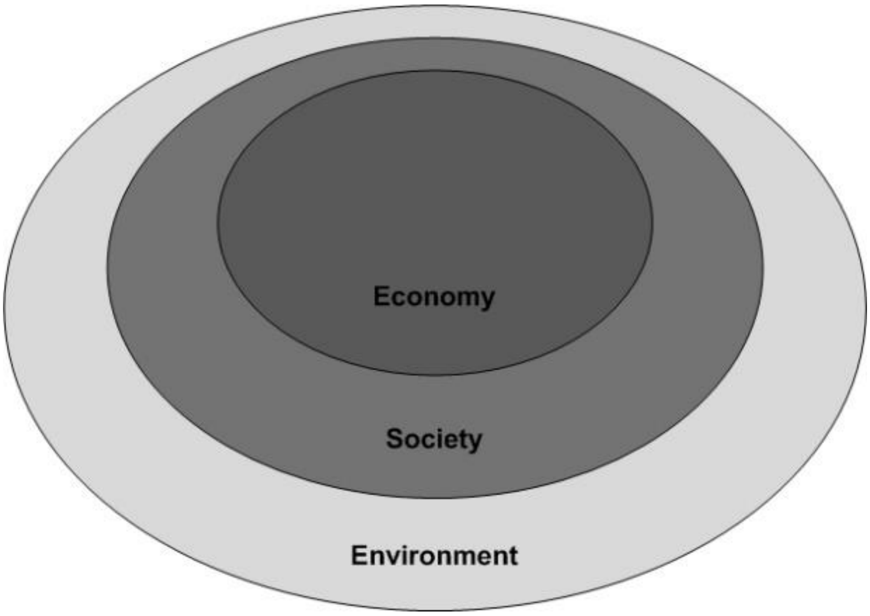


Figure 2.4: The "three-pillars" model of sustainability

(image source: adapted from (Caradonna, 2014))

In one variant of this so-called "three-pillars" model, the environment is viewed as the foundation of sustainability, and society and economy are nested inside. Victor (2021) argued that without the environment, society and the economy could not be supported. In other words, the environment should always be taken as the conceptual priority in any model of sustainability.

Due to its significance and research scope, this thesis concentrates on the environmental aspect of sustainability and a more detailed review of environmental sustainability of AM is provided in Section 2.3.

2.2.2.1 Environmental sustainability

According to Goodland (1995), promoting environmental sustainability is defined as seeking "to improve human welfare by protecting the sources of raw materials used for human needs and ensuring that the sinks for human wastes are not exceeded, in order to prevent harm to humans”. Generally, the term environmental sustainability tends to be seen as a detailed expression of sustainable development by specifying the needs as "resources and services" from an ecosystem's perspective. Specifically, environmental sustainability could also be a condition of keeping balance, resilience, and interconnectedness that allows human society to meet its needs from two aspects (Morelli, 2011):

- Without exceeding the capacity of its supporting ecosystems to continue to regenerate the necessary services.
- Without diminishing biological diversity through human activities.

The development of an accepted definition of environmental sustainability forms an important part of efforts to organize future human and economic development in a sustainable way. To do so, Morelli (2011) summarized 15 guidelines to provide more clarity of purpose and direction, as shown in Table 2.1.

Table 2.1 Fifteen guidelines to support the development of environmental sustainability (Morelli, 2011)

Dimensions	Guidelines
Societal needs	• Fabricating nothing will need further generations to maintain vigilance. • Delivering goods and services that facilitate a sustainable economy. • Supporting regional employment. • Supporting fair business. • Selecting the raw materials for new products and services based on environmental sustainability.
Preservation of biodiversity	• Choosing raw materials that sustain the biodiversity of natural resources. • Applying environmentally friendly and renewable energy sources.
Regenerative capacity	• Maintaining harvest rates of renewable source inputs within the regenerative capacities of the natural system. • Keeping depletion rates of nonrenewable resources inputs below the rate at which renewable substitutes are developed.
Reuse and recycling	• Designing for reusability and recyclability. • Designing manufacturing and business processes based on a circular economy, reducing emissions, and achieving zero waste.
Constrains of nonrenewable and waste generation	• The scale of the human economic subsystem should be constrained to a level. • Keeping waste emissions within the assimilative capacity. • Developing low-impact modes for transportation criteria. • Considering product development and management decisions from a complete cycle perspective.

The system's perspective is particularly helpful when considering the sustainability of a process or technology. When considering sustainability as an activity or system, three significant questions need to be addressed including (Bell and Morse, 2012): (1) what is the system to be protected and where is the system boundary? (2) what is the time scale? (3) what is the system quality that would be improved?

Forming a general framework for the assessment of a system's quality, Smeets and Weterings (1999) identified five indicators of environmental sustainability shown in Figure 2.5.

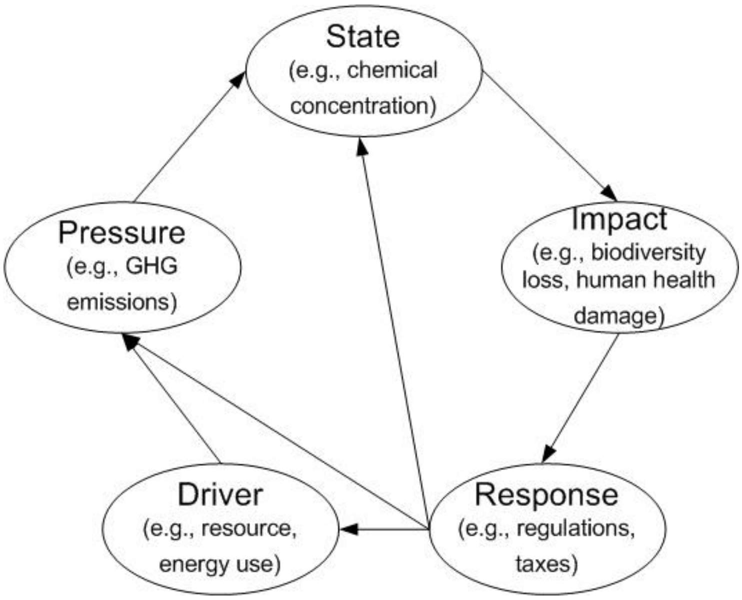


Figure 2.5: Five indicators of environmental sustainability

(image source: adapted from Smeets and Weterings (1999)**)**

In this figure, each indicator represents a specific type of environmental impact, and five indicators form the Driver-Pressure-State-Impact-Response (DPSIR) framework. Starting from D, "driver" reflects the resource needs of individuals and industrials. This leads to human activities that put "pressure" (e.g., GHG and chemical emissions) on the environment. Consequently, the "state" of an environment may be changed and pose a threat to the environment ("impact"), for example, biodiversity loss and human health damage. This finally triggers the "response" from the government including regulations and taxes.

Environmental sustainability refers to varied elements from different aspects, for example, emissions, resources, and regulations. Due to the scope of the investigation, this thesis only considered energy consumption, resource consumption (e.g., material), and waste to study the environmental sustainability of additive manufacturing. A more detailed literature review is presented in Section 2.3.

2.2.3 Operations management

Operations Management (OM) is associated with the activity of managing resources to produce and deliver products and services (Slack et al., 2010). OM can also be considered as the design, operation, and improvement of productive systems that are designed for getting work done. Operations are more than planning and controlling; it's doing. Whether it's superb quality, customization or low cost, excellence in operations is crucial to a company's success (Russell, 2011).

Operations is usually defined as a transformation process as shown in Figure 2.6.

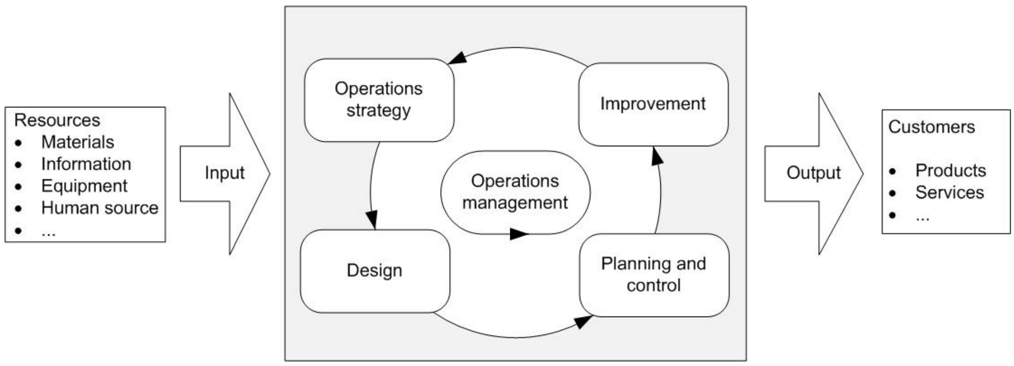


Figure 2.6: Overview of operations management

Specifically, inputs (e.g., material and information) are transformed into outputs (e.g., products and services) (Holweg et al., 2018). In OM, the transformation process is required to perform efficiently so that the output is of greater value than the sum of inputs. Therefore, operations has a significant role to play in creating value. This allows us to view the transformation process as a sequence of activities along a value chain extending from supplier to customer (Russell, 2011). The transformation process consists of three OM activities (i.e., design, planning and control, and improvement) and an operations strategy.

Importantly, the view of an operations system as transforming inputs into outputs also identifies it as the focus of environmental impacts and sustainability-related factors. This implies that OM approaches and methods can also have a significant effect on the performance of industrial systems such as AM technologies.

2.2.3.1 Planning and control

Planning and control are associated with the reconciliation between the market requirements and the operation's resources that can be delivered (Chapman, 2006). Specifically, planning is a formalization of what is intended to happen at some time in the future. Control is the process of handling changes in these variables. It may mean that plans need to be redrawn.

Planning and control require the reconciliation of supply and demand in terms of volume, timing, customer contact, and quality (Chapman, 2006). This literature review focuses on an overview of volume and timing because the main part of this study focused on these issues. According to Olhager (2013), four overlapping activities related to planning and control can be identified, as shown in Figure 2.7.

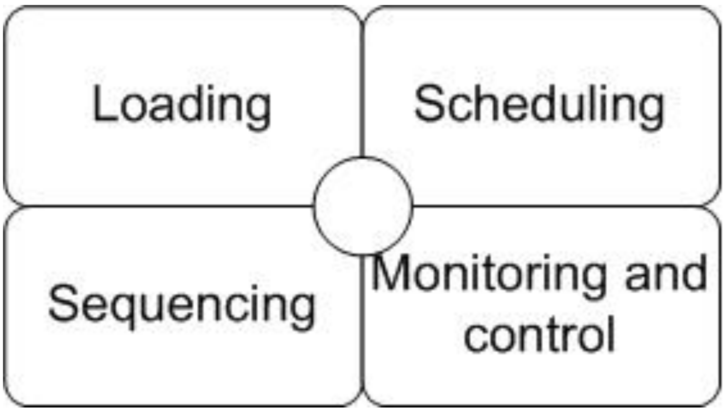


Figure 2.7: Planning and control activities

Loading means the amount of work that is arranged for a workshop. For instance, a machine on the shop floor of a manufacturing business is available 84 hours a week. However, this does not mean that 84 working hours would be loaded onto that machine due to the subject of the production tasks and situations (Slack et al., 2010).

When work arrives, decisions must be made on the order in which the work will be handled. This activity is called ***sequencing***. The priorities given to work in an operation are often determined by some predefined set of rules, for example, due date, last-in-first-out, and first-in-first-out (Pinedo, 2012).

Once the sequence of work has been determined, the next step is to allocate the available jobs on machines based on a detailed timetable showing the start time/date and end time/date of jobs. This process is called ***scheduling*** (Parente et al., 2020).

Having formulated a plan for the operation through loading, sequencing, and scheduling, the final step is ***monitoring and control***. Each part of the operation needs to be monitored to ensure the progress of the planned activities. Any deviation from the plans can be rectified through some interventions in the operation, which itself will probably involve replanning (Jones et al., 2001).

2.2.3.2 Operations performance objectives

OM can have a significant role in a business by affecting financial performance. Even when compared with the effects of other parts of the business, the contribution of operations can be considerable. To understand the strategic contribution of the operations, it is important to understand and measure its performance (Jacobs et al., 2004). According to Slack et al. (2010) and de Burgos Jiménez and Céspedes Lorente (2001), six operations performance objectives have been identified, as shown in Figure 2.8.

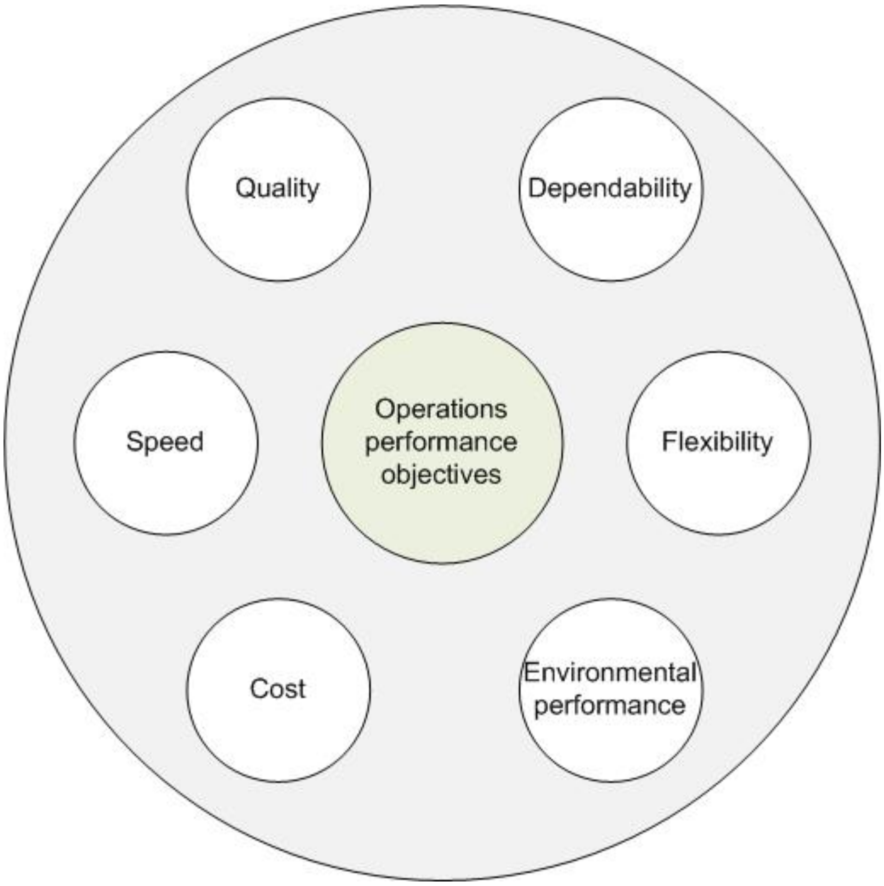


Figure 2.8: Operations performance objectives

Quality is consistent conformance to customer's expectations, but the things which the operation needs to do right will vary according to the type of operation. All operations view quality as a particularly significant objective. In some ways, quality is the most visible part of what an operation does (Akkerman et al., 2010).

Speed indicates the elapsed time between customers requesting products or services and receiving them. The main benefit to the operation's customers of speedy delivery of goods and services is that the faster they can have the product/service, the more likely they are to buy it, or the greater the benefit they receive (Powell and Schmenner, 2002).

Dependability is delivering products or services on time for customers exactly when they need them.

Flexibility represents being capable of changing the operation in some way. This may need to change what the operation does, how the operation does it, or when the operation does it (Slack, 2005). According to customers' needs, four types of requirements in terms of operational flexibility can be provided: (1) product or service flexibility – the operation's ability to produce new or improved products and services; (2) mix flexibility – the operation's ability to produce a wide range of products and services; (3) volume flexibility – the operation's ability to change its level of output to produce different quantities or volumes of products and services over time; (4) delivery flexibility – the operation's ability to change the timing of the delivery of its services or products.

Cost competes directly with the price of the companies, which will be the companies' major operations objective (Bettley and Burnley, 2008). The lower the cost of producing goods and services, the lower can be the price to the customers. Every pound reduced from an operation's cost base is a further pound added to its profits. In essence, low cost is a universally attractive objective.

Environmental performance is an objective towards sustainable development by products and processes innovation in firms in order to efficiently use raw materials and reduce the risks derived from environmental responsibility (de Burgos Jiménez and Céspedes Lorente, 2001).

2.3 Environmental sustainability of AM

OECD (2008) estimated that industrial users are the largest consumers of energy and that their consumption will continue to grow until 2050. In this context, it has been stressed that the energy consumption of manufacturing processes is a key determinant of sustainability for manufacturers (Baumers et al., 2013, Bourhis et al., 2013, Cappucci et al., 2020, Peng et al., 2019a, Peng et al., 2019b, Wang et al., 2017, Wang et al., 2018a, Wang et al., 2019a).

To measure the ecological impact of manufacturing activities, Kellens et al. (2012) stressed that information relating to manufacturing energy consumption, process productivity, and emissions is essential. However, it has been noted that the long supply chains and complex distribution networks in manufacturing increase the challenge of registering the resource flows (Surana et al., 2005). In this context, an important role falls to the measurement of carbon emissions originating from electricity consumption (Jeswiet and Kara, 2008). Building on such data, the main goal of "design for environment" methodologies is to minimize resource consumption during the manufacturing process (Telenko et al., 2008).

Compared to conventional manufacturing (e.g., machining, injection moulding), AM affords new possibilities in product design (Hague et al., 2004), digital supply chain deployment (Tuck et al., 2007), and the use of new build materials (Huang et al., 2013). In addition, AM has the potential for creating a positive impact on sustainability. The energy footprint of AM activities can be low, especially for those processes that do not involve long-term processing at elevated temperatures. Furthermore, there is no need for AM process to use cutting fluids, casting release compounds and forging lubricants, which pose a threat to the environment and health.

Some AM processes, particularly those based on metallic powder deposition methods, for example, Direct Metal Deposition (DMD) and Laser-Engineered Net Shaping (LENS) are particularly well suited for automated part repair. A significant amount of energy can be saved when a part is repaired or remanufactured and returned to working condition rather than being disposed of or sent to a landfill. Using AM, the entire production chain of tooling is eradicated. Since AM is characteristic of being regional or delocalized, transportation can be reduced. This lessens carbon footprint and overall environmental impacts. Finally, the advantage of AM on design freedom allows parts to be fabricated with superior energy consumption in service. Examples include gas flow paths, streamlined geometry and lightweight parts (Herrmann et al., 2008).

In summary, AM offers the potential for process sustainability improvement by improving resource efficiency (Despeisse et al., 2017), extending the lifecycle of products and eliminating the use of harmful ancillary process enablers (Gong et al., 2019, Jiang et al., 2019a, Sreenivasan et al., 2010, Verboeket and Krikke, 2019, Wang et al., 2018b). To complement sustainable AM, there is a need to improve manufacturing efficiency via less impactful supply chains (Huang et al., 2013), efficient processes and resource recycling (Despeisse et al., 2017, Kohtala, 2015).

2.3.1 Energy consumption of AM

An interesting topic to manage the growing global energy demand and the global CO_2 emissions requirement seemingly impossible balance was proposed at the "MIT A + B Applied Energy Symposia" conference (Li et al., 2020). This event aimed to emphasize the socio-economic and technical solutions with "A-Action before 2040" and "B-Beyond 2040 technologies", without irrevocable environmental and socio-economic impacts in the next decades (Sun et al., 2021). AM technologies hold great potential for saving energy embodied in the manufacturing process by reducing material waste and eliminating complex machining steps. It is reported that an extensive application of AM technologies is likely to lead to a significant saving of global energy use by as much as 27% (Verhoef et al., 2018).

A body of literature has investigated the energy consumption of various AM technology variants. Several studies have investigated the energy consumption of metal AM. Mognol et al. (2006) proposed a process capability criterion (i.e., topological and geometrical criteria) based method to manufacture the mould in multiple components using Laser Powder Bed Fusion (LPBF). Kellens et al. (2010) investigated the overall environmental impact of metal LPBF and Polymer LPBF (P-LPBF) in productive and non-productive modes. Baumers et al. (2010) presented a comparative assessment of the energy consumption of metal LPBF based on standardized geometry. Baumers et al. (2011b) provided an overview of energy consumption across different AM technology variants and suggested that the effect of capacity utilization on energy efficiency varies significantly across different platforms. Peng et al. (2021b) studied the impact of process parameters on part quality, electrical energy consumption, and corresponding energy effectiveness of AlSi10Mg specimens fabricated by metal LPBF. These studies provide a guideline for investigating the energy consumption of metal AM based on modelling, manufacturing modes, comparative research, and parameters.

In addition to metal AM, polymer-based AM also received much attention. Luo et al. (1999) presented a method to analyse the environmental performance of Stereolithography (SLA), P-LPBF, and Fused Deposition Modelling (FDM) considering the material, energy consumption, processes wastes, and disposal. Sreenivasan and Bourell (2009) and Sreenivasan et al. (2010) presented a sustainability analysis of the P-LPBF process from an energy standpoint using a LabVIEW 8.6 circuit. Faludi et al. (2015) performed a Life-Cycle Assessment (LCA) approach to compare the environmental impacts of FDM and inkjet/polyjet with a traditional Computer Numerical Control (CNC) milling machine to determine the most sustainable manufacturing method. Wiese et al. (2021) developed a model for the evaluation of energy and resource utilization based on a case study with an automotive exterior series part using P-LPBF and Multi-Jet Fusion (MJF) technologies. Lopes et al. (2022) intended to evaluate the impact of energy density on the dimensional, geometric, mechanical, and morphological properties of P-LPBF parts produced with Polyamide 12 material. The aforementioned literature lays a foundation for studying energy consumption in polymetric AM from modelling, LCA adoption, and comparative research perspectives.

Sun et al. (2021) reported that the AM processes and printed products must be validated and qualified to satisfy the standards of critical parts in energy production (e.g., nuclear energy, oil, and gas), conversion, and storage systems (e.g., battery and fuel cell). Di and Yang (2022) investigated the economic and environmental benefits of the integrated Production-Inventory-Transportation (PIT) supply chain structure and suggested that this structure enabled by AM allows a reduction of approximately 26% of Greenhouse Gases (GHGs) emissions.

Additionally, the energy embedded in the used raw materials and the process energy consumption is considered in some studies. Morrow et al. (2007) calculated the energy consumption of DMD in this way for virgin H13 steel powder. Baumers et al. (2017b) measured the energy embedded in recycled Ti-6Al-4V cast material. Gao et al. (2021) analysed the energy consumption of raw metal material extraction and subsequent AM processes. Liao and Cooper (2020) investigated the embedded energy of feedstock material (powder and any inert shielding gas) in metal powder bed processes. Van Sice and Faludi (2021) compared the environmental impacts of AM and conventional manufacturing, showing that metal AM has a significantly higher environmental footprint than some conventional processes (e.g., metal machining, and casting). Monteiro et al. (2022) undertook a literature review in terms of metal AM and summarized four aspects of resource efficiency strategies including design, material, process, and end-of-life extension.

2.3.2 Material consumption of AM

AM has a great potential for improving materials use, alleviating environmental issues, and enabling greater engineering utility compared to conventional manufacturing technologies. This can be attributed to factors such as freedom from special tooling or moulds in fabrication, rapid tooling manufacturing and, significantly compared to extractive processes, material waste reduction. Taking advantages of these sustainability opportunities, AM has the potential to exert a positive influence on the performance of a part from "gate to grave" which is a significant part of the complete life cycle (i.e., “cradle to grave”) (Sreenivasan et al., 2010). A creative design, for example combining multiple components into a single part is likely to facilitate recycling and disposal in AM, particularly for plastics and metals.

Though LPBF is 97% material-efficient in theory and wasting only a small amount of raw material in the form non-reusable powder (Allwood et al., 2011, Achillas et al., 2015, Peng et al., 2018), the material efficiency reached is usually much less than this in practice due to failed parts and material loss. Investigating material losses, Ruffo et al. (2006) modelled material wastage by applying a waste factor, between 0 and 1, to unprocessed powder in a study of polymeric laser sintering. Similarly, Kellens et al. (2011) applied a refresh rate of around 45%, as suggested by Dotchev and Yusoff (2009), to quantify the waste streams occurring in laser sintering. For polymeric powder bed fusion, Baumers and Holweg (2019) found that approximately 90% of powder remains in the build space without being converted into parts, and approximately 10% to 50% of this remaining powder is typically discarded depending on the material used.

In addition to the refresh rate, a set of literature has studied the impact of material on environmental impacts. Kerbrat et al. (2016) presented a new methodology to accurately evaluate the environmental impacts of an AM part and the results indicated that material consumption should be taken into consideration for a complete environmental impact assessment. Similar research can be found in references (Kellens et al., 2017a, Kamps et al., 2018), to support the argument that materials have significant effects on the environmental impacts of AM since the energy embedded in the material is the largest contributor to the energy footprint. To mitigate its impact on the environment, the reduction in material use has been investigated based on model analysis, assessment approach, process planning, and optimisation.

In terms of model analysis and assessment, Meteyer et al. (2014) created a Unit-Process (UP) level model to analyse energy and material flows in the Binder Jetting (BJ) process. Le Bourhis et al. (2014) presented a new resource consumption assessment methodology including electricity, fluids, and raw material for the DMD process to help engineers obtain an environmentally friendly design for AM parts. Yosofi et al. (2018) presented a generic method for the acquisitions and characterization of inventory data for parts made by AM processes to accurately assess the environmental impact of a product, including energy consumption and material use. These studies allow the possibility of lessening the environmental impacts of material aspects in AM by using modelling and assessment approaches.

Regarding process planning, Jin et al. (2017a) proposed a design strategy relevant to process planning focusing on the material consumption of relatively large-volume solid parts in AM. Jiang et al. (2019b) proposed a new support generation strategy considering both interior and exterior support through AM process planning to reduce the total amount of material use, production time, and process energy consumption. Jiang et al. (2019c) presented a support generation method to reduce the use of support material through printing path planning in AM. Jiang et al. (2019d) constructed a four-step strategy to reduce the use of support material in AM for multi-part production and the results indicated that this strategy can significantly reduce the support waste and total build time. Jiang and Ma (2020) offered a review and discussion in terms of path planning strategies from three aspects: improving printed qualities, saving materials or time, and achieving objective printed properties. These investigations offer an angle of view to reduce material use by using process planning approaches.

It is reported that machine chips account for a large share (e.g., 13.7% aluminium and 14.6% steel) of the waste produced from all conventional manufacturing processes globally (Cullen and Allwood, 2013). A promising area of research could be the exploration of AM feedstock generated from other manufacturing processes (Huang et al., 2013, Frosch and Gallopoulos, 1989, Sutherland et al., 2020). This might involve some examples including taking machined chips either directly or after modest processing as the raw material of AM process, leading to less material consumption and environmental impacts. Such materials need further treatment to ensure that are intrinsically environmentally friendly, including the requirement to be non-ecotoxic and biodegradable.

2.3.3 Waste and pollution of AM

To make a product, subtractive manufacturing is likely to generate a large amount of waste. This may be reduced by as much as 90% when using AM instead (Janicke and Jacob, 2013). Although AM seems to be more resource-efficient than conventional manufacturing processes, it still produces a small portion of waste. Examples of AM waste include powder materials that cannot be recyclable, scraped material due to build failure, unexpected defects, and support structures used in metallic additive processes (Huang et al., 2013, Baumers et al., 2017b). These either generate material waste or introduce extra raw material consumption.

To date, only a small research effort has been directed at optimizing the printing path and support structure for raw material reduction, and this particularly for FDM (Jin et al., 2017b). Research on assessing metallic and ceramic AM waste is rare. One reason could be that no actions or regulations have been conducted to investigate the management of material waste, even at the frontline of upgrading sustainable manufacturing, which might be due to the fact that the current AM industry still accounts for a relatively small share of industrial manufacture (Drizo and Pegna, 2006). Data is missing to showcase the total amount of waste generated through AM technologies (Dotchev and Yusoff, 2009).

Concerning material waste, Jiang et al. (2018a) presented a new support strategy including Printable Threshold Overhang Angle (PTOA) and the Longest Printable Bridge Length (LPBL) to reduce material use. Jiang et al. (2018b) investigated the parameters of printable overhang angle size to reduce build time and material waste by reducing support structures. The results found that a lower threshold overhang angle tends to reduce support waste. Mohammed et al. (2018) demonstrated that using a nanogrid device to power instrumentation for melt extrusion of waste polymers into 3D printer filaments is beneficial to supporting near-zero carbon footprint. Jiang et al. (2019d) offered a four-step strategy of multi-part production to reduce material waste for a support structure in AM. Romani et al. (2021) explored the interdisciplinary relationship among design, material science, and AM in the context of the circular economy. Ferreira et al. (2021) provided a literature review in terms of industrial symbiosis and AM to identify the use of waste as input material during AM processes and the resource exchanges in an industrial symbiosis environment. In all this work it was shown that support structures have a significant role in material waste in AM.

In addition to material waste, the research on the pollution of AM also received much attention. Sun et al. (2021) stated that advanced manufacturing technologies, such as AM, are capable of extensively cutting GHGs emissions, and pollution, and shortening the time-to-market. Huang et al. (2013) mentioned that it is necessary to investigate particulate matter formation during the printing process and the explosive hazard of powder material during the handling and use processes. Byard et al. (2019) adopted the Gigabot X, an open-source industrial 3D printer for a wide array of recyclables, to assess the economic potential of AM. Based on these studies, it is suggested that some efforts should be put into mitigating pollution problems during the additive process.

However, study of the toxicity and damage impact of AM materials is rare (Dotchev and Yusoff, 2009). Compared to conventional manufacturing, AM rarely use potentially hazardous consumables, such as cutting fluids, forging lubricants, and casting release compounds. For example, FDM produces parts with non-toxic thermoplastic materials, e.g., polylactic acid, and polyethylene terephthalate, which are processed under the melting temperature (Tabone et al., 2010), which has less demand on heating energy for the nozzle and worktable (Peng and Sun, 2017). The emission of Ultra-Fine Particles (UFPs) has raised many concerns, and Stephens et al. (2013) suggested that attention should be paid to the operating process, particularly in an unvented or unfiltered indoor environment.

2.3.4 Life cycle analyses of AM

Although adopting AM has great potential for improving processing sustainability, the sustainability of other stages in AM (e.g., raw material extraction and use) should not be ignored (Ford and Despeisse, 2016). These include “cradle to gate” and “cradle to grave” life cycle analysis and the development of green supply chains. As suggested by Sreenivasan et al. (2010), it is important when predicting and assessing the sustainability of AM products to include life cycle perspectives.

The origins of life-cycle centric product development can be traced back to the 1960s when the environmental movement provoked some designers to consider some environmental issues, for example, resource depletion and environmental damage from material production into product design (Fuller, 1963, Fuller, 2008). To this end, the concept of sustainable product development was formally introduced in the Brundtland report (Haapala et al., 2013, van Weenen, 1995). This led to the development of many design tools to support sustainable product development (Bovea and Gallardo, 2006, Luttropp and Lagerstedt, 2006, Ramani et al., 2010). Most of these tools, particularly those adopted by companies, are in the form of checklists and guidelines that were largely established based on expert viewpoints. However, Hocking (1991) judged that the environmental performance of products is rather a complex choice since energy or material consumption and emissions over the complete life cycle of the product must be considered. This insight raised many concerns about the effectiveness of sustainable design approaches because only isolated recommendations are available from the checklists and guidelines. Fortunately, LCA methodologies have been developed over a similar timeline to that of sustainable product development (Standardization, 2006).

LCA investigates resource exchanges and flows, such as material and energy flows from and to the environment across the complete life cycle of a product ("cradle to grave"). As a widely used tool for environmental impact assessment, LCA offers a large amount of information to support sustainable product development. This approach has received much attention in AM-related research, which could be divided into two categories including review and technical comparison.

Regarding the review of LCA in AM, Frazier (2014) provided a comprehensive review of the state-of-the-art of metallic AM from the technology, mechanism, business, and environmental perspectives. Agrawal and S (2019) reviewed sustainable additive manufacturing considering energy consumption, design optimisation, and LCA aspects. Colorado et al. (2020) offered a comprehensive review in terms of the sustainability of AM from the circular economy and recycling of materials to other environmental challenges involving the safety of materials and manufacturing. Gao et al. (2021) reviewed the life cycle of metal parts printed by AM technologies and provided a comprehensive and timely discussion in terms of energy efficiency. The above literature offers a detailed review of LCA adoptions in AM from an environmental sustainability perspective.

Other research in this area focuses on a comparison of environmental impacts of AM with conventional manufacturing technologies. Faludi et al. (2015) adopted LCA to compare the environmental impact of two AM machines with a traditional CNC machine. Bours et al. (2017) established a framework that combines LCA with sustainable design metrics, including the considerations of both human health and environmental impact in the later stages of AM life cycle. Bekker and Verlinden (2018) performed a cradle-to-gate LCA to compare Wire and Arc Additive Manufacturing (WAAM) with green sand casting and CNC milling, developing a new insight into the environmental impact of WAAM. Stieberova et al. (2022) quantified the environmental and economic benefits across the entire life cycle of the application of DMLS in the production of metal moulds compared with their die casting. Landi et al. (2022) analysed and compared the environmental impact between CNC and LENS technologies using LCA. These studies provide comparative investigations between conventional manufacturing and additive manufacturing, aiming to support the selection of environmentally friendly manufacturing technology in production.

2.3.5 Risk of build failure in AM

Build failure poses a risk to product quality and further influences the energy and material flow in AM through the need for reprinting. This failure may change energy demand, material supply, and the nature of production planning (Holmström et al., 2016). The existing literature investigating build failure in AM is divided into four categories: software-based simulation (Bresson et al., 2022, Chakraborty et al., 2022, Ge and Flynn, 2022), design optimisation (Misiun et al., 2021, Xu et al., 2022), data-based estimation (Jirandehi et al., 2022, Wang et al., 2021), and mechanism exploration (Osswald et al., 2021, Roh et al., 2021).

Baumers and Holweg (2019) conducted build failure-related experiments and observed four types of failure: outright build failure, permanent part rejection, reparable part rejection, and mechanical property failure. Table 2.2 compares each type of build failure, including assumed consequence, model element, assumption, and probability.

Table 2.2: Overview of build failure modes

Failure mode	Outright build failure	Permanent part rejection	Reparable part rejection	Mechanical property failure
Consequence	Loss of the entire build	Loss of individual parts	Remedial work to the affected part	Loss of the entire build
Model element	Probability of build failure as a function of the cumulative number of printable layers	Constant probability of part rejection due to identical test geometries	Constant probability of part rejection due to identical test geometries	N/A
Assumption	The probability of build failure is subject to a constant probability of failure per layer $(P_{constant})$	Fixed probability $(P_{non-correctable})$	Fixed probability $(P_{correctable})$	N/A
Probability	$P_{constant} = 0.016\%$	$P_{non-correctable} = 2.500\%$	$P_{correctable} = 0.833\%$	N/A

Outright build failure, the first failure mode, is seen as an unforeseen event that happens at some point during operation, resulting in the failure of all parts contained in a build and the premature termination of the printing process. Adopting a variant of the Mean Time Before Failure (MTBF) metric, this failure can be estimated in the form of the reliability of AM process (Hopp and Spearman, 2011). Specifically, it is represented by a ratio of the number of outright build failure events and the total printed layers in the experiments. In this failure mode, each build layer is assumed as an independent additive process and the failures are randomly distributed per layer.

The second failure mode, permanent part rejection, is relevant to localized events appearing during the printing process and causes the loss of individual parts. As the classical manufacturing defect, it might occur, for example, when foreign objects appear in the build volume and impact the printing process, resulting in part deformation.

Reparable part rejection, the third failure mode, occurs when an individual part is rejected but it is possible to be corrected after the build has been finished. This type of failure can be identified by visually inspecting and the dimensional measurement of test geometries.

The fourth failure mode, mechanical property failure, is identified as an unacceptable variation in the mechanical properties of the product. The feature of this mode is determined via the test of tensile specimens contained in each build experiment. In practice, this failure may be derived from insufficient refreshment of the powder remaining in the AM machine.

According to Baumers et al. (2017a), risk-related costs account for approximately 26% of total cost in the real AM build configuration. However, such impact on the environmental performance of AM, in terms of both process energy consumption and the energy embedded in the used raw materials, has not yet been investigated directly and in combination. This forms a significant omission in the currently available literature on AM.

Although AM supply chains can use significantly less energy, due to the shorter transportation and less material use, the high energy needs of some AM processes and material preparation should not be underestimated (Li et al., 2017a). Due to the risk of build failure, which can be substantial in AM (Baumers and Holweg, 2019), it is likely that the available methodologies for measuring the energy impact of AM understate the actual levels of energy consumption.

2.4 Workflow optimisation for sustainable AM

As discussed, the application of AM may form a route to enhance manufacturing sustainability. For example, such improvements may occur through improvements in resource use efficiency (Allwood et al., 2022, Duflou et al., 2012) or by prolonging the in-service life of parts (Wang et al., 2017, Verboeket and Krikke, 2019, Govindan, 2022, Ijomah et al., 2007, Jiang et al., 2020). To realize sustainability benefits from AM, complementary innovation is required in terms of new supply chain configurations (Huang et al., 2013) as well as more efficient process and resource recycling practices (Despeisse et al., 2017, Kohtala, 2015).

The process flow in AM is dependent on a set of activities relevant to the design, printing process, and downstream considerations. To better understand the scope, this research formulated a general framework by combining the digital manufacturing process with the generic workflow of AM and downstream, which is shown in Figure 2.9.

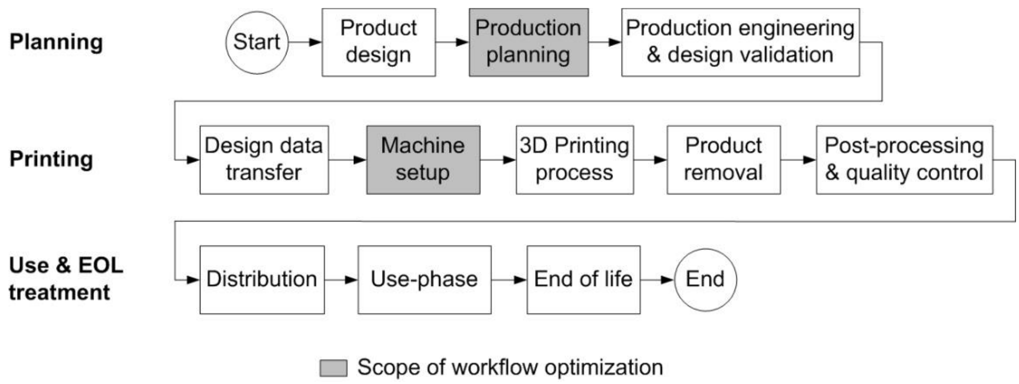


Figure 2.9: Scope of workflow optimisation in the overall process flow of AM (image source: adapted from Baumers et al. (2016))

According to Baumers et al. (2016), the combination of production planning and machine setup in a single optimisation-based framework is capable of maximizing the performance of AM execution and determining appropriate supply chain configurations.

This study operated from the premise that how the AM workflow is managed has a strong and underappreciated bearing on the sustainability of the additive process. The management of AM workflow chiefly requires the tasks of machine scheduling over time and assembling individual AM build operations, also referred to as *builds*, by allocating and placing in geometries within the build space internal to AM machines. This task is known as *build volume packing* and is usually executed to maximize capacity utilization (Che et al., 2021). In this context, it has been shown that the manufacturing process of AM dominates its environmental impacts (Kellens et al., 2017a) and that improvements in the pattern of operation can reduce AM's energy footprint as well as its financial costs. Increasing the capacity utilization ratio of machines tends to reduce unit costs and energy consumption (Baumers et al., 2017a, Baumers et al., 2011b).

The combinatorial problems of optimizing the workflow in AM, which can be labelled *capacity aggregation*, have been studied extensively. In the extant literature, four distinct categories of research are identifiable in the literature. These are: packing optimisation, schedule optimisation, separate optimisation of scheduling and packing, as well as integrated optimisation of scheduling and packing.

To illustrate the function of a workflow optimisation system that deals with scheduling and packing in sequence, Figure 2.10 summarizes the system that composes a workflow from *P* parts for *M* AM machines with a fixed sequence of build volume packing and then scheduling.

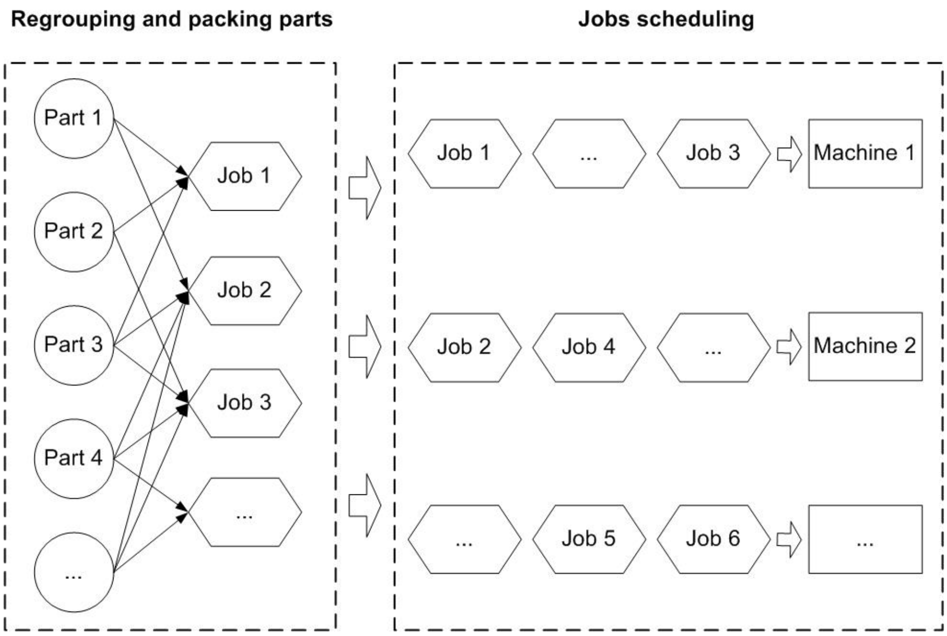


Figure 2.10: Workflow of scheduling and packing

(image source: adapted from Chergui et al. (2018))

2.4.1 Build volume packing in AM

AM, a parallel manufacturing process, is capable of processing different part geometries in a single build volume simultaneously (Ruffo and Hague, 2007). There arises a build volume packing problem resulting from the machine setup process, which is best addressed through computational approaches (Hur et al., 2001, Nyaluke et al., 1996).

Romanova et al. (2019) studied a packing problem in AM for ellipses that are placed into an arbitrary disconnected polygonal domain. Araújo et al. (2019) reviewed existent general cutting and packing taxonomies and provided a new specification to classify the problems that appeared in AM. Yılmaz (2020) established an optimisation model for the problem of AM build processes and vehicle scheduling in a two-stage supply chain, where parts are processed on AM machines and delivered to customers. Altekin and Bukchin (2022) addressed the simultaneous allocation of parts to jobs and jobs to the AM machines as well as considered the cost and makespan (i.e., the time difference between the start and finish of a sequence of jobs or tasks) as objectives for the Direct Metal Laser Sintering (DMLS) technology. These studies offer an understanding of packing issues and the solutions to solve them.

Before arranging the parts on the bed, the representation of the parts to be produced is required. This can be achieved, for example by projecting geometric information onto the horizontal plane or by a Boolean union of all slices of parts after a slicing process (Canellidis et al., 2013, Zhang et al., 2016). In other cases, 3D geometry can be extracted directly from a CAD software package, for example in the STL format.

After obtaining the required geometrical data, geometries are usually converted into a format that can be used by packing algorithms. The simplest method is to use the bounding rectangle based on the projection of the part on the horizontal plane to represent the real part. In this way, such a problem is named 2D packing (Bennell and Oliveira, 2008). This kind of method tends to be efficient and accurate to represent some kinds of polygons but may add some complexity when dealing with curves or more irregular shapes.

Furthermore, the geometric shape of parts may not easily representable, for example if it has a complex internal structure. In this situation, the aforementioned projection method may not be able to precisely represent the geometries when meeting special features, for example, cavities inside a geometry.

In practice, the implementation and use of such computational tools must balance solution efficiency and quality. Nevertheless, the bounding box of geometry is often used to represent the real part. Depending on the ways of packing parts in a build volume, such a problem is named 2D or 2.5D packing (Novak et al., 2019).

In addition to the above approaches that have been used to build volume packing in AM, many other possible solutions for the 3D Irregular Packing (3DIP) problem, for example, pixel/raster and Deepest Bottom-Leftfill Packing (DBLF) (Bennell and Oliveira, 2008, Araújo et al., 2020).

In summary, current approaches to build volume packing problems in AM include one dimensional (Yılmaz, 2020, Altekin and Bukchin, 2022, Kucukkoc, 2019, Ransikarbum et al., 2020), two-dimensional (Che et al., 2021, Hu et al., 2022, Oh et al., 2018a, Tafakkori et al., 2022), and three-dimensional packing (Araújo et al., 2020, Wu et al., 2014, Yau and Hsu, 2022).

A variety of packing approaches have been investigated to achieve the specific objectives. The selection of the best packing technique is dependent on the attributes of the problem, the production constraints of the AM technology used, and material requirements (Hur et al., 2001, Canellidis et al., 2006, Ikonen et al., 1997).

Some algorithms, for example, address the free allocation of parts within the build volume. This may result in an unwanted configuration in that one part is placed on top of others (Araújo et al., 2019). These approaches tend to be used for relatively unconstrained AM technologies such as P-LPBF where a support structure is not required

(Gibson, 2015). Other AM technology variants may need more consideration of the need of support structures, for example, SLA, SLM, and EBM.

Cutting and Packing (C&P) algorithms have been a long-standing subject of investigation in the field of Operations Research (Chernov et al., 2010, Côté and Iori, 2018, ElShishtawy et al., 2022, Gomes et al., 2016). From this viewpoint, build volume packing forms a type of combinatorial optimisation problem where a set of arbitrarily shaped items must be packed into given build volumes or chambers. In this way, the total empty room between parts is minimised (Wäscher et al., 2007). Such optimisation problems are classified as NP-Hard (Garey and Johnson, 1979). To this end, the packing algorithms have been investigated extensively.

Some studies have investigated the Genetic Algorithm (GA) for build volume packing optimisation. Wodziak et al. (1994) employed GA to obtain a near-optimal arrangement of parts by considering their bounding boxes to make the utmost use of the available build space and minimize the build time. Hur et al. (2001) developed a hybrid BL and GA approach to determine the best build layout considering the orientation and packing of multiple parts in P-LPBF. Canellidis et al. (2006) adopted the GA technique to identify the satisfied fabrication orientations and packing arrangements of parts in conjunction with a new improved packing rule. Canellidis et al. (2010) combined GA, Bottom-Left (BL), and effective placement rules as a means of optimizing the build volume of AM. Zhang et al. (2018) proposed an integrated strategy including AM feature-based orientation optimisation and parallel nesting with GA to solve the 2D packing optimisation of multiple parts. These investigations allow build volume packing improvement by using metaheuristics, facilitating the shift from digitalization to intellectualization in AM.

Local search methods for packing optimisation have also received much attention. Egeblad (2009) adopted a local search algorithm to obtain an optimized placement of irregular shapes in 2D or 3D in a build without shapes overlap. Egeblad et al. (2009) used an efficient approach to pack d-dimensional polytopes within the bounds of a polytope build volume using local search, aiming to minimize the volume of overlap with all other polytopes. Lee et al. (2009) developed a local search-based method to allow an efficient implementation of key operations, including wall overlapping detection of particle–particle and particle–container, accurate identification of the overlapping region, as well as particle shifting and rotation. Lutters et al. (2012) proposed a local search-based algorithm for 3D packing of complex-shaped geometries, including the determination of the preferred orientation of a part and actual packing stages. Liu et al. (2015) proposed a local search-based algorithm for the 3D packing of irregularly shaped parts with minimum total energy. The above literature lays a basis for obtaining optimized solutions through a computational way in build volume packing.

A set of studies have been conducted on Tabu Search (TS), a heuristic method to various combinatorial problems, for addressing 3D packing optimisation problems. Lodi et al. (2004) used a tabu search method to address 2D and 3D bin packing problems, as well as exhibited virtually any of their variants requiring the minimization of the number of bins. Crainic et al. (2009) utilized a two-level tabu search approach to solve the 3D orthogonal bin packing problem where a set of boxes must be orthogonally packed into the minimum number of bins.

Compared to using heuristics, mathematical modelling, a conventionally analytical approach, has also been used in build volume packing optimisation. Stoyan et al. (2005) developed a mathematical model to address the problem of packing convex polytopes into a parallelepiped of minimal height. Chernov et al. (2010) established mathematical models and used practical algorithms to solve C&P problems.

In summary, it has been found that there are many approaches to address build volume packing problems in AM. A feasible way is to select those methods based on the attributes of the specific problems (Jian and Wang, 2014).

2.4.2 Production scheduling in AM

As outlined previously in this review, AM systems are capable of producing multiple parts simultaneously, subject to the capacity and printing area for parts. This characteristic benefits AM in settings which require the manufacture of medium/low volume or small batch products with complex structures and geometric designs and in mixed configurations (Li et al., 2017b, Mellor et al., 2014).

In AM machine scheduling, a job is defined as a group of parts to be printed in the same batch, i.e., forming a single build operation. Any part allocated in a job cannot be removed until the whole job is finished. To begin with, in a new job on an AM machine, a sequence of operations is implemented to set up the machine, for example, parameters setting, powder material filling, machine adjustment, and atmosphere creation, as shown in the relevant parts of Figure 2.11.

The problem of production scheduling in AM was treated by Kucukkoc et al. (2016) who established that complex packing problems need to be addressed by assembling tasks into different jobs and implementing jobs on various AM machines. The authors defined the structure of the production scheduling problem and provided a numerical example for the verification of the proposed heuristics. Following this seminal research, Li et al. (2017b) introduced the problem of production planning in AM and 3D printing. They integrated a mathematical model in CPLEX and proposed two heuristics: 'best-fit' and 'adapted best-fit' rules developed in JavaScript to address the above problems.

Due to its significance in production, scheduling optimisation has been studied considerably. Fera et al. (2018) offered a mathematical model to investigate production scheduling in metal LPBF. Kucukkoc (2019) proposed a mixed-integer linear programming model to achieve scheduling optimisation in single and multiple AM machine scenarios. Kapadia et al. (2022) developed a random keys-based GA method to address production schedule issues, satisfying all technological constraints, including orientation and rotation of parts within the build volume. Arık (2022) proposed a Mixed-Integer Programming (MIP) model and adopted a local search-based heuristic to address the single-machine batch scheduling problem. Wu et al. (2022) constructed a mixed integer linear programming model to minimize the average cost per volume of material in AM scheduling. These studies provide solutions to solve scheduling optimisation problems based on modelling and metaheuristics methods, laying a basis for sustainable production in AM.

2.4.3 Integrated optimisation in AM

To achieve a high degree of production efficiency and resource utilization in AM, both build volume packing and scheduling must be executed to a high standard in AM (Aloui and Hadj-Hamou, 2021). The available literature investigating both aspects simultaneously can be divided into two categories: (1) separate optimisation of scheduling and packing; and (2) integrated optimisation of scheduling and packing.

Concerning separate optimisation, Freens et al. (2015) proposed a two-stage approach to automatically generate batches for multiple AM machines including (1) allocating parts to a batch, an extension of the bin packing problem; and (2) determining the positions of planned parts using 3D packing software from the provider Shapeways (Shapeways, 2023). Li et al. (2017b) formulated the problem of production planning of AM with a mathematical model incorporating Best-Fit (BF) and Adapted Best-Fit (ABF) heuristics. Chergui et al. (2018) converted the multi-parts production planning and scheduling in AM into two stages: parts assignment and jobs scheduling. Oh et al. (2018b) developed an AM-based production plan for the scenario of multiple parts and multiple machines. This consisted of three stages: (1) determining build orientation; (2) 2D packing of parts within the available build space; and (3) scheduling parts on multiple AM machines. Karimi et al. (2021) proposed a systematic approach to realize energy-aware production scheduling for AM and address process-level and scheduling-level controls. These studies offer a way of improving resource utilization from the production planning perspective, facilitating the mitigation of environmental impact of additive processes.

With respect to integrated optimisation, Zhang et al. (2020) developed an improved evolutionary algorithm to address scheduling and packing integrally in AM by combining GA with a heuristic placement strategy. Ransikarbum et al. (2020) proposed a decision-support tool to integrate production scheduling and distribution planning in Material Extrusion (ME), SLA, and P-LPBF. Aloui and Hadj-Hamou (2021) used a mixed linear programming to solve the packing and scheduling problem on powder-based laser and multi-jet fusion platforms. Tafakkori et al. (2022) proposed a novel integrated framework for packing and scheduling in AM.

To better address the packing and scheduling problems in AM, some studies have investigated alternative solution approaches, including mathematical models and heuristics. In terms of the mathematical models, Chergui et al. (2018) formalised the packing and scheduling problem in AM to satisfy the orders received from different distributed customers by due dates. Kucukkoc (2019) proposed mathematical models to address scheduling problems in single and multiple AM machine scenarios. Hu et al. (2022) established a mixed integer linear programming model to address AM scheduling problem considering unrelated parallel machines.

However, when relying on mathematical models (Alicastro et al., 2021), the relevant scheduling approaches can often not be executed with reasonable run time. To speed up the identification of optimized solutions, considerable research has been implemented on heuristics (Zhang et al., 2020, Fera et al., 2020, Gopsill and Hicks, 2018, Griffiths et al., 2019, Kim, 2018, Kapadia et al., 2019, Rohaninejad et al., 2022).

Compared to separate optimisation, integrated optimisation of scheduling and packing has been shown to allow higher utilization of capacity utilization and a more flexible production mode (Tafakkori et al., 2022).

Alongside the study of optimisation methods, a body of literature has investigated the objective criteria used in the scheduling and packing of AM. While some studies have studied time-related optimisation criteria (Chergui et al., 2018, Araújo et al., 2020, Oh et al., 2018b, Dvorak et al., 2018) or cost criteria (Li et al., 2017b, Freens et al., 2015, Ransikarbum et al., 2017) on their own, other studies have combined cost and time criteria (Fera et al., 2020, Griffiths et al., 2019, Feraa et al., 2018, Zhang et al., 2017). Additionally, some technical characteristics originating from the resulting workflow have been proposed as criteria. These include build height (Araújo et al., 2020, Wu et al., 2014, Attene, 2015, Chen et al., 2015, Zhang et al., 2002) and nesting rate (Canellidis et al., 2013, Canellidis et al., 2006, Wodziak et al., 1994, Canellidis et al., 2016, Wang et al., 2019b, Yang et al., 2008).

Sustainability-related criteria have so far only received little attention. Karimi et al. (2021) studied production scheduling towards the minimum energy cost of AM. Tafakkori et al. (2022) constructed a multi-objective model including financial profit, energy consumption, and losses to investigate the sustainability of AM. Baumers et al. (2013) showed the extent to which the available build volume is filled is an important determinant of the overall level of process energy consumption. An important gap in the extant literature is thus that there are so far no realistic studies that combine integrated scheduling and packing approaches with sustainability-related optimisation criteria.

2.5 Platforms, network effects and AM platforms

When investigating the efficiency of systems that consist of multiple elements, such as telephone networks and manufacturing operations featuring multiple AM systems, the concept of the platform has emerged as extremely helpful.

2.5.1 Industrial platforms

Platforms exist in various industry sectors, particularly in high-tech companies driven by information technology. Examples include the tech giants such as Apple, Google, and Microsoft, hardware and software producers for computers, phones, and consumer electronics devices. Such companies in one form or another serve as what are called industry platforms (Gawer and Cusumano, 2014).

The term, *platform*, appeared in the following three aspects: (1) the new product development and OM (Harland and Uddin, 2014, Wang et al., 2019c); (2) technology strategy (Cusumano, 2008, Cusumano, 2010a); and (3) industrial economics (Jiang, 2021, Xiao, 2022).

Concerning industry platforms, innovations and integration have become growingly common in daily lives. An instance is microprocessors embedded within laptops or smartphones that access the Internet, on top of which search engines such as Google exist.

Through a variety of analyses for industrial cases, Gawer and Cusumano (2014) suggested two forms of platforms, including *internal* (company-specific) *platforms* and *external* (industry-wide) *platforms*. The *internal platforms* represent a set of assets operating in a structure that a company is capable of efficiently developing and making a family of products (Muffatto and Roveda, 2002). The *external platforms* mean a cluster of products, services or technologies offering the foundation upon which outside companies can develop their complementary products, services, or technologies (Gawer and Cusumano, 2002, Gawer, 2011).

Internal platforms are referred to that a firm can produce a family of products or a set of new characteristics on products. It is reported that product designers and engineers tend to be trained to systematically reuse patterns, styles, and design rules based on previous work and improve upon prior art and others' work (Baldwin and Clark, 2000, Le Masson et al., 2010, Le Masson et al., 2011). However, the creation of a reusable feature for new product development needs specific planning and management. To this end, Guide (2000) identified and discussed seven complicating features that need major changes in production planning and control activities, as well as described the research opportunities of the complex features. Asif et al. (2021) proposed a methodological approach to support product design for multiple lifecycles to keep products and components as well as materials at their highest utility and value. Wang et al. (2022a) investigated the barriers to circular product design.

The above studies have identified that some potential benefits can be obtained from internal platforms including savings in fixed costs, efficiency gains in product development via the reuse of parts and modular design, and design flexibility of product features. One of the significant objectives of new product development on the platform is likely to be the ability to increase the product variants and satisfy various consumers' requirements, business needs, and technical advancements. At the same time, it needs to keep the economies of scale and scope within manufacturing processes. This renders an approach relevant to mass customization (Bregazzi et al., 2021, Hu, 2013).

Like internal platforms, *external platforms* can offer a foundation of reusable common elements or technologies. The difference lies in that external platforms are open to outside companies. The degree of such openness is dependent on a set of dimensions, for example, the level of access to information on the interface to connect the platforms or use its capabilities, rules of using the platform, or costs of accessing the platform (Anvaari and Jansen, 2010, Broekhuizen et al., 2021).

The early research on industry platforms mostly focused on telecommunications, computing, and other information technology-based industries. For example, Bresnahan and Greenstein (1999) considered computers as platforms and stressed the significance of technological competition between computer platforms. Levin and Iansiti (2004) named a keystone principle that a firm facilitates industrywide innovation for an evolving system of separately developed components. Cusumano (2010b) considered Software as a Service (SaaS) and cloud computing as new platforms for business and personal computing.

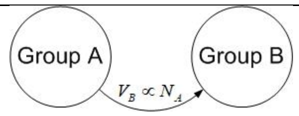
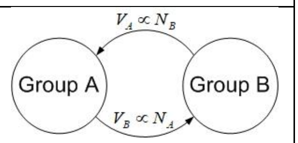
These studies suggest several generalizations regarding the factors to produce the best industry platform and the anticipated effects on the competitive dynamics. Industry platforms are likely to promote and increase the degree of innovation on complementary products and services (Gawer and Cusumano, 2014). The more innovation in the complementary products and services, the more value they produce for the platform and its users under network effects. Retrospectively, this may form cumulative advantages for the platforms. As users grow, the platforms become more difficult to be supplanted by competitors or new entrants.

2.5.2 Network effects and AM platforms

One key characteristic of platforms is that they generate what is known as network effects, also known as network externalities. Network effects represent a phenomenon that “the membership to one user is positively affected when another user joins and enlarges the network in the markets” (Katz and Shapiro, 1994, Shapiro and Varian, 1999). The majority of models consider network effects as exogenous and fixed, triggering platform competition. Such effects form a self-reinforcing feedback loop to amplify the members' early benefits. In this situation, according to Eisenmann (2006), strong network effects are capable of stimulating competition between platforms to a "winner-take-all" result.

Based on the extant literature, there are three types of network effects: *direct network effects*, *cross-group network effects,* and *indirect network effects*, which are illustrated in Table 2.3. Direct network effects, also called same-side network effects, appear when the benefit of a platform or technology to a member is positively dependent on the number of other members in this platform, for example, telephone network and Skype network. The cross-group network effect, as defined by Hagiu and Wright (2015), arises if the benefit to members in at least one group (for example A) relies on the number of other members in another group (for example B) in a single direction. Building on the cross-group network effect, the indirect network effect indicates that the decision of one group can be affected by the number of members in the opposite group. This means B's participation decision relies on the number of members in group A and vice versa. In other words, the benefit to a member in group B is dependent on the number of members in group A.

Table 2.3: Types of network effects

Name	**Types of network effects**		
	Direct	**Cross-group**	**Indirect**
Description	The more members, the more benefits for each member in this group.	The more members in Group A, N_A, the more benefits for each member in Group B, V_B single direction.	The more members in Group A, N_A, the more benefits for each member in Group B, V_B vice versa.
Diagram	$benefit \propto N_{members}$		
Examples	The telephone network, Skype	Hardware	Microsoft 365

Alongside the types of network effects, to narrow down the scope to the manufacturing sector, a body of literature has investigated its effects in manufacturing platforms. Atrostic and Nguyen (2005) first adopted data from approximately 30,000 U.S. manufacturing plants to investigate the effect of computer networks on productivity and found that there is a positive and important relationship between computer networks and plant labour productivity. Sung and Carlsson (2007) analysed the determinants of firms' innovative activity focusing on the role of external networks and technological opportunity in performing innovative activities. Park et al. (2010) studied the effects of firm size, age, and industrial networking on determining firm growth and found that the size and age of firms have significant negative effects on firm growth and significant positive impacts on firm survival. Mai et al. (2016) developed a cloud platform to improve the efficiency of AM resources and the variety of AM services. Wang et al. (2019c) proposed a cloud platform to integrate AM resources (e.g., equipment and materials) and test data, supporting design and process planning as well as printing.

However, there are some limitations to network effects. Boudreau (2012) investigated the ecosystems of mobile computing and communications platforms and found that the positive feedback loop to the number of complementors does not perpetuate itself ad infinitum. At the same point, most complementors tend to discourage extra companies from investing to participate in the ecosystem.

Network effects provide the potential for exponential growth on platforms and "winner-take-all" market result. However, there are several challenges to measuring and managing platform performance. As indicated by Cusumano (2022), the prerequisite for understanding platform performance, operations, and strategic management is to obtain a larger sample of companies. However, the size of such a number is a question. It is found that the measurement of network effects from publicly existing data is extraordinarily difficult.

Based on the aforementioned literature, network effects play a key role in increasing the benefits of each member in such a network and facilitating new product development and business innovation (Banton, 2023, Farrell and Klemperer, 2007). Baumers (2019) conducted an exploratory study in terms of network effects in AM platforms. It has been identified that cloud-based AM platforms have great potential on resource efficiency improvement at network level (Mai et al., 2016, Simeone et al., 2020). However, the network effects of environmental aspects have yet to be studied, which forms a significant knowledge omission in the currently available literature on sustainable AM.

2.6 Summary of the literature review

This chapter provided a systematic review of several relevant areas of the published literature, including sustainability, operations management, and additive manufacturing. As identified in this review, there are still important limitations regarding knowledge in the sustainability performance of AM processes. (Kellens et al., 2017a, Faludi et al., 2017, Liao and Cooper, 2020, Peng et al., 2018, Kerbrat et al., 2016). Building on this, the key gaps in research are outlined as follows.

Firstly, the impact of ill-structured aspects, for example, the risk of build failure has a significant effect on costs in AM (Baumers et al., 2017a). However, it is rarely considered to assess the environmental impacts of P-LPBF (Baumers et al., 2017a, Son, 1991). This omission limits the realism of existing studies on P-LPBF resource consumption.

Secondly, there are so far no realistic studies that combine integrated scheduling and packing approaches with sustainability-related optimisation criteria (Che et al., 2021, Tafakkori et al., 2022, Karimi et al., 2021, Lee and Kim, 2023). Thus, so far it has remained unclear what sustainability improvements can be obtained by employing computation-based production planning methods in the context of P-LPBF.

Last but not least, the platform perspective and the concept of network effects may have a significant role to play. For the commercial performance of many manufacturing processes, network effects have proved decisive (Banton, 2023, Katz and Shapiro, 1994, Farrell and Klemperer, 2007). However, the interaction between network effects and environmental sustainability, perhaps in the form of environmental network effects, has so far not been investigated beyond exploratory work by Baumers (2019).

Chapter 3: Methodology

The following sections detail the methodology used for geometry design, data processing as well as the simulation method applied in this study. A diagrammatic description of the methodology is presented in Figure 3.1. It mixes experimental and computational methods.

Three knowledge gaps were summarized in section 2.6. Firstly, the impact of risk of build failure is rarely considered on the environmental impact of P-LPBF. This could be done by factoring build failure into the environmental impact model based on the model in Ashby and Cebon (2005) and Baumers et al. (2017a). Four experimental steps in Figure 3.1 are implemented to achieve the objectives 1 and 2. Secondly, there is a lack of studies that combine integrated scheduling and packing approaches with sustainability-related optimisation criteria. Integrated optimisation of scheduling and packing is an NP-hard combinatorial optimisation problem, and it needs computational methods to address (Hu et al., 2022, Dvorak et al., 2018). The simulation work was conducted to accomplish objective 3. Thirdly, the network effects in terms of environmental impacts in AM platforms has so far not been investigated beyond exploratory work by Baumers (2019). Building on production planning, this needs to be uncovered by computational approaches. Another simulation work was used to accomplish objective 4.

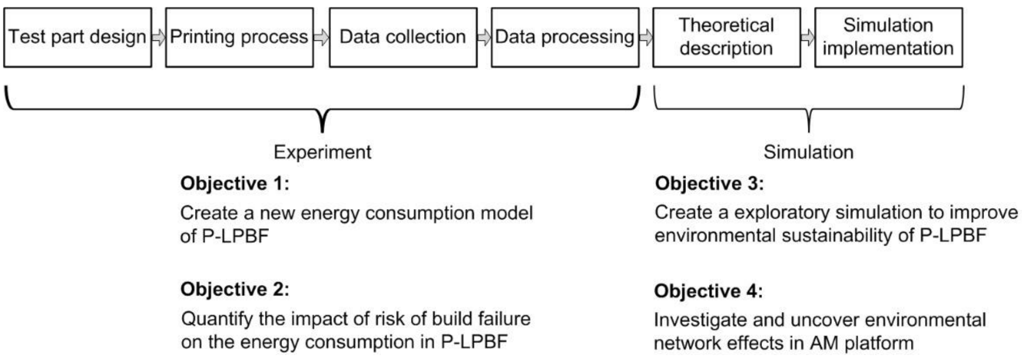


Figure 3.1: A diagram of the methodology followed to deliver objectives

3.1 Introduction

This section presents an integrated methodology combining experimental and computational elements. It contains six main steps: designing parts, implementing printing experiments, collecting experimental data, analysing data, formulating models, and conducting simulations.

The methodology used in this research aims to implement a simulation for workflow optimisation in AM, which can be broken down to the following parts:

1. Designing a standardized test part.

2. Implementing printing experiments based on the test part.

3. Collecting experimental data during the additive process.

    a. Monitoring build time based on standardized test parts.

    b. Monitoring real power consumption based on standardized test parts.

4. Analysis of experimental data regarding build time and power consumption.

5. Formulating build time and energy consumption predictive models.

6. Implementing simulation based on the build time and energy consumption predictive models.

Step 1 was based on reviewing the literature and dimensional constraints of AM machine. The aim of designing a standardized test part was to investigate the parameters of the environmental sustainability model.

Step 2 was carried out using an EOSINT P 100 AM machine (EOS, Germany) to obtain raw data of build time and energy consumption and then to establish predictive models regarding build time and energy consumption. The AM machine was used to print a number of standardized test parts.

Steps 3a and 3b were based on a series of stages during the additive process, including warm up, material deposition, and cool down. Specifically, the elapsed time and energy consumption of these stages were recorded.

Step 4 was implemented based on the machine log files and Excel datasheet. The machine log files were obtained from the operating system of EOSINT P 100. The datasheet was generated from a CW240 digital power meter (Yokogawa, Japan) when monitoring the real power consumption of the additive process.

Step 5 was conducted using an Ordinary Least Squares (OLS) regression method based on the data in **Step 4**, which was consistent with the method in Baumers et al. (2013). After this, the build time and energy consumption predictive models were established.

Step 6 was implemented using the systems were developed using MATLAB (version R2019b) (MathWorks, USA). These systems were computational tools designed to conduct the simulation and optimisation for workflow in AM. The predictive models constructed in **Step 5** were embedded in these systems. Optimized results can be obtained after implementing the simulation.

The following sections provide more detail on the steps listed above.

3.2 Test part design

The test part was designed to frame the formulas of build time and energy consumption in LPBF and was created using Creo (PTC, USA) software. It should have a relatively complex geometric shape within the boundaries of the build volume. An example of such a test part can be found in Baumers et al. (2011b) shown in Figure 3.2. The "spider" shape of the test specimen restricts the attainable overall packing density, leading to a realistic level of build volume utilization. It has a relatively complex shape that could represent a general part for testing. In addition, the feasible dimensions allow the AM machine to pack multiple parts on the bed.

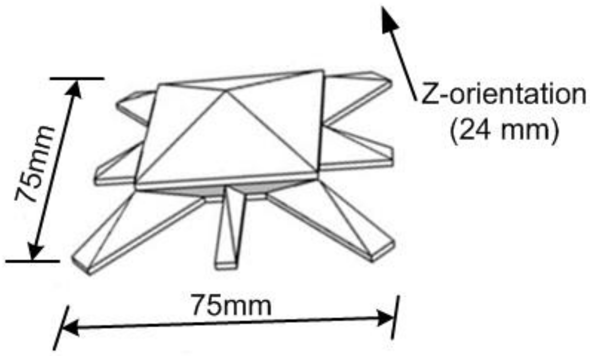


Figure 3.2: An example of the standardized test part

(image source: adapted from Baumers et al. (2011b))

3.3 Printing process

Once the test part was designed, the next step was to implement the printing experiments. This study used an EOSINT P 100 machine, a typical Polymer Laser Powder Bed Fusion (P-LPBF) technology used to build parts from polymeric powders. The raw material used in these experiments was PA2200. A number of test parts were packed on the build platform of the AM machine. The experimental setup was consistent with the setup in Baumers et al. (2015).

LPBF process

The LPBF processes use the laser as a heating source to melt and fuse the material powder layer by layer. This process consists of five main steps, as discussed below and a schematic of the process is shown in Figure 3.3.

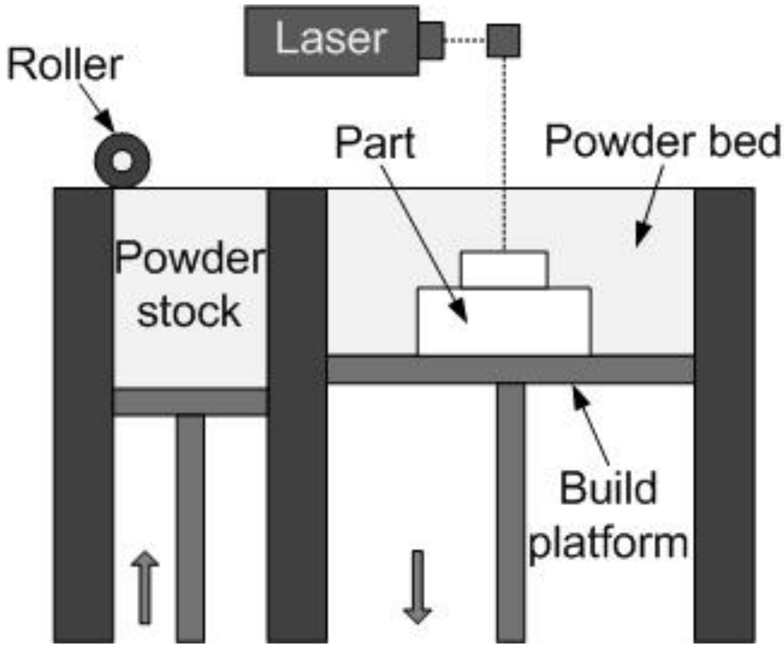


Figure 3.3: A schematic of a generic LPBF process

1. A layer of material (typically 0.1 mm thickness) is spread over the build platform.

2. A laser fuses the first layer or cross-section of the digital model.

3. A new layer of powder is spread based on the previous layer using a roller.

4. Further layers or cross-sections are fused and added.

5. The above steps repeat until the entire part is created.

Raw material

The raw material used in this study is PA2200 (Evonik, Germany), also known as Nylon 12 powder. The parts fabricated from nylon are robust, stable for long periods, chemically resistant and extremely versatile. It has been proven that printed end products are just as strong, flexible, and durable as moulded parts (EOS GmbH, 2021). The melting temperature of PA2200 is 176°C in environmental conditions (20°C) and its density is 930 kg per m^3.

3.4 Data collection

The data in terms of build time and energy consumption were obtained from the warm up, deposition, and cool down stages of the printing process. The activities and operations during the additive process were recorded in the machine log files. The real power consumption data were recorded in an Excel datasheet. The information in the two documents was regarded as the source data of build time and energy consumption. The real power consumption data were monitored once per second and presented in machine log files and an Excel datasheet.

Monitoring process

To date, four methods are available to measure build time, as shown in Table 3.1.

Table 3.1: Methods of measuring build time

Methods	System-embedded methods		Device supported methods	
	Build report	Machine log files	Digital power meter data	Manual recording
Accuracy	N/A	1 s	0.1 s~1 s	varied
Description	A report is generated from the control system of AM platform.	The files are compiled by the AM machine operating system.	Build time during the printing is obtained by analysing the recorded energy consumption data.	The time is recorded by the operator using a timer.

This study combined the information from machine log files and digital power meter data. In terms of machine log files, once an AM machine is turned on, a real-time data file is compiled by its operating system. In this file, the information on activities and operations within an operating system is recorded per second. Concerning power measurements, a CW240 power meter was used to monitor the real power consumption per second and recorded in an Excel datasheet. The measurement procedures were in line with the experimental implementations in Baumers et al. (2015).

3.5 Data processing

Once the experimental data were obtained, the following step was used to prepare the data for use by classifying and aggregating the raw data. Firstly, combining machine log files and Excel datasheet, the raw data were classified into three categories based on the three main stages of the additive process: warm up, deposition and cool down. Secondly, the data were aggregated. LPBF is a layer-by-layer industrial process. A set of data points per layer was created when implementing depositing operations. Building on this, data points per layer were regarded as a unit. A series of units of data were aggregated into several sections according to the activities recorded in the machine log files, for example, adding a layer of powder on the build platform and fusing a layer of powder.

Specifically, the elapsed time of an activity (e.g., fusing a layer of powder and moving the platform down by a layer thickness) was obtained based on the end time and start time of such an activity in the machine log files. The accumulated power consumption of an activity was gained through a sum of the real power consumption of this activity based on the Excel datasheet. Therefore, the energy consumption of this activity was obtained by multiplying the elapsed time and accumulated real power consumption. As a result, the elapsed time and energy consumption data per activity during the additive process were obtained. The procedures of data processing were in line with the method of Baumers et al. (2013).

Building on this process, the elapsed time and energy consumption per layer can be obtained. The handled data were prepared for framing linear regression formulas in terms of build time and energy consumption.

3.6 Theoretical description

Once the processed data were obtained, the next step was to frame the data into formulas. OLS, one of the most popular regression methods, was used to generate linear regression formulas in terms of build time and energy consumption (Abdi and Williams, 2013). This was in line with the method of Baumers et al. (2013). According to Wang et al. (2022b), the build time consists of job-dependent time, layer-dependent time, and geometry-dependent time. The time related to the job and layer is fixed and can be obtained through a calculation of the time consumption data directly. The geometry-dependent time is relevant to the geometric shape of parts. To determine this, OLS was adopted to investigate the relationship between geometry-relevant time and geometric shape.

The energy consumption includes job-dependent energy, layer-dependent energy, time-dependent energy, and geometry-dependent energy (Wang et al., 2022b). Building on the build time model, the time-dependent energy consumption can be determined. Energy consumption associated with the job and layer is fixed and this can be obtained based on the energy consumption data. Likewise, OLS was adopted to investigate the relationship between geometry-relevant energy and geometric shape. As a result, the build time and energy consumption formulas can be framed.

Ordinary least squares

OLS is a type of linear least squares method in statistics. It is usually used to find a linear model to fit to data. An example of the simple linear regression model is presented below.

$$y_i = \alpha + \beta \cdot x_i + \varepsilon \tag{3.1}$$

Where y_i is the dependent variable; x_i represents the independent variable; α is the constant of intercept; β is the slope or coefficient; ε represents the error term.

Therefore, the least squares estimate of parameters in this example can be framed as:

$$\hat{\beta} = \frac{\sum_{i=1}^{n}(x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3.2}$$

$$\hat{\alpha} = \bar{y} - \hat{\beta} \cdot \bar{x} \tag{3.3}$$

Where $\bar{x}$ and $\bar{y}$ represent the mean value of x_i and y_i in the dataset. n means the number of data points.

Building on this example, the principle of least squares lies in minimizing the sum of the squares of the difference between the observed dependent variable y_i in the input dataset and the output of the linear function of the independent variable x_i. In general, the smaller the differences, the better the model fits the data.

3.7 Simulation implementation

Based on the predictive models obtained in Section 3.6, an exploratory simulation was adopted. This includes three main phases: designing sample parts, measuring information, and developing systems.

The simulation method used in this study was based on a development of manufacturing execution systems, aiming to improve the sustainability of AM through workflow optimisation, as shown below.

1. Design a number of sample parts.

2. Measure geometric information of parts.

   a. Measure volume and total cross-section area of parts.

   b. Measure dimensions of parts.

3. Develop the system based on the obtained information and the predictive models.

Phase 1 was implemented using Creo CAD software (PTC, USA). This software package was used to design a number of sample parts and generate STL files of these parts.

Phases 2a and 2b were carried out using the Netfabb software program (version Premium 2019) (Autodesk, USA) and the Meshmixer software application (Autodesk, USA). Netfabb was used to identify volumetric information and the total cross-sectional area of parts. Meshmixer was used to obtain the dimensional information of parts.

Phase 3 was conducted when the required information of parts in **Phases 2a and 2b** had been obtained. The systems were developed using MATLAB (version R2019b) (MathWorks, USA). MATLAB is allowed to maintain full application portability and is suitable for the development of most operating systems (Etter, 1993). Compared to C++ and Python, MATLAB is more user-friendly because many functions or algorithms are available to use directly, for example, GA in the toolbox of this software package (Andrews, 2012). In these systems, the predictive models and dimensional information of parts were embedded. A number of functions (e.g., input demand, output results, optimisation) were designed and realized. In addition, the implementation of simulation was based on two stages: solution space generation and optimized solution exploration.

Chapter 4: Investigation of the environmental sustainability model of P-LPBF

4.1 Introduction

This Chapter presents work aimed at modelling the environmental sustainability of P-LPBF. To do so, a set of experimental specifications are made in Section 4.2. Section 4.3 establishes the environmental sustainability model. The results from application of the predictive models and environmental impacts of P-LPBF are presented in Section 4.4. The developed models support the investigation of integrated optimisation in Chapter 5 and environmental network effects in Chapter 6. Finally, a summary of this chapter is provided in Section 4.5.

4.2 Experimental specifications

4.2.1 Process map

Due to the research scope as discussed in Section 2.2, the environmental sustainability of AM in this study is dependent on resource consumption (e.g., material use, energy consumption). Understanding the consumption of resources plays a key role in any investigation of the commercial and environmental performance of AM. In the construction of such resource consumption models, the first step is usually to establish a process map representing the elements of the process under investigation. Process maps are specific to individual AM systems and this study constructed a model for the EOSINT P 100 system, which is a widely used industrial polymeric AM machine. The technology variant, Polymer Laser Powder Bed Fusion (P-LPBF), was chosen because it is frequently adopted in the manufacture of end-use products (Ruffo and Hague, 2007). However, the model and methodology introduced in this thesis can easily be extended to other machines and processes. A summary of modifications required to translate this work to other types of AM is shown in Table 4.1. The modifications contain three aspects: predictive models, process parameters and bounding boxes. Due to the different energy performance of different AM technologies, it is necessary to determine the predictive model regarding build time and energy consumption for the specific AM machine. In addition, the configuration of process parameters for each AM process may be different and should be modified. Finally, the bounding box related parameters (e.g., dimensions of bounding box, orientation of bounding box) need to be changed based on the packing pattern of the specific AM process.

Table 4.1: Modifications to fit other categories of AM processes

AM processes	SLA	MJ	BJ	ME	Metal LPBF	SL	DED
Predictive models modification	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Process parameters modification	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bounding box modification	No	No	No	Yes	Yes	Yes	Yes

The general operating process in P-LPBF is shown as follows. A layer of material is deposited on the printing platform. Following this, the system selectively scans the surface of the powder bed with a laser, generating a thin, planar slice of solid part geometry surrounded by unfused powder. Once the sintering of a layer is finished, a fresh layer of powder is added, and this process repeats layer by layer until the part is completed. It is important to note that P-LPBF systems of this kind allow the construction of multiple parts per build and do not require the deposition of auxiliary supporting structures (Mueller, 2012). Figure 4.1 summarizes the general activity flow of P-LPBF, identifying the material, energy, and information flows investigated in this research.

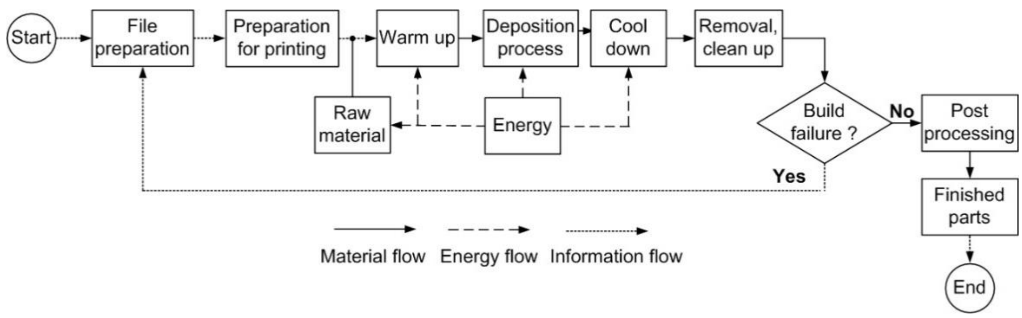


Figure 4.1: Process map of P-LPBF

As seen in Figure 4.1, the P-LPBF process consists of a sequence of steps beyond the deposition operations described above. The initial steps cover file preparation and preparation for printing (e.g., control system setup, machine preparation, and build release). Following this, the build process takes place, involving machine warm up, the actual material deposition cycle and machine cool down. The next steps are retrieval of the parts and machine cleaning. After this, should the build process have failed, the process re-initiates at the file preparation step; otherwise, the final step is the post-processing of the parts. Figure 4.1 also shows that energy inputs are modelled as flowing into the raw material, alongside the machine warm up, deposition process, and machine cool down steps. The energy consumption during the removal and post-processing is not included in the scope of the modelling because it is related to the geometric complexity, and investigation of this is not an aim of the thesis (Baumers et al., 2017b). To this end, a single geometry was used in the printing experiments and analysis.

4.2.2 Designing a standardized test part and parameters setting

A standardized part, as shown in Figure 4.2, was designed to investigate the build time elements and energy consumption compositions. This test part has a relatively complex shape (i.e., multiple slices and multiple cuboids). The feasible dimensions allow the AM machine to pack multiple test parts on the bed. The build time elements consist of layer-dependent time and geometry-dependent time. Energy consumption compositions include job-dependent energy consumption, layer-dependent energy consumption, time-dependent energy consumption, and geometry-dependent energy consumption. This experiment aimed to construct layer-based predictive models including build time and energy consumption during the warm up, deposition, and cool down stages.

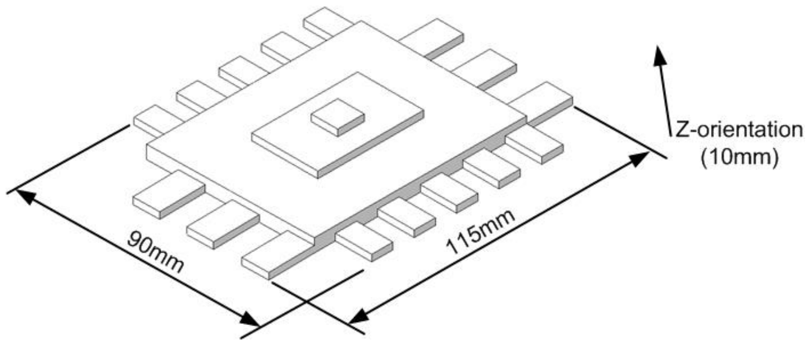


Figure 4.2: The standardized test part

In many other AM technologies, parts can only be packed in 2D on the print bed, however, in LPBF parts can also be packed in the Z-direction in bands, known as 2.5D packing. In this experiment, five bands of test parts in the Z-orientation were adopted. Considering the build volume constraints, each band can only contain two standardized test parts. Therefore, ten test parts were packed for the energy consumption experiment.

As can be seen in Figure 4.2, the standardized test part contains four slices, which follow a 2.5 mm increment in Z-orientation. The top slice, second slice, and third slice are cuboids with different dimensions. After that, six small cuboids are situated on the left and right sides of the bottom slice. In addition, ten small cuboids are tied to the front and back of the bottom slice. The dimensions of the above cuboids and cross-sections per layer are presented in Table 4.2.

Table 4.2: Detailed information on each slice of the standardized part

Name	Dimension	Cross-section area per layer
Top slice cuboid	$10mm \times 10mm \times 2.5mm$	100 mm^2
Second slice cuboid	$40mm \times 25mm \times 2.5mm$	1,000 mm^2
Third slice cuboid	$80mm \times 62.5mm \times 2.5mm$	5,000 mm^2
Bottom slice and surrounded cuboids	$17.5mm \times 10mm \times 2.5mm$ $13.75mm \times 8mm \times 2.5mm$	7,150 mm^2

Once the standardized test part was designed, the following step was to implement the printing experiments. The measurement procedures and parameters setting of this study were in line with the processes in Baumers et al. (2015). The set of experimental parameter values used with the EOSINT P 100 are shown in Table 4.3.

Table 4.3: The specifications and parameters of the EOSINT P 100 machine

Parameter	Value
Layer thickness	0.1 mm
Scan paths overlap	0.25 mm
Contour scanning speed	1500 mm/s
Contour beam power	16 W
Outer skin scanning speed and beam power	3000 mm/s
Outer skin beam power	25 W
Post-contour scanning speed	1500 mm/s
Post-contour beam power	16 W
Processing chamber temperature	172.5 ℃
Removable build chamber temperature	150 ℃

4.3 Environmental sustainability model

The environmental sustainability of AM was investigated in this study, focusing on material use and energy consumption. The energy consumption model is established based on the extant model in Baumers et al. (2013). The difference is that the model in this work considered the risk of build failure and embedded energy. Material use refers to the mass of material fused into parts and the mean fresh virgin material introduced into the system that is used to offset the material waste and unaccounted-for powder losses. The material consumption model is constructed based on the static resource equilibrium model in Gutowski et al. (2009). The embedded energy consumption model is constructed based on the model in Morrow et al. (2007). The impact of risk of build failure on energy consumption can be quantified by factoring build failure into the energy consumption model, which is based on the extant model in Ashby and Cebon (2005) and Baumers et al. (2017a). Building on this, an environmental sustainability model was developed including build time, energy consumption, material consumption, and embedded energy models as well as other factors, for example, risk of build failure. In addition, an environmental network effects model was established based on two targets: specific energy consumption and schedule attainment.

4.3.1 Build time model

Once the build configuration was determined, the next step was to estimate the total build time, this being a prerequisite for energy consumption. Based on the build time predictive models in Baumers et al. (2013), the total build time, T_{total}, as shown in Eq. (4.1), consists of job-dependent time, T_{job} and build time, T_{build}. The build time contains the layer-dependent time and geometry-dependent time as shown in Eq. (4.2).

$$T_{total} = T_{job} + T_{build} \tag{4.1}$$

$$T_{build} = \left(T_{layer} \times l\right) + \left(T_{area} \times A_{cross}\right) \tag{4.2}$$

- Job-dependent time, T_{job}, fixed time per build operation including warm up and cool down.

- Layer-dependent time, derived from multiplying the fixed time per layer T_{layer} by the total number of deposited layers in builds l.
- Geometry-dependent time, obtained by multiplying the fixed time per mm^2 T_{area} by the total cross-sectional area in builds A_{cross}.

4.3.2 Energy consumption model

Building on the energy consumption model in Baumers et al. (2013), the energy embedded in the material and the impact factors including the risk of build failure and capacity utilization were considered in this study. A scheme of the conceptual model of energy consumption developed in this thesis is presented in Figure 4.3.

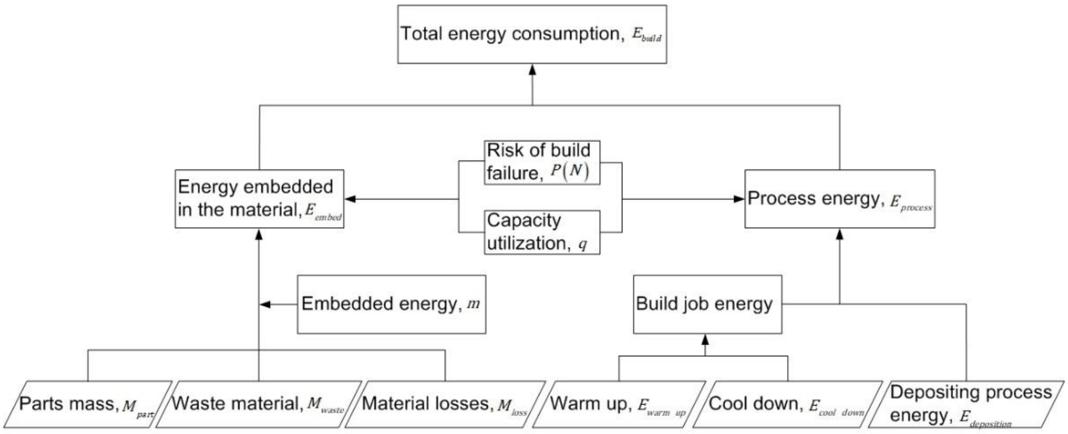


Figure 4.3: Scheme of the energy model

As can be seen in Figure 4.3, the total energy consumption in megajoules (MJ), E_{build}, is composed of the energy embedded in the material, E_{embed}, and the process energy, $E_{process}$, which are both affected by the risk of build failure $P(N)$, and capacity utilization, q, expressing the number of parts in builds. The total energy embedded in the material depends on the material consumption during the process and the mean embedded energy of that material, m. The material consumption in grams includes the mass of the parts, M_{part}, waste material, M_{waste}, and material losses, M_{loss}. The process energy consists of build job energy, for example, warm up, $E_{warm\ up}$ and cool down, $E_{cool\ down}$ as well as deposition process energy, $E_{deposition}$.

The sub-model adopted to represent the elements of process energy consumption of the AM systems $E_{process}$ is shown in Eq. (4.3).

$$E_{process} = E_{job} \times M + \left(\dot{E}_{time} \times T_{build}\right) + \left(E_{layer} \times l\right) + (E_{area} \times A_{cross}) \tag{4.3}$$

In this model, job-dependent energy consumption, E_{job} represents the fixed energy consumption during the warm up and cool down processes per build. The value of 41.65 MJ was taken for this based on experimental measurements on the machine EOSINT P 100. M represents the number of AM machines or builds used for printing. The time-dependent energy consumption is relevant to the continuous operation of the machine with minimum power consumption, which is a product of energy consumption rate $\dot{E}_{time}$ (measured in MJ/s) and build time consumption T_{build}. Analogous to build time estimation, E_{layer} indicates the fixed energy consumption per layer, for a total number of layers, l, which forms the layer-dependent energy consumption. Further, the geometry-dependent energy is denoted by the energy consumption associated with the deposited area, E_{area} (measure in MJ/mm^2), which is multiplied by the total cross-sectional area of parts on beds, A_{cross}. The empirical data on E_{area} and E_{layer} is determined by monitoring energy consumption during the printing and then subtracting the time-dependent energy consumption. The total cross-sectional area of parts, A_{cross} is obtained using the Netfabb software program with a configuration of 0.1 mm on layer thickness. The above energy consumption data was measured with a digital power meter (Yokogawa CW240).

4.3.3 Material consumption model

In P-LPBF, the powder that is not fused during the printing process can be, in principle, recycled for use in future builds. However, the recycled powder may be thermally degraded due to exposure to the high-temperature environment during the printing process. Therefore, virgin powder is normally added and mixed with the used powder, both to replace the consumed powder and to improve the powder's processability (Ruffo et al., 2006).

To simplify the estimation of material consumption, this model assumes that the AM system operates in a steady state in which, on average, the mass of the virgin powder introduced into the system is in equilibrium with the mass of the material exiting the system. Therefore, the amount of fresh powder material introduced into the system, M_{input}, equates to the mass of powder fused as parts, M_{part}, the powder waste due to degradation, M_{waste}, and any other unaccounted-for powder losses, M_{loss}, for example, due to powder evaporation during the sintering process or powder losses during machine cleaning. Figure 4.4 and Eq. (4.4) summarize this model. All subsequent material-specific values in this research refer to PA2200, which is a nylon 12 polymer powder.

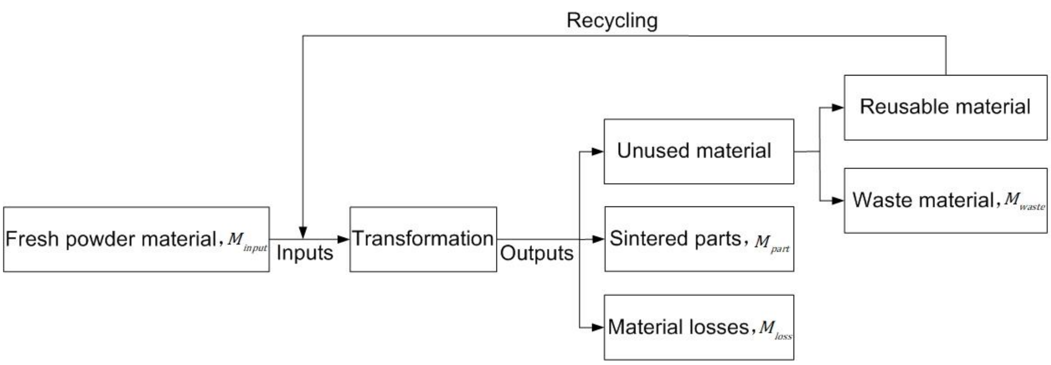


Figure 4.4: A material process model of AM

$$M_{input} = M_{part} + M_{waste} + M_{loss} \tag{4.4}$$

Eq. (4.5) can be used to determine the mass of the material fused, where ρ_1 is the density of the material as fused (0.93 g/cm^3, (EOS GmbH, 2021), V_{part} is the volume of single geometry fused, and q is the number of parts contained in a build.

$$M_{part} = \rho_1 \times V_{part} \times q \tag{4.5}$$

Eq. (4.6) specifies the waste streams resulting from the printing process, where ρ_2 is the density of the virgin powder (0.45 g/cm^3, (EOS GmbH, 2021), V_{bed} is the volume of the available build space of the machine and α is the waste factor, as suggested by Ruffo et al. (2006). As suggested by Baumers and Holweg (2019) and Kellens et al. (2011), the waste factor is equal to the refresh rate. This value is typically between 10% and 50% for polymer LPBF, dependent on the operator's discretion and the material used. In this work, a value of 30% was used.

$$M_{waste} = \rho_2 \times \left(V_{bed} - V_{part} \times q\right) \times \alpha \tag{4.6}$$

As in the above, the measurement algorithm for the combined estimator of build time, energy consumption and material consumption can be expressed in pseudo-code, as shown in Appendix A.

4.3.4 Embedded energy model

The energy embedded in the material (measured in megajoule, MJ), E_{embed}, reflects the total energy required to produce the raw material (Morrow et al., 2007), and is specified in Eq. (4.7). A series of studies (Kellens et al., 2017a, Wang et al., 2022b) have reported that energy embedded in the material dominates the environmental impacts of AM and should not be ignored.

$$E_{embed} = m \times M_{input} \tag{4.7}$$

In this model, m is the mean embedded energy of the raw material processed, (148 MJ/kg, according to Ashby and Cebon (2005)) and M_{input} is the overall mass of raw material consumed by the build operation, according to the steady state assumption shown in Eq. (4.4).

4.3.5 Risk of build failure model

In this research, any unrecoverable disturbance during the build process is treated as build failure. It is assumed that failure events emerge with a given probability in a way that reflects the layer-by-layer deposition process. The probability of failure per layer may be dynamic due to the number of printed layers and cross-section area etc. Considering these factors may help obtain the precise probability of failure per layer. However, it will be difficult to obtain the overall expected energy consumption with build failure when printing a number of layers. Because the expected energy consumption with build failure is not only associated with probability failure per layer but the number of layers. This work studied the probability of failure per layer from a statistical perspective. Multiple printing experiments with thousands of layers have been implemented and found that the build failure due to the failed layers occurred with a probability. To keep this model as simple as possible, it is assumed that the probability of build failure occurring with the processing of each layer is a constant, entering the model as the probability of failure per layer, $p_{constant}$. Baumers and Holweg (2019) investigated a similar build failure model and reported that the constant probability of failure per layer, on average, is 0.016% for the P-LPBF machine investigated in this research. To obtain the overall probability of successfully finishing a build, a discrete probability tree model is established (Figure 4.5).

Following the approach by Baumers and Holweg (2016), the probability of completing a build can be specified as a function of the total number of layers, N:

$$P(N) = (1 - p_{constant})^N \tag{4.8}$$

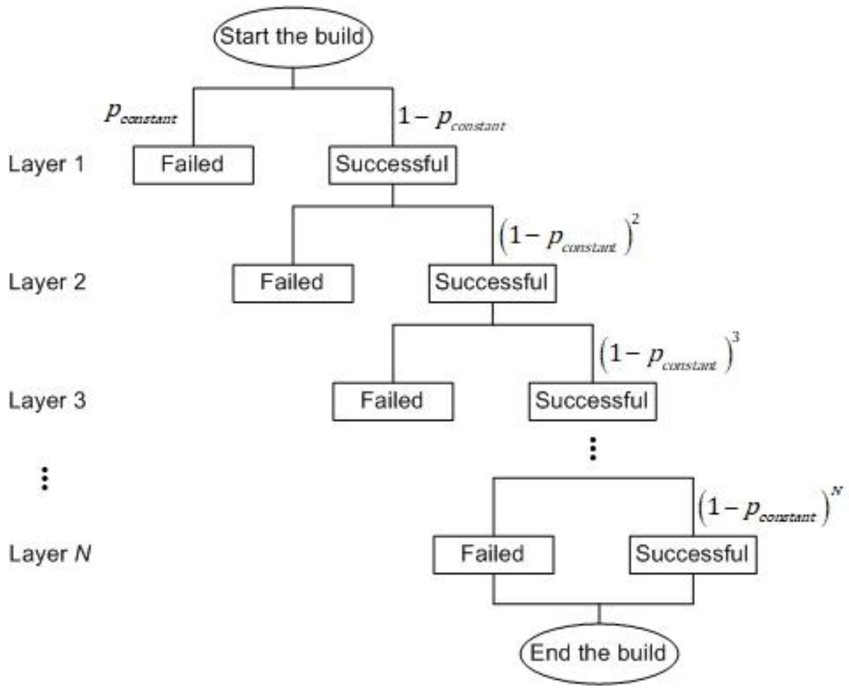


Figure 4.5: Probability tree model

(image source: adapted from Baumers et al. (2017a))

4.3.6 Expected total energy consumption model

Building on the model in Ashby and Cebon (2005), this probability can then be attached to the estimators, $E_{process}$ and E_{embed} , to form a model of expected total energy consumption with failure, E_{build}:

$$E_{build} = \frac{E_{process} + E_{embed}}{P(N)} \tag{4.9}$$

4.3.7 Environmental network effects model

Environmental network effects aim to investigate the network effects in terms of environmental impacts in the AM platform. This concept reveals the environmental benefits gained by changing the number of machine operators and customers.

Environmental impact of AM can be indicated to material use, energy consumption, waste material etc. According to Faludi et al. (2017), Specific Energy Consumption (SEC) is used to reflect the energy performance of additive processes. To investigate the operational performance of AM, Schedule Attainment (SA) was adopted in this study (Bozarth et al., 2009). Therefore, SEC and SA were chosen to uncover the environmental network effects in the AM platform.

Once the process energy, $E_{process}$ and material consumption of parts, M_{parts} has been determined, the specific energy consumption, SEC, of P-LPBF can be obtained, as shown in Eq. (4.10).

$$SEC = \frac{E_{process}}{M_{parts}} \tag{4.10}$$

Schedule attainment, SA, is defined as a ratio of the number of completed planned geometries packed on a specified day n_{pack} and the total number of geometries planned to be packed on this day n_{total}:

$$SA = \frac{n_{pack}}{n_{total}} \times 100\% \tag{4.11}$$

4.4 Application of predictive models and investigation of environmental impact

4.4.1 Build time and energy consumption predictive models

Building on the layer-by-layer nature of AM, the correlation of build time, energy consumption, and total cross-section area was investigated. The OLS method was used to handle the data points. The data were recorded during the printing of each layer of the standardized test part shown in Section 4.2.2. This test part is of layered design, leading to five different build time and energy consumption levels, as shown in Figures 4.6 and 4.7. Compared to the study by Baumers et al. (2013), this research has one more level of build time and energy consumption due to the considerations of data generated from the warm up stage to depositing the first layer of the test part. As a result, these models are more accurate in predicting the build time and energy consumption of AM.

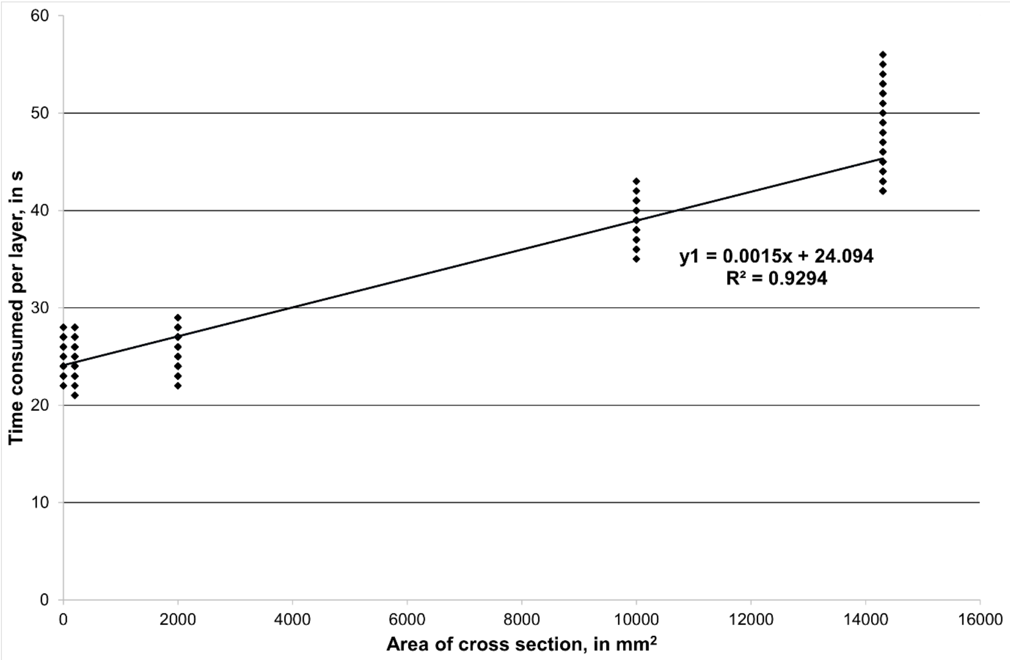


Figure 4.6: Regression cross-section area against build time

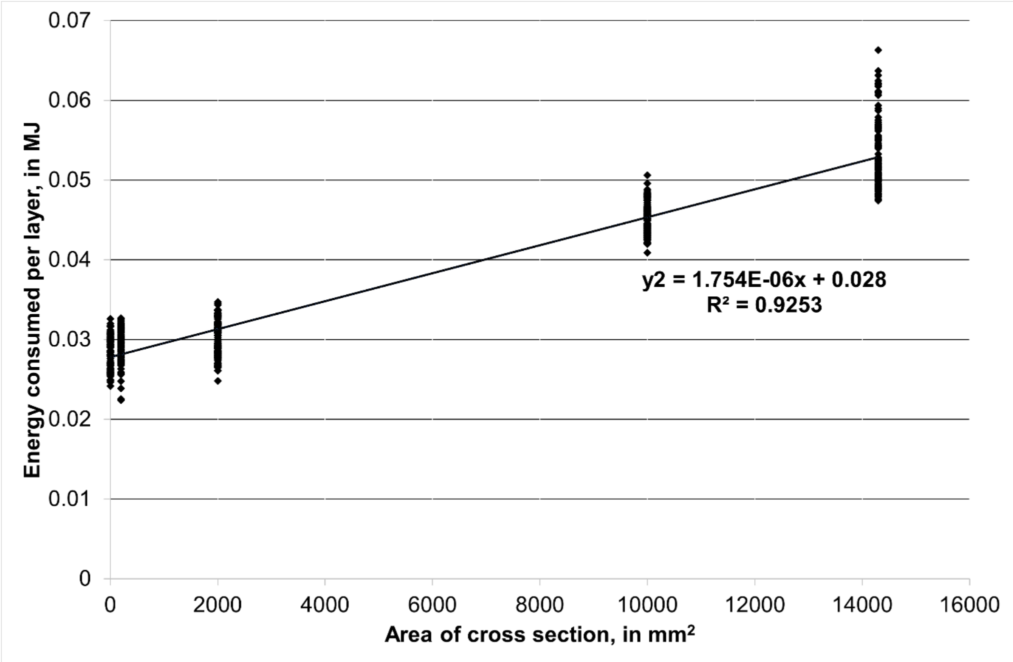


Figure 4.7: Regression cross-section area against energy consumption

$$y_1 = 0.0015 \cdot x + 24.094 \tag{4.12}$$

$$y_2 = 1.754 \times 10^{-6} \cdot x + 0.028 \tag{4.13}$$

Where y_1 and y_2 represent the time consumed per layer and energy consumed per layer respectively. x is the area of cross section.

The correlation between build time per layer and cross-section area is demonstrated in Figure 4.6. Figure 4.7 reveals the correlation between energy consumption per layer and cross-section area. R-Squared (R^2) is a statistical measure to show how well the data fit the regression model. This measurement was used in this study and the results show that the data fit the regression models well by approximately 93%. The two regression models, as shown in Eq. (4.12) and Eq. (4.13), constituted the geometry-dependent time and geometry-dependent energy consumption respectively. These can be done by combining the regression models with the total cross-section area of parts in a build. The total cross-section area of parts was obtained by using the Natfabb software program.

4.4.2 Breakdown of P-LPBF energy consumption

As displayed in Section 4.2.1, one focus of this study was to investigate the energy consumption during the warm up, deposition, and cool down stages, which was in line with Baumers et al. (2011a). In addition, the impact of the risk of build failure on energy consumption was quantified for both single and full-capacity build configurations.

Figures 4.8 (a) and (b) show the energy consumption for the single part (q=1) and full capacity build (q=40) configurations considering the risk of build failure. The total expected energy consumption is broken down into the model components. Comparing both pie charts, it is evident that the composition of the energy consumption changes with the build capacity utilization. The energy embedded in the material is the largest contributor in both the single-part build (57.40% in Figure 4.8 (a)) and the full capacity build (47.93% in Figure 4.8 (b)), which is in line with the results in Kellens et al. (2017a) and Faludi et al. (2017). This emphasizes that a significant share of the overall energy consumption in P-LPBF is due to the energy embedded in the raw material. However, compared to P-LPBF, the largest environmental contributor is process energy consumption (51.90%) in metal LPBF (Kellens et al., 2011).

The risk-related energy consumption is obtained for both levels of capacity utilization by subtracting $E_{process}$ and E_{embed} from E_{build}. The results suggest that the energy associated with the risk of build failure is substantial at high levels of capacity utilization, at 31.06% of the total expected energy consumption. However, this is decreased when the available capacity is not fully utilized. For the single part build configuration, the share of the total energy consumption falls to 22.75%. The reason for this pattern is the increase in the number of deposited layers in line with higher levels of capacity utilization, which leads to an accumulating risk of build failure. An interesting point is that the risk of build failure has a similar level of effect on the unit cost (26.00%) as reported by Baumers et al. (2017a).

Excluding the risk-related energy consumption and the energy embedded in the material, the energy for warm up is the major contributor to the process energy consumption (51.08%) in the single part build configuration, followed by the deposition process energy (26.19%) and energy for cool down (22.73%). Based on the identical AM machine and test part, this result shows a similar share distribution of process energy consumption in Baumers et al. (2015) in single part build configuration.

However, in the full capacity build scenario, the deposition process consumes the most energy (84.67%) during the printing process, and warm up and cool down processes use smaller amounts of energy, at 10.61% and 4.72% respectively. While Baumers et al. (2015) indicated that energy for warm up (43.37%) dominates the process energy consumption, followed by deposition process energy (33.87%) and energy for cool down (22.76%). This is because five parts on the bed represented the full capacity build in their experimental setup while this thesis used fifty-five parts in the full capacity build configuration.

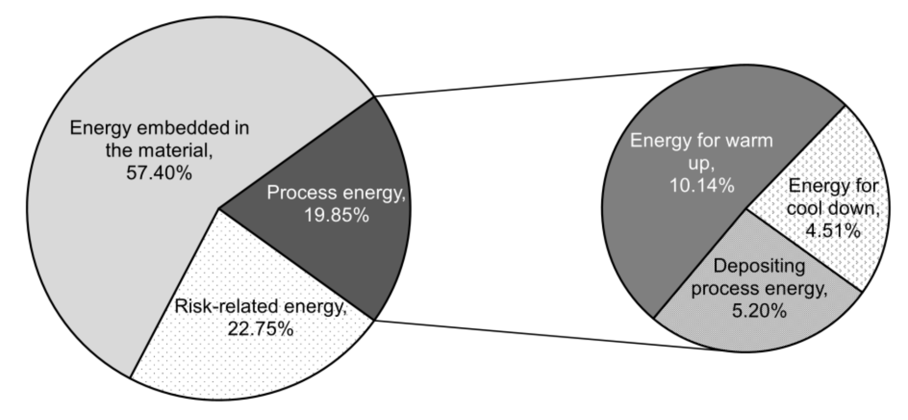


Figure 4.8: (a) Breakdown of total expected energy consumption (MJ) in the single part build configuration (*q*=1)

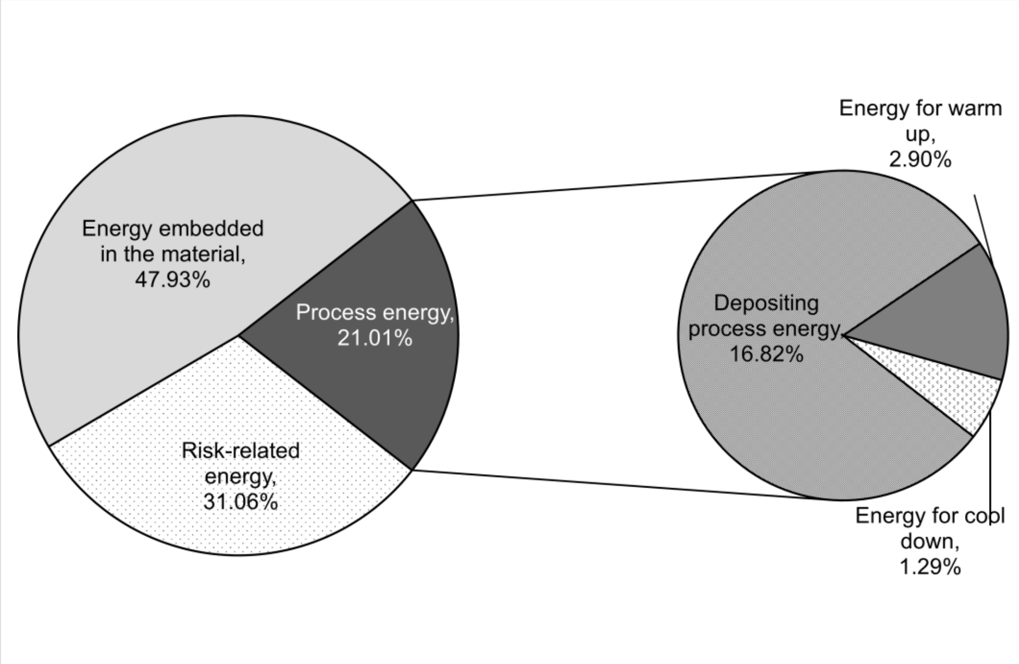


Figure 4.8: (b) breakdown of total expected energy consumption (MJ) in the full capacity build configuration (*q*=40)

4.4.3 Energy consumption per unit of P-LPBF

To further investigate the effects of capacity utilization on energy consumption, four unit-based models of energy consumption were established, as shown in Eqs. (4.14) -(4.17). The capacity utilization, q, is represented by the number of parts in a build and ranges from 1 to 55.

$$E_{part\_a} = \frac{E_{process} + E_{embed}}{q \times P(N)} \tag{4.14}$$

$$E_{part\_b} = \frac{E_{process} + E_{embed}}{q} \tag{4.15}$$

$$E_{part\_c} = \frac{E_{process}}{q \times P(N)} \tag{4.16}$$

$$E_{part\_d} = \frac{E_{process}}{q} \quad (4.17)$$

In addition, the specification of the total expected energy consumption model, E_{build}, is adjusted to separate the contributions of embedded energy and risk-related energy consumption. Four model specifications arise: model ***a*** as in Eq. (4.14) originally, model ***b*** with embedded energy but excluding build failure as in Eq. (4.15), model ***c*** with build failure but excluding embedded energy as in Eq. (4.16), and model ***d*** covering process energy consumption with no embedded energy and build failure as in Eq. (4.17). The unit-based model allows these energy consumption behaviours to be explored across the entire range of build capacity utilization, depicted in Figure 4.9.

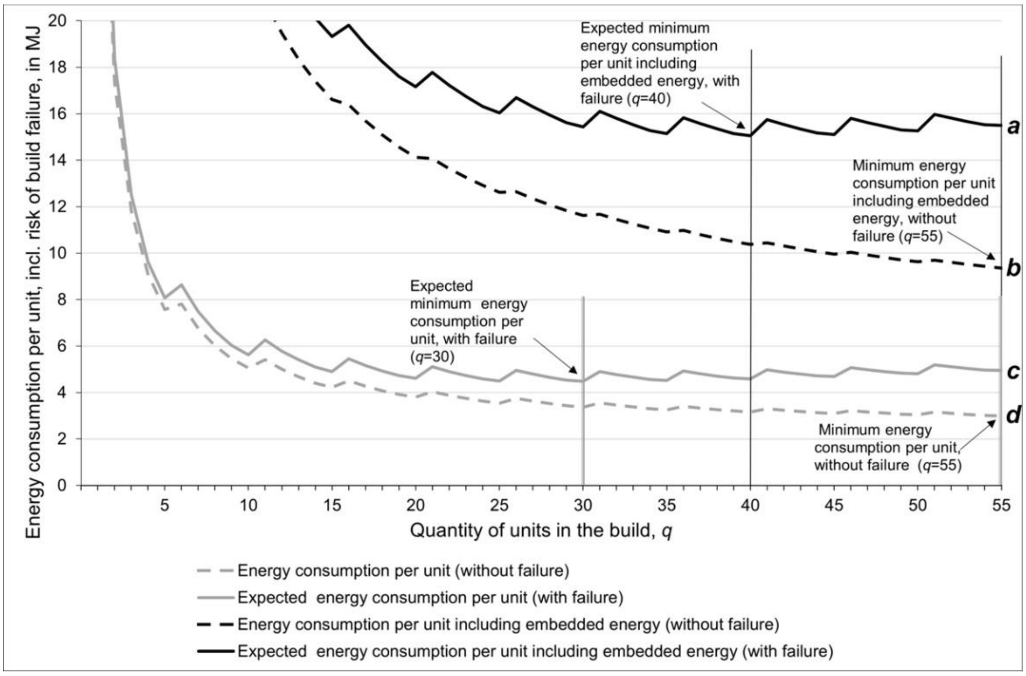


Figure 4.9: Relationship between energy consumption per unit (MJ) and quantity

As can be seen in Figure 4.9, the unit energy consumption follows a non-monotonously decreasing saw-tooth pattern across all four model specifications, which is a result of packing five parts in each band of build space. This effect is caused by the layer-wise filling of the available build capacity, as documented for P-LPBF production costs by Baumers and Holweg (2019) and Ruffo and Hague (2007).

Figure 4.9 also shows that increasing capacity utilization generally results in decreasing per-unit energy consumption in sparsely filled builds. Interestingly, though, the model specifications that include failure (models ***a*** and ***c***), show that an accumulating risk of build failure begins to overwhelm aforementioned efficiency gains at higher levels of capacity utilization. This results in a U-shaped pattern of energy consumption in which the minimal per-unit energy consumption occurs at q=40 in the full model (model ***a***). A similar U-shaped pattern of unit cost can be found in Baumers and Holweg (2016). At this level of capacity utilization, the total energy consumed for the manufacture of a sample part is 15.05 MJ.

A pairwise comparison of models ***a*** to ***c***, and ***b*** to ***d***, shows that the energy embedded in the material leads to a dramatic increase in the per-unit energy consumption as the quantity increases. The increase in total energy consumption is from approximately 210% to 390% across the entire range of capacity utilization.

4.5 Summary

This chapter describes the process of modelling the environmental sustainability of AM and shows the results on predictive models and environmental impact of AM consistent with the published paper. It has found that:

(1) The energy associated with the risk of build failure accounts for approximately 31% of overall expected energy consumption at full capacity utilization.

(2) Inclusive of the risk of build failure, the expected minimum energy consumption is likely to appear at a middle-high level of capacity utilization in AM.

(3) Embedded energy dominates the total energy consumption in both single part build and the full capacity build configurations in AM.

(4) Embedded energy contributes a dramatic increase in total energy consumption from approximately 210% and 390% across the entire range of capacity utilization.

Chapter 5: Investigation of integrated optimisation in P-LPBF

5.1 Introduction

This Chapter details the methods and results of integrated optimisation of scheduling and packing. The experimental setup is presented in Section 5.2. Section 5.3 provides the details of the integrated optimisation method. Following this, an implementation of the method is presented in Section 5.4. Section 5.5 presents and discusses results from the implementation of the integrated optimisation method. Finally, a summary is presented in Section 5.6.

5.2 Experimental setup

5.2.1 Designing a number of sample parts

To understand system applications in predicting process energy consumption and build time, five sample parts were designed. The shape complexity of parts has a weak correlation with the energy consumption of AM process (Baumers et al., 2017b). In other words, the design of parts has little impact on the measurement of process energy consumption and build time during the additive process.

To cover a wide range of applications for polymeric parts, one part with long and slim features, two parts with complex inner structures, and two parts with aerodynamic functionality were designed using Creo. The details of the designed parts are described below.

Table 5.1: Part 1 — Headphone holder

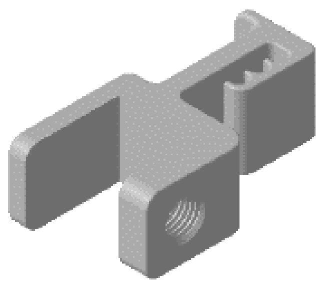
Geometry	Part 1	
Name	Headphone holder	
Length	127 mm	
Width	67 mm	
Height	42 mm	
Volume	126640.00 mm^3	

Table 5.2: Part 2 — Semi-circular fan duct

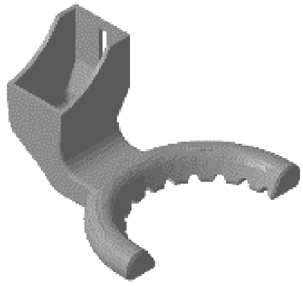
Geometry	Part 2	
Name	Semi-circular fan duct	
Length	58 mm	
Width	56 mm	
Height	36 mm	
Volume	4687.57 mm^3	

Table 5.3: Part 3 — Vent ring

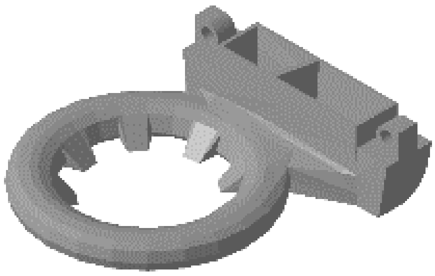
Geometry	Part 3	
Name	Vent ring	
Length	49 mm	
Width	51 mm	
Height	17 mm	
Volume	3901.75 mm^3	

Table 5.4: Part 4 — Motor cooling fan

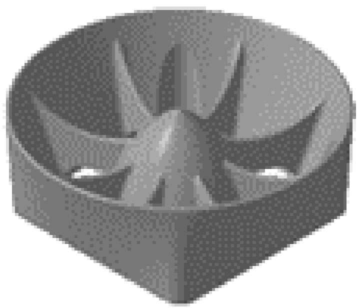
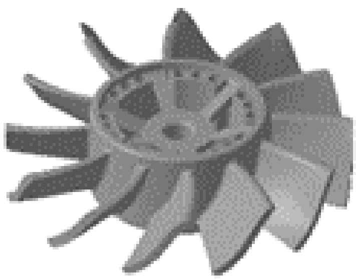
Geometry	Part 4	
Name	Motor cooling fan	
Length	59 mm	
Width	59 mm	
Height	22 mm	
Volume	8755.38 mm^3	

Table 5.5: Part 5 — Jet turbine blade

Geometry	Part 5	
Name	Jet turbine blade	
Length	84 mm	
Width	84 mm	
Height	24 mm	
Volume	18582.00 mm^3	

A basket of parts was designed for the build experiments performed on the EOSINT P 100. Detailed information on these parts is shown in Tables 5.1-5.5. In these tables, part 1, part 2, part 3, and part 4 were selected to support the development of System 1: integrated optimisation of scheduling and packing. To satisfy the requirements for the simplifications in environmental network effects, all five parts were chosen to support the development of System 2: investigating environmental network effects.

Once a basket of parts was selected, the next step was to import the STL file of these parts into Meshmixer to obtain the dimensional information. In addition, the same importing operations were conducted to obtain the volumetric value and total cross-section area of parts by using the Netfabb software program.

To implement packing efficiently, this research converted the part into a bounding box, a rectangle that surrounds an object as shown in Figure 5.1 (Oh et al., 2018a). A gap of 2 mm is required between the adjacent parts to avoid them fusing during the printing process (Baumers et al., 2013). Therefore, the dimensions of a bounding box were larger than the real part's size by 2 mm, which was adopted in the developed system for computation and optimisation during the packing and scheduling processes.

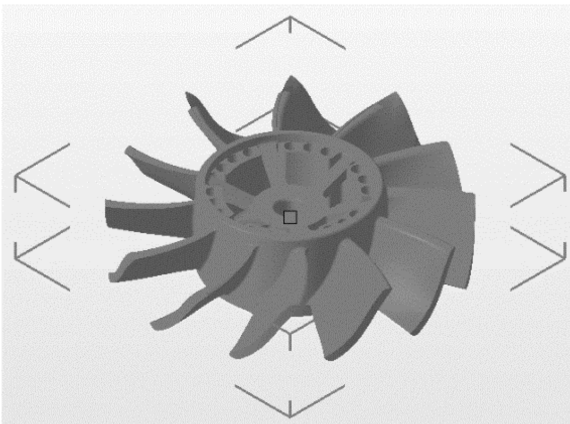


Figure 5.1: Bounding box of a sample part

The first part is a headphone holder used in daily life. Compared to other parts, part 1 is the largest part in terms of dimensions and geometric volume. Therefore, this part was regarded as the first insertion precedence into the system. The second part is a semi-circular fan duct with similar length and width. However, the geometric volume of this part is not as large as part 1. A vent ring, part 3, shows a similar geometric shape to part 2. Part 2 and Part 3 have complex inner structures but with relatively small geometric volumes. The next part is a motor cooling fan, part 4, with equal length and width. The last part is part 5, a jet turbine blade, which has similar dimensional features to part 4. Part 4 and Part 5 have aerodynamic characteristics with complex surfaces and symmetrical shapes.

It can be seen that the designed parts reflect common features during the practical printing of a variety of five parts, for example, tall and slim geometric shapes, and complex inner characteristics.

5.2.2 Rotating operations for parts

Converting parts into bounding boxes enables efficient implementation of the packing procedure. To effectively use the available space of chambers, it is necessary to implement a rotating operation for parts (Zhang et al., 2018, Oh et al., 2020). However, with more rotating operations for parts, particularly geometries with 3D irregular shapes, there is higher computational complexity, and more CPU time (Araújo et al., 2020). To mitigate computational burden during the optimisation process whilst improving the capacity utilization ratio, the rotating operations for each part were set to rotate along the axis with an increment of 0^{o} and 90^{o}, which was based on the rotating method in Zhang et al. (2018). An example of one rotating operation is shown in Figure 5.2.

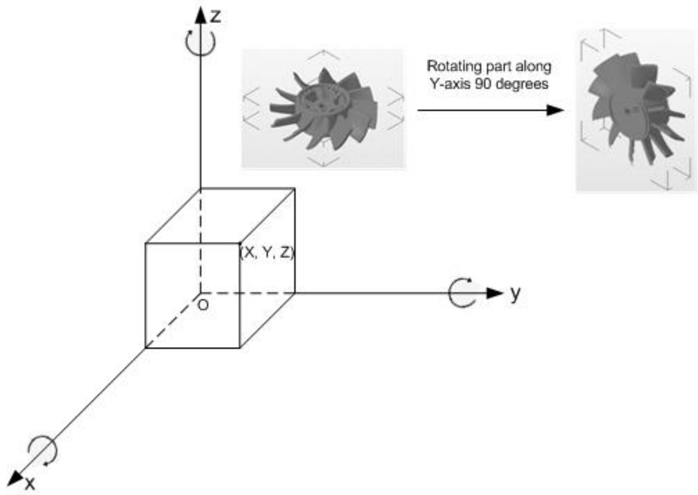


Figure 5.2: Schematic of rotating operations and vertex coordinate of the bounding box

As can be seen in Figure 5.2, the coordinate, e.g., (X, Y, Z) represents the position of a sample bounding box in the 3D coordinate system. When implementing a rotating operation, the position of the sample bounding box is changed. In other words, the new position of the sample bounding box can be represented by the updated vertex coordination.

Building on this, a series of rotating operations are summarized. To reveal this change, the updated vertex coordinates of the sample bounding box under all feasible rotating operations are presented in Table 5.6.

Table 5.6: Rotating operations and updated vertex coordinate

No rotation			
Rotating operation	No rotation		
Updated coordinate	(X, Y, Z)		
Single rotating operation			
Rotating operation	Along X-axis 90^0	Along Y-axis 90^0	Along Z-axis 90^0
Updated coordinate	(X, Z, Y)	(Z, Y, X)	(Y, X, Z)
Two rotating operations			
Rotating operation	Along X-axis 90^0 first and then Y-axis 90^0	Along Y-axis 90^0 first and then X-axis 90^0	Along Y-axis 90^0 first and then Z-axis 90^0
Updated coordinate	(Y, Z, X)	(Z, X, Y)	(Y, Z, X)
Rotating operation	Along Z-axis 90^0 first and then Y-axis 90^0	Along X-axis 90^0 first and then Z-axis 90^0	Along Z-axis 90^0 first and then X-axis 90^0
Updated coordinate	(Z, X, Y)	(Z, X, Y)	(Y, Z, X)
Three rotating operations			
Rotating operation	Along X-axis 90^0 first and then Y-axis 90^0 and finally Z-axis 90^0	Along X-axis 90^0 first and then Z-axis 90^0 and finally Y-axis 90^0	Along Y-axis 90^0 first and then X-axis 90^0 and finally Z-axis 90^0
Updated coordinate	(Z, Y, X)	(Y, X, Z)	(X, Z, Y)
Rotating operation	Along Z-axis 90^0 first and then X-axis 90^0 and finally Y-axis 90^0	Along Y-axis 90^0 first and then Z-axis 90^0 and finally X-axis 90^0	Along Z-axis 90^0 first and then Y-axis 90^0 and finally X-axis 90^0
Updated coordinate	(X, Z, Y)	(Y, X, Z)	(Z, Y, X)

As can be seen in Table 5.6, sixteen types of rotating operations were identified in this research. However, multiple rotating operations generated the same coordinates for the bounding box, for example, rotating along Y-axis 90^0 first and then Z-axis 90^0 option is equivalent to rotating along Z-axis 90^0 first and then X-axis 90^0 option. To avoid redundant rotating operations for the bounding box, a filtering procedure was implemented. The filtered results are shown in Table 5.7.

Table 5.7: Filtered rotating operations and updated vertex coordinate of the bounding box

Rotating operation	No rotation	Along X-axis 90^0	Along Y-axis 90^0
Updated coordinate	(X, Y, Z)	(X, Z, Y)	(Z, Y, X)
Rotating operation	Along Z-axis 90^0	Along X-axis 90^0 first and then Y-axis 90^0	Along Y-axis 90^0 first and then X-axis 90^0
Updated coordinate	(Y, X, Z)	(Y, Z, X)	(Z, X, Y)

Six rotating operations can be seen in Table 5.7. These six rotating rules were embedded in the developed systems to enable effective packing of parts in the build volume.

5.2.3 Demand profiles

To implement System 1, four types of geometry were chosen in this study as shown in Tables 5.1-5.4 in Section 5.1.1. The basic information on the parts, including dimensions, volume, and total cross-sectional area, was hard coded in the system.

The following step was to input the demand for parts on Day One and Day Two separately. A similar implementation procedure can be found in Baumers et al. (2013). However, this study focused on the integrated optimisation of scheduling and packing, which is an extension of the previous work in scheduling and packing jointly or separately (Araújo et al., 2020, Li et al., 2017b, Zhang et al., 2020). To demonstrate the advantages of integrated optimisation, a comparison with separate optimisation was implemented in this study, keeping in line with the procedure of Little et al. (2013). The difference between integrated optimisation and separate optimisation was the adoption of a capacity aggregation algorithm in this study. To trigger the integrated optimisation, a series of demand profiles were designed. These demand profiles allow the capacity aggregation to be involved in scheduling and packing operations including within-capacity and out-of-capacity scenarios. A similar instance scale for optimisation implementation in AM can be found in Zhang et al. (2020). The details of the demand profiles are shown in Table 5.8.

Table 5.8: Demand profiles for System 1

Demand profile	Day One					Day Two					Total no. of parts
	Part 1	Part 2	Part 3	Part 4	No. of parts	Part 1	Part 2	Part 3	Part 4	No. of parts	
S1	30	30	30	30	120	20	20	20	20	80	200
S2	35	35	35	35	140	20	20	20	20	80	220
S3	40	40	40	40	160	20	20	20	20	80	240
S4	45	45	45	45	180	20	20	20	20	80	260
S5	50	50	50	50	200	20	20	20	20	80	280
S6	55	55	55	55	220	20	20	20	20	80	300
S7	60	60	60	60	240	20	20	20	20	80	320
S8	65	65	65	65	260	20	20	20	20	80	340
S9	70	70	70	70	280	20	20	20	20	80	360
S10	75	75	75	75	300	20	20	20	20	80	380
S11	80	80	80	80	320	20	20	20	20	80	400
S12	85	85	85	85	340	20	20	20	20	80	420

The energy consumption across multiple AM machines through exploratory simulation was studied in this thesis, which is an extension of the energy consumption study in a single AM machine as reported in Wang et al. (2022b).

5.3 Integrated optimisation method

Scheduling and packing were investigated in this study to fulfil demands from individual customers. Due to the research scope, this study only considered identical AM machines. The method could be easily extended to a range of different machines, however, many print bureaus operate with a bank of the same machines so this is a reasonable assumption. The production process of P-LPBF operates on a build-by-build basis. Depending on the maximum available build space of the chamber, the capacity of the AM machine can be regarded as one of the constraints in production. The selected P-LPBF machine was also assumed to operate with fixed warm up and cool down energy consumptions as well as fixed processing parameters, for example, layer thickness and scanning speed. The fixed job energy consumption was obtained from the experimental data. Warm up energy consumption is fixed due to the fixed operations in the control systems of P-LPBF. The cool down energy consumption is dependent on the cool down time entered by machine operators. This research used a relatively long cool down time to cover most production scenarios (i.e., a large number of parts in a build) in P-LPBF. The experimental results in the lab have shown that the difference in cool down time/energy consumption has little impact on the overall process energy consumption of P-LPBF. As for fixed processing parameters, these follow the configurations in extant literature and form a feasible comparison with published work. The processing sequence of these parts was generated in descending order based on the volumetric value of the parts. The problem was formulated as: how to allocate and place parts on AM machines based on the customer demands with minimal energy consumption.

The process of assembling individual builds, whether considered on its own or together with other builds, is complex and can be formulated as an NP-hard combinatorial optimisation problem (Hu et al., 2022, Dvorak et al., 2018). Specifically, the problems are intrinsically very difficult in computation, and these require using heuristics to choose the best solution from a finite or countably infinite number of alternatives.

One way to begin characterizing this problem is by viewing it as a machine allocation problem in which a flow of production parts is allocated to a stream of available builds. Figure 5.3 illustrates this problem formalization by expressing AM capacity as a stream of available builds on *M* machines in a sequence of *N* consecutive production days, where one build operation can be completed per day. In this sense, AM machines can be regarded as proving a set of available builds to be filled with product geometry to meet some demand profile (Araújo et al., 2019). Since the actual machine allocation is dependent on some measures of the goodness of build volume packing, the scheme shown in Figure 5.3 shows that the problems of build volume packing and scheduling can be investigated as a joined-up problem, which is reflected in the approach chosen to address the problem. In this context, it is important to note that computationally addressing any build volume packing problem of a useful size, results in a very large solution space (Baumers et al., 2013). This means that all such problems are NP-hard and require heuristic solutions (Burke et al., 2006, Fleszar and Hindi, 2002).

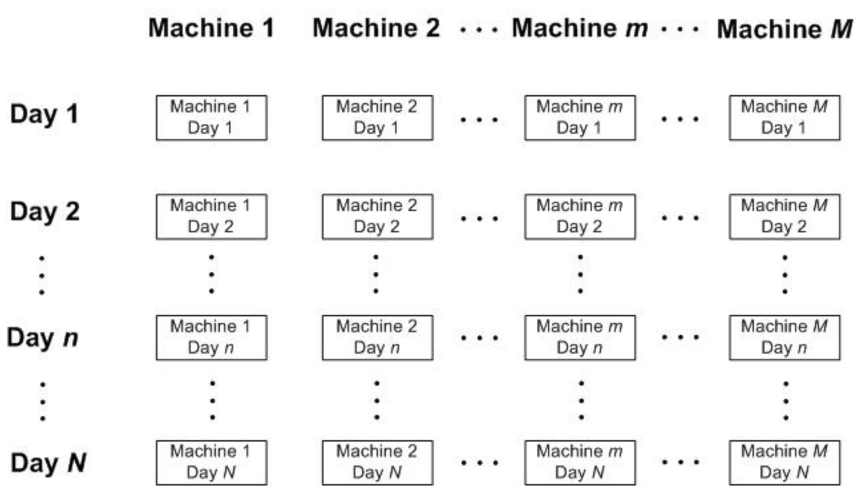


Figure 5.3: Production scheduling decision in AM

(image source: adapted from Baumers (2012))

An integrated optimisation problem was investigated in this study, which is different from the separate optimisation of scheduling and packing in AM addressed previously. According to Chergui et al. (2018), production scheduling and packing can be divided into two sub-problems: (1) parts/jobs assignment; and (2) jobs scheduling, as shown in Figure 5.4.

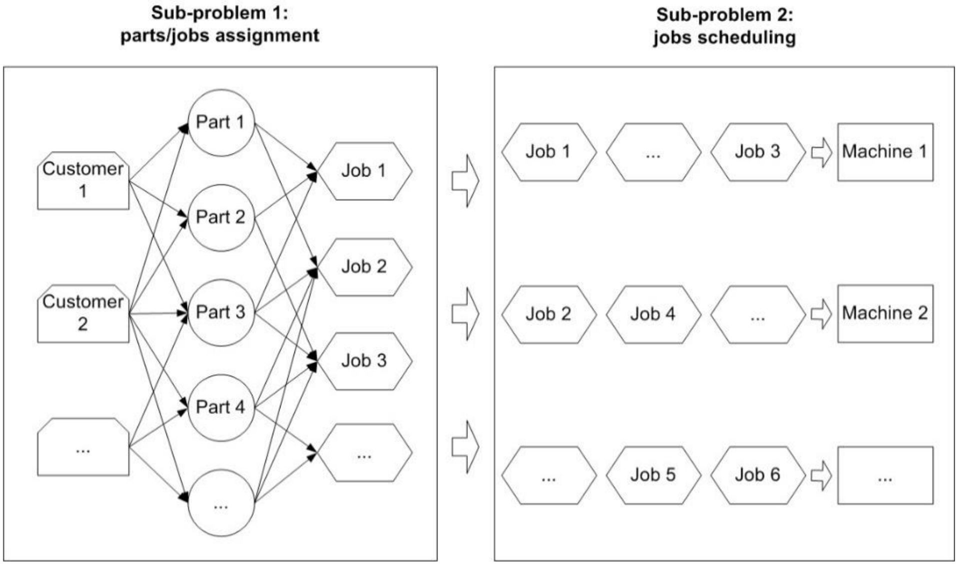


Figure 5.4: Separate optimisation of scheduling and packing in AM

(image source: adapted from Chergui et al. (2018)**)**

In this case, the packing and scheduling were optimized individually. However, compared to an integrated/joint optimisation, separate optimisation is unlikely to achieve the best solution due to being subject to a local optimum rather than the global optimum (Tan et al., 2018, Tao, 2004). To this end, a new framework for integrated optimisation of scheduling and packing was established in this work, as shown in Figure 5.5.

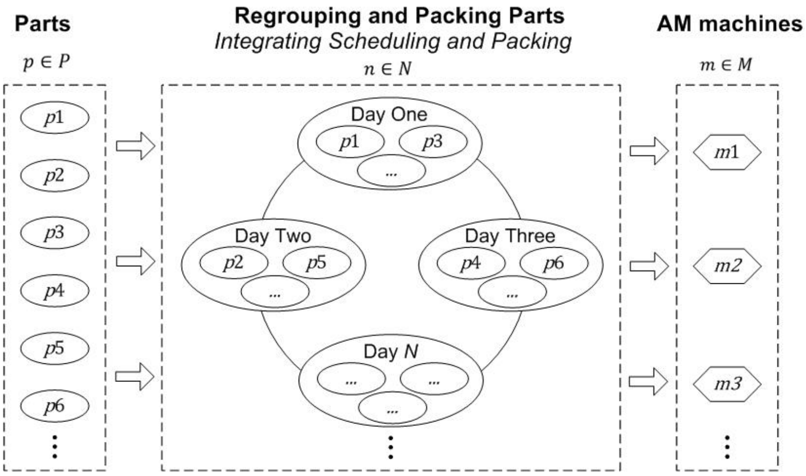


Figure 5.5: Integrated optimisation of scheduling and packing in AM

Figure 5.5 presents an integrated optimisation process of scheduling and packing from *P* parts for *M* AM machines on *N* production days. A set of parts are regarded as input with various geometric volumes and dimensions. The demand for each type of part is specified by the operator. According to the production plan, parts are regrouped into several categories. Multiple groups of parts are packed in AM machines over multiple production days. Orientations of parts were considered in packing strategy for this study. Specifically, each type of part was subjected to rotating operations around the x, y and z-axes. Each type of AM machine has its specification, including production capacity, operation costs, and energy consumption.

In some previous approaches (Baumers et al., 2013, Araújo et al., 2020), the sequence in which part geometries are fed into the AM workflow optimisation scheme is fixed. This sequence can be determined, for example, by measurement of part size or by the date at which the part is required. For working implementations that involve build volume packing, for example using 1D, 2D, or 3D irregular packing approaches, further functions for insertion, collision checking, translation, and rotation are normally required (Baumers et al., 2017b). Moreover, different orientations and positions of parts will lead to different dispersions of parts in the available build volumes and variation in the vertical height, also known as Z-height, of a build, which, in turn, may have an effect on the prospect of successfully executing the build at all (Baumers and Holweg, 2019, Oh et al., 2018b). Importantly for this thesis, different configurations and allocations of parts will lead to different levels of resource consumption and process efficiency (Baumers et al., 2013).

Specifically, different orientations and positions of parts are likely to cause different Z-height and total deposition areas in a build (Oh et al., 2018b). Furthermore, different combinations of parts in a group with specific production dates tend to result in different resource consumption and delivery dates. This is because the total energy consumption of printing a group of parts is influenced by the total volume of parts and Z-height of the build rather than the geometric shape complexity of parts (Baumers et al., 2011a, Baumers et al., 2011b, Baumers et al., 2017b). Due to the varied properties of each type of AM machine, some parts may not be produced in some specific machines. For example, if the maximum dimension of a part is out of the boundary of the available build space.

On a practical level, the problem may further be complicated by the presence of technical constraints dictating that certain parts cannot be made on certain machines. For example, if a particular machine's build volume size is inadequate or certain orientations are not allowed to safeguard product quality.

To efficiently optimize scheduling and packing, it is necessary to reduce the size and complexity to a manageable level through several simplifications in the form of system design decisions (Wu et al., 2013). The core of this problem is that parts should be allocated and packed to make full use of the available build space of AM machines within their capacity (Oropallo and Piegl, 2016).

The starting point for developing a system is the development of a computationally efficient packing algorithm for use in offline workflow optimisation scenarios. Taking inspiration from Baumers and Holweg (2019), the packing algorithm developed in this work follows a 2.5-dimensional (2.5D) approach to the problem, which is addressed by filling up machine space successively in stacked, horizontal portions, referred to as *bands*, of build space. Within each band, the developed algorithm follows the logic of the bottom-left heuristic — attempting to fill machine available build space near the origins of the XY coordinate system (Burke et al., 2006, Chazelle, 1983). A fixed horizontal gap of 2 mm is placed between bands to ensure horizontal separation of parts. In this band-by-band manner, the parts are inserted until the Z-height of the build exceeds the maximum available Z-height of build volume. Figure 5.6 illustrates such an algorithm by showing a vertical cross-section of a packing layout with inserted parts denoted by $p1$, $p2$, etc.

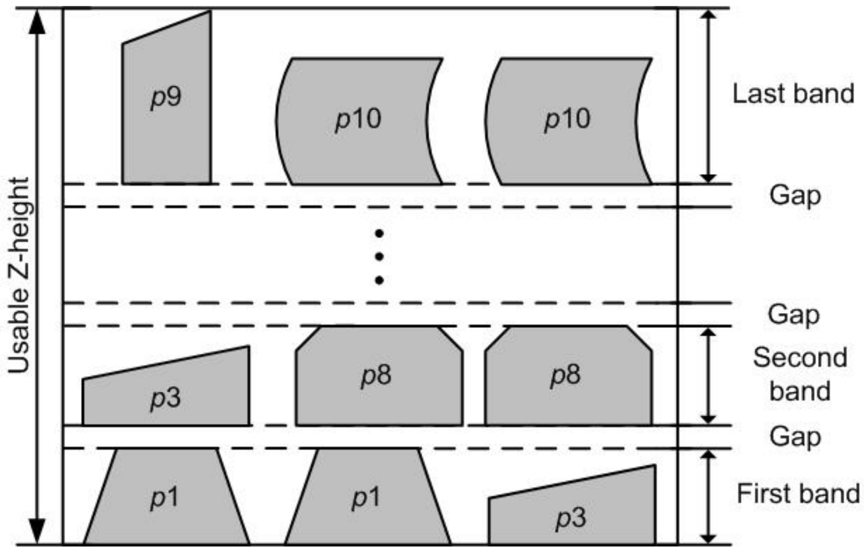


Figure 5.6: Scheme of 2.5D packing in a build from a front view

5.4 Implementation of integrated optimisation

Integrating scheduling and packing in AM refers to allocating parts to machines according to the due date and placing parts on the bed. This forms an opposite situation, i.e., the separate optimisation of scheduling and packing in Lee and Kim (2023). "Optimal packing does not guarantee optimal scheduling. The packing and scheduling must be considered simultaneously to ensure feasibility", says Kucukkoc (2021).

P-LPBF is a typical AM technology variant with the capability of a single build per day. The available build space represents the capacity of each AM machine. Taking P-LPBF as an example, two production days (Day One and Day Two) and two P-LPBF machines (Build A and Build B) were considered to implement the integrated optimisation of scheduling and packing, which are presented in Figure 5.7. The pseudo-code of integrated optimisation of the scheduling and packing algorithm is shown in Appendix B. “AM adopters may find it profitable to pool demand to realize maximum capacity utilization”, says Baumers (2012). Building on this, a capacity aggregation algorithm was developed in this research. Specifically, there were two available machines (i.e., two builds) per day to print parts. Integrating the capacity of two machines on two production days, when demand on a specific day meets the situation — out of capacity, the excess parts will be moved to another day, forming the updates on demand. This may impact the delivery date. However, by virtue of capacity aggregation, the build volume of AM machines can be fully used. More detail is shown in Figure 5.7.

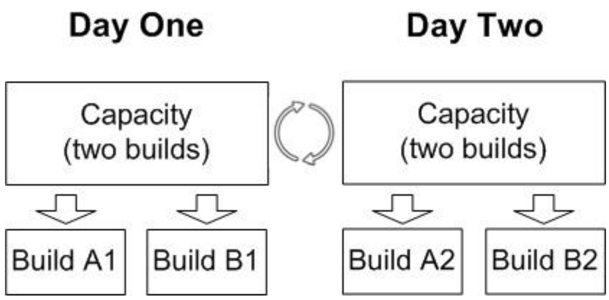


Figure 5.7: Scheme of capacity aggregation in P-LPBF

Exploratory simulations are a popular way to solve production planning problems in AM operations (Gopalswamy and Uzsoy, 2018, Irdem et al., 2010, Bueno et al., 2020, Liu et al., 2011). To achieve this in this work, a manufacturing execution system, also called a computational tool in this study, was developed to handle the integrated optimisation of scheduling and packing in AM. This system (System 1: integrated optimisation of scheduling and packing) was developed and implemented using MATLAB.

Figure 5.8 presents the brief logic of System 1. This system is initialised by inputting the demand information for parts. Following this, System 1 attempts to insert parts into the available build space using a Bottom-Left heuristic and capacity aggregation algorithm, leading to well-packed workflows. Bottom-Left heuristic, a universal approach for 2D parking in AM, is used to pack parts on the bed, laying a basis of 2.5D packing in this system (Wu et al., 2014). The capacity aggregation algorithm attempts to pick a build date that corresponds to the part's due date but allows for overspilling into the other time period where necessary, supporting capacity aggregation across all builds. This algorithm facilitates the interconnection between scheduling and packing through part allocation, forming one of the novelties of this system. A more detailed flowchart of the integrated optimisation process can be found in Appendix C.

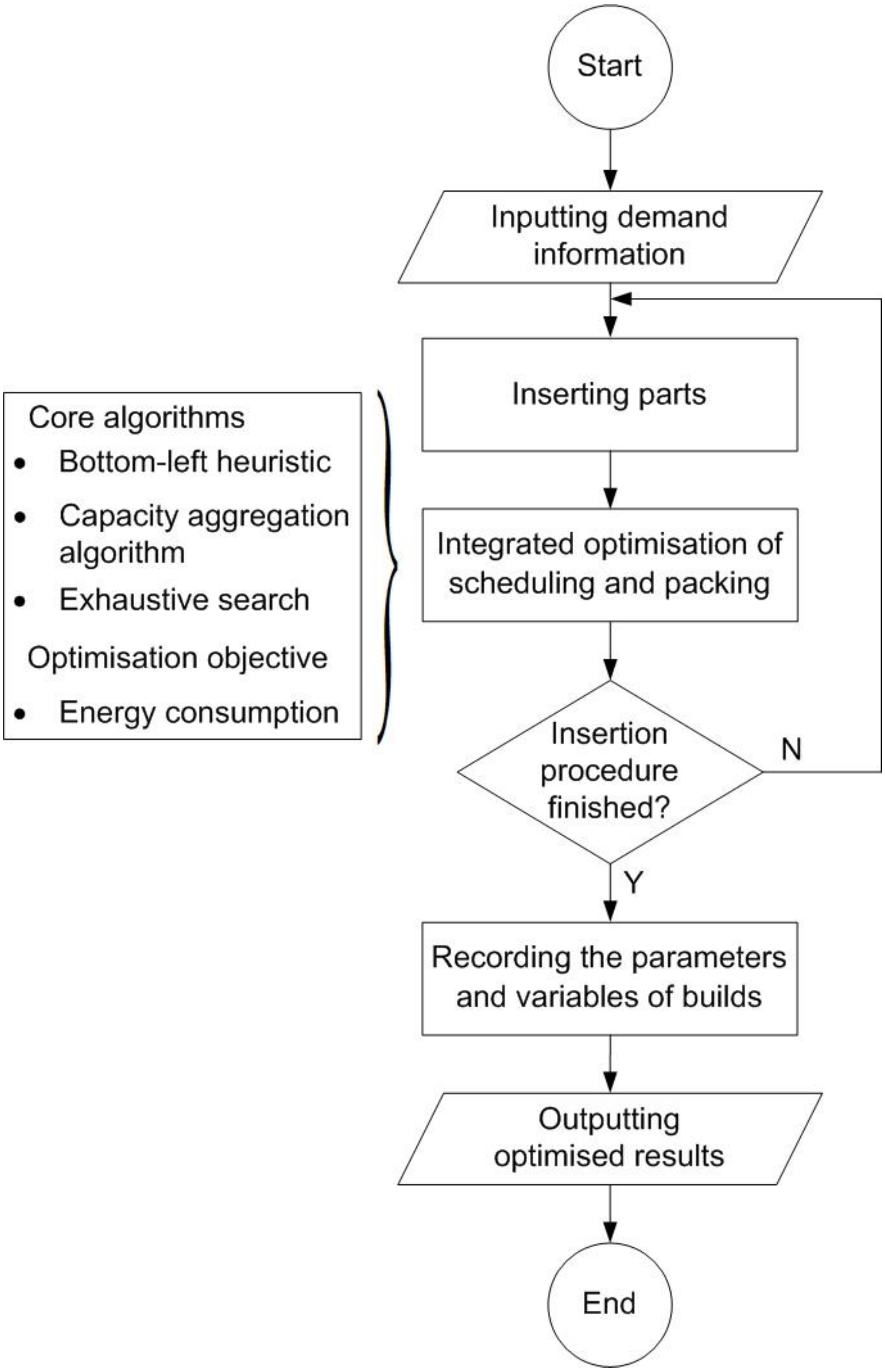


Figure 5.8: Flowchart of System 1 — Integrated optimisation of scheduling and packing

This system is re-run for all rotational instances of each type of part based on 90 degrees increments around the X, Y and Z axes, which is an extension of the rotating method in Zhang et al. (2016), i.e., rotation with 90 degrees increments on the plane (only X and Y axes). This facilitates the maximum capacity utilization for each build. Building on this, a solution space is created by permutating all combinations of rotations, which forms one of novelties of the System 1. The pseudo-code for the solution space generation is presented in Appendix D.

Energy consumption is considered the optimisation objective and relevant energy-based scheduling in AM can be found in extant literature (Tafakkori et al., 2022, Karimi et al., 2021). An exhaustive search is then conducted to find the 'best' solution, which in this case is the energy-minimal scheduling and packing scheme. Together with the solution space generation approach, using exhaustive search reduces the complexity of the solution process to a finite number of solutions (Williams, 2010). Once the insertion procedure is finished, the system outputs the optimized results in terms of the layout of builds and the value of parameters and variables.

To evaluate the energy performance when applying the integrated optimisation developed in this work, a set of experiments using different problem configurations were conducted and the results compared to a scenario with the scheduling and packing optimized individually. In the latter, the capacity aggregation algorithm was not implemented. This meant that the computational tool only allowed AM machines to pack parts within the capacity on each production day.

5.5 Results of integrated optimisation

Following the demand profiles in Table 5.8, the SEC result of each demand profile is presented as follows. The obtained SEC results are optimized solutions because scheduling and packing are typical NP-hard combinatorial optimisation problems. It is impossible to exhaustively list all the solutions to these problems. To this end, heuristics are usually applied to obtain the satisfactory solutions within a feasible time (Tafakkori et al., 2022, Colorni et al., 1996). Combining the developed capacity aggregation algorithm, a BL heuristic and the exhaustive search algorithm were used to generate optimized SEC results.

Figure 5.9 illustrates the change of SEC under different demand profiles with integrated and separate optimisation approaches.

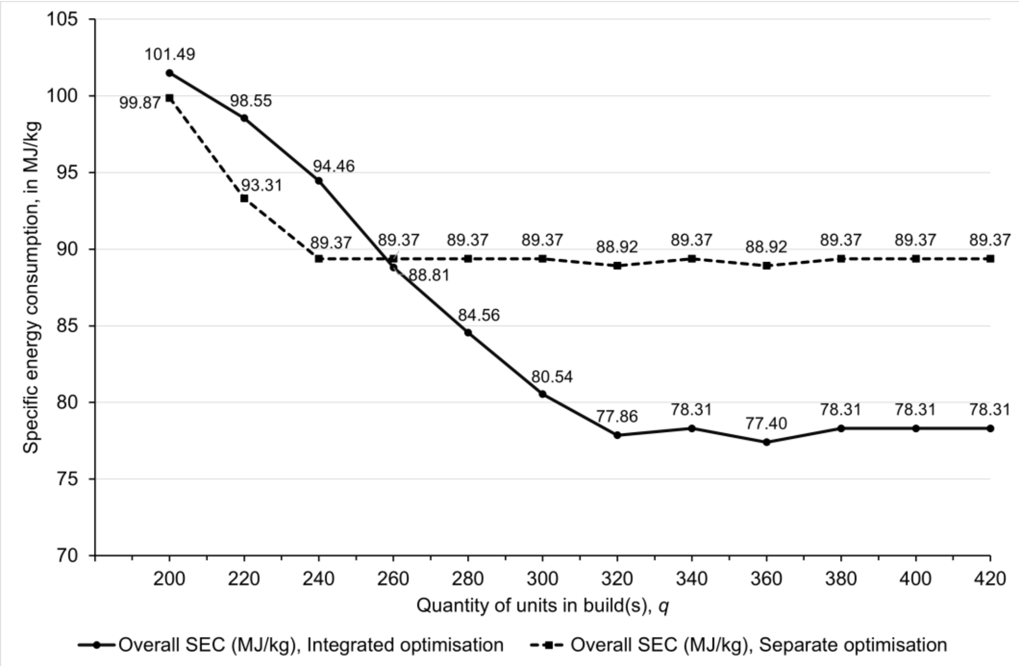


Figure 5.9: SEC comparison between integrated and separate optimisation

Overall, SEC results show a decreasing trend with quantity of units in build in Figure 5.9. Using the integrated optimisation approach helps to reduce approximately 0.63-14.88% of energy consumption when the number of parts is over 260 (demand profile S4 in Table 5.8).

The minimum SEC value (77.40 MJ/kg) occurs at q=360 when using the integrated optimisation method. While adopting the separate optimisation method, the minimum SEC value (88.92 MJ/kg) is observed at q=320.

A special demand profile S4 was studied because this is a turning point for choosing an integrated or separate optimisation approach to achieve minimal energy consumption in AM. Figure 5.10 presents the optimized part allocation results of demand profile S4. The part allocation results on Day One are the same using integrated or separated optimisation methods while the results on Day Two show different. The allocation results show a similar scenario although the demand on Day One dramatically exceeds the capacity of AM machines. As can be seen in

Figure 5.10, using integrated optimisation allows AM machines to pack more parts by 25.69% compared to using separated optimisation (181 parts vs. 144 parts). Table 5.9 illustrates the results of this demand profile.

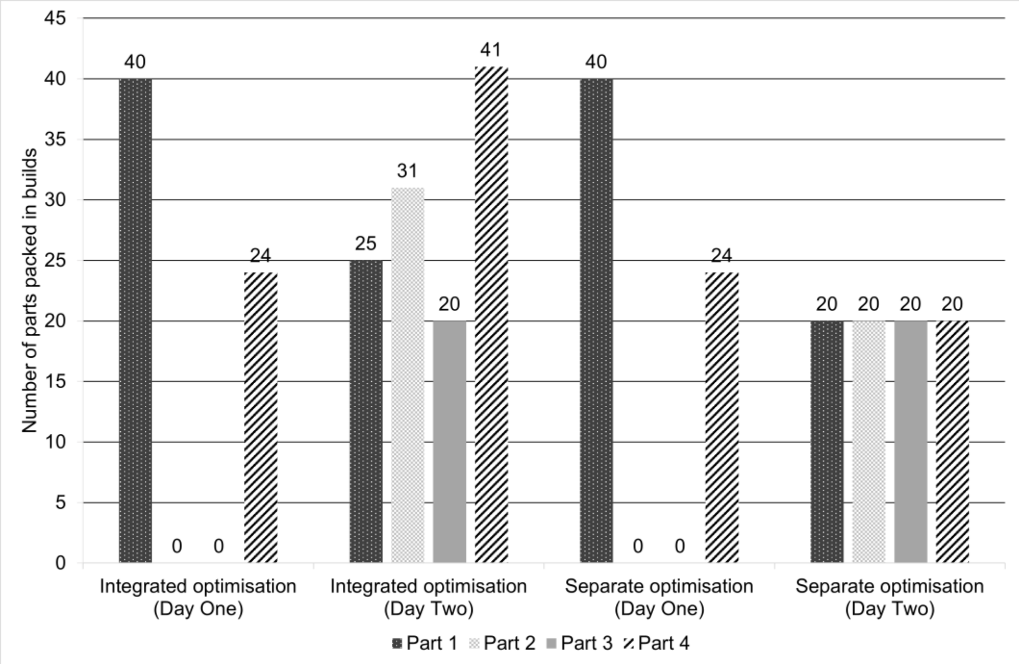


Figure 5.10: The optimized allocation of parts to the machines in demand profile S4

Table 5.9: Results comparison in demand profile S4

Experiment	Integrated optimisation	Separate optimisation
No. of builds	4	4
Total height of builds	1101 mm	961 mm
Total number of layers deposited	11010	9610
Model overall energy estimate	745.30 MJ	677.77 MJ
Model overall material estimate	8392 g	7584 g
Model overall SEC	88.81 MJ/kg	89.37 MJ/kg
Overall capacity utilization ratio	21.32%	19.26%
Mean probability of a successful build	64.39%	68.61%

Specifically, four builds were designed to pack parts for integrated and separate optimisation use. Applying the integrated optimisation approach tends to generate taller builds (1101 mm vs. 961 mm). The layer thickness is fixed (0.1mm in this study), which is in line with Baumers and Holweg (2016). As a result, there are more depositing layers (11010 vs. 9610) by adopting the integrated optimisation approach. This leads to a lower mean probability of a successful build when using the integrated optimisation method (64.39% vs. 68.61%). This is because adopting the integrated method allows more parts to be allocated and packed in AM machines, which can be verified by determining the overall capacity utilization ratio. This is the mean ratio of the volume of parts packed and the volume of available build space and was calculated at 21.32% vs. 19.26%, for the individual against integrated optimisation methods respectively. The capacity utilization ratio in this research is approximately double compared to the 10% for a well-packed build volume reported by Baumers and Holweg (2019).

More importantly, thanks to the effective optimisation algorithms for packing and scheduling in the system, the minimum SEC value generated by using either the integrated or separate optimisation approaches developed in this work (see Figure 5.9), on average, is lower than the results in the extant literature at full capacity build configuration (Kellens et al., 2010, Luo et al., 1999, Baumers et al., 2015).

5.6 Summary

This chapter describes the development and implementation of an integrated packing and scheduling optimisation method and presents the results for a number of scenarios of AM parts and machines. It was found that:

(1) The integrated optimisation method allows approximately 0.63-14.88% savings in energy in AM at higher demand profiles than the implementation of separate scheduling and packing methods.

(2) The integrated optimisation approach allows the AM machines to pack more parts by 25.69% than using separate scheduling and packing methods.

(3) The SEC value obtained in this study is lower than the energy performance level in extant literature due to the adoption of the integrated optimisation approach developed in this work.

Chapter 6: Investigation of environmental network effects in P-LPBF

6.1 Introduction

As established in the literature review, network effects are an important phenomenon as part of value creating processes in industry in the present. Relevant for the growth of businesses, they also serve as an important tool to explain the commercial success of many businesses. So far, however, the question of if and how network effects impact the sustainability performance of industrial processes and machinery has not received much attention.

In this research, the exploratory simulation approach is employed to address the previous research questions and a modified version of the workflow optimisation system is applied in an investigation of the impact of network effects on the process energy consumption of P-LPBF technology. In its structure and its results, this investigation builds on the methodology presented by Baumers (2019), who identified the concept of “environmental network effects” occurring at the machine level when groups of AM systems are organized in conjunction with each other.

As outlined in the literature review, the general logic of network effects is that they result in a technical advantage resulting from the growth of the size of the network, as measured in the discrete number of its nodes. As shown by Baumers (2019), this idea is applicable to networks of AM machines and their customers or users; both groups can equally grow in numbers. Figure 6.1 summarizes the core logic of how such network effects arise as the consequence of the growth of networks. The figure also identifies the two main groups this investigation focused on, the machine operators, who are each assumed to operate a single AM machine, and the customers, who are each assumed to require a number of parts of the same type. It should be noted that both Figure 6.1 and the remainder of this chapter investigate very small networks with very few, three to five, nodes in order to keep complexity to a manageable level. Actual networks of this kind encountered in industry are likely to be far larger.

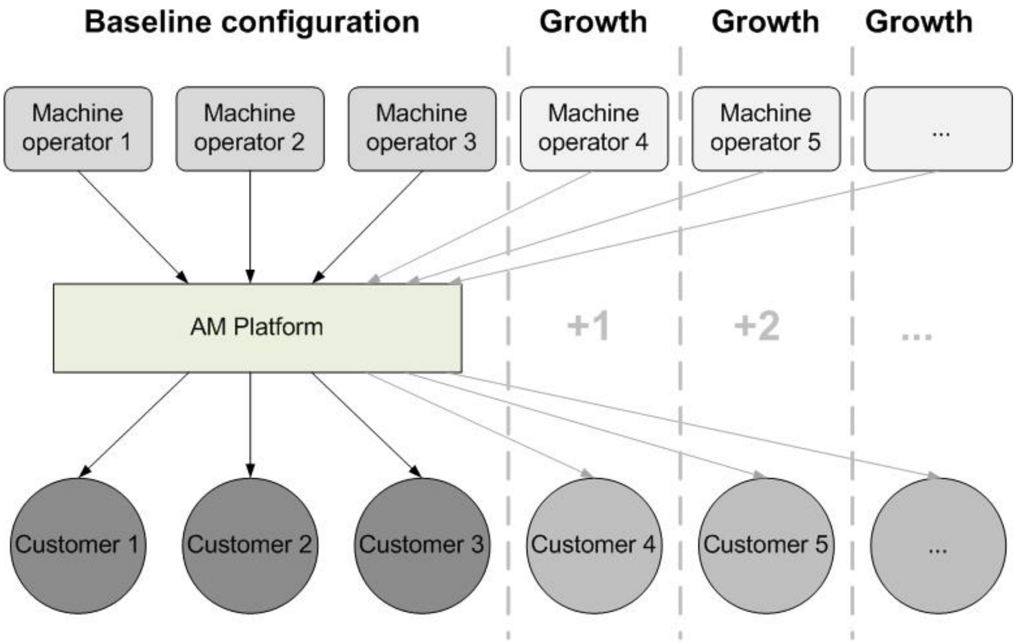


Figure 6.1: Illustration of network growth in an AM network

(image source: adapted from Baumers (2019))

Addressing the identified research question (Ford and Despeisse, 2016, Hegab et al., 2023), this chapter describes the use of the developed workflow optimisation functionality to measure network effects in terms of actual or potential gains in the efficiency of AM processes. To this end, Section 6.2 provides an account of how the simulation was set up, including the definition of network performance metrics and a summary of the modifications to the workflow optimisation system to measure efficiency gains arising in these metrics. Section 6.3 summarizes the execution of the modified system. Section 6.4 provides the results of this analysis. Finally, a summary is presented in Section 6.5.

6.2 Experimental approach

6.2.1. Network performance metrics

In order to assess any changes to the performance and efficiency of AM technology resulting from growth of the network, either in terms of AM machine operators or in terms of customers, it is first necessary to define a set of performance metrics for each group.

In this exploratory study, a major assumption is made that the operators of AM systems are interested in ***process efficiency***, for example in terms of cost and energy performance. The product users, however, are assumed to be interested in minimizing ***lead time***. As discussed in the introduction, assessing the performance of the workflow optimisation in the presence of more than one group in this way can provide an insight into the type of network effects created by the AM platform.

Building on the model in Baumers (2019), this study assumed that machine operators only focus on ***Specific Energy Consumption (SEC)*** (i.e., the lower SEC, the higher competitiveness among peers and customers only concern ***Schedule Attainment (SA)*** (i.e., the higher SA, the shorter the lead time). As discussed in Section 4.3.7, the two metrics were used to reflect the energy and operational performance of AM respectively.

Assessing the energy and operational efficiency of the overall AM platforms, for example in the form of the SEC and SA metrics respectively as outlined in this thesis, provides an insight into whether environmental network effects arise through network growth if multiple AM systems and product users join such platforms.

6.2.2 Experimental assumptions and selecting sample parts

As outlined in the literature review, network effects, particularly cross-group or indirect network effects, are phenomena that arise from the interaction of two groups operating as part of the same platform. As shown elsewhere, such phenomena can be observed by recognizing the change of the overall network performance in one group as the size of another group increases, for example from new members joining (Briscoe et al., 2006).

For simplicity, this study focused on small networks with initially three operators of AM technology, which operate one identical AM system each, and three customers, who require a single component each, which can be seen in Figure 6.2. In this investigation, **m** represents the number of machine operators present as members of the platform and **c** indicates the number of customers present as members of the platform.

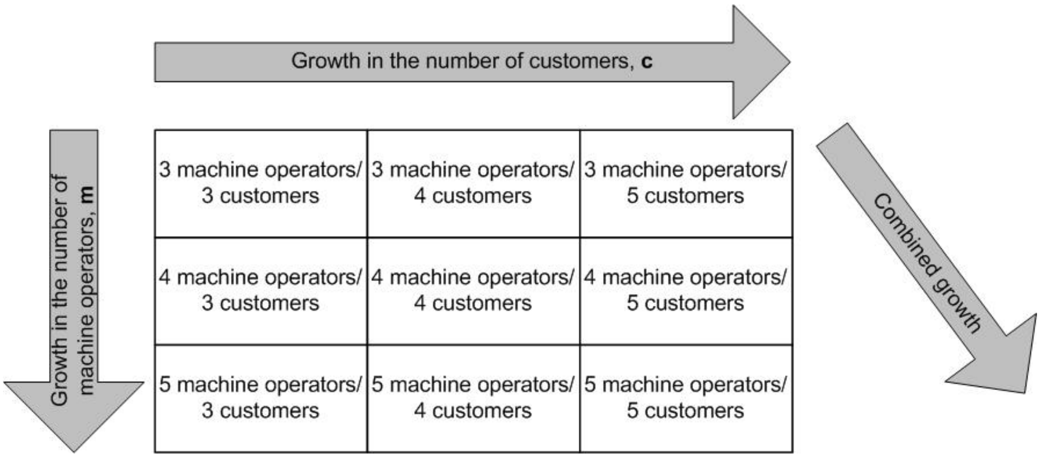


Figure 6.2: The growth cases and the number of group members

(image source: adapted from Baumers (2019))

As can be seen Figure 6.2, this model is able to assess three types of network growth: (1) unilateral growth in the number of customers (**c**); (2) unilateral growth in the number of machine operators (**m**); and (3) combined growth in both groups.

This analysis results in the investigation of nine instances, each of which is analysed for process efficiency and lead time, using the identified metrics. Due to the computational complexity inherent to the workflow optimisation problem, a set of simplifications is made in this study. These simplifications include:

1. One AM machine represents one manufacturer, and one geometry represents one customer.
2. It is assumed that the AM machines used by the machine operators, of which there are three to five, are identical (EOSPINT P 100).
3. There are up to five customers and at least three join the AM platform to provide demand at one time.

4. The demand for each customer is fixed, e.g., 100, and occurs only at one time.

To support this model and in order to assign a type of part demanded by each customer, a basket of five parts, as shown in Section 5.2.1 was selected. The types of parts were chosen based on the sequence of numbers. For example, selecting four types of parts means part 1, part 2, part 3, and part 4 were chosen to study the environmental network effects.

To proceed with the simulation, a series of demand profiles were devised, as shown in Table 6.1. As can be seen, each customer can demand a different quantity of components.

Table 6.1: Demand profiles for System 2

No. of machine operators	Customer 1	Customer 2	Customer 3	Customer 4	Customer 5	Cases
3	100	100	100	0	0	Case 1
	100	100	100	100	0	Case 2
	100	100	100	100	100	Case 3
4	100	100	100	0	0	Case 4
	100	100	100	100	0	Case 5
	100	100	100	100	100	Case 6
5	100	100	100	0	0	Case 7
	100	100	100	100	0	Case 8
	100	100	100	100	100	Case 9

Each instance contains specific configurations (e.g., capacity utilization ratio and the total height of builds), leading to specific energy footprint (i.e., SEC) and operational performance (i.e., SA). In other words, there are nine specifications in terms of SEC and SA in this research.

6.3 Executing the workflow optimisation system to investigate network effects

The start of running System 2 is from inputting demand and forms a matrix but only for a single production day as shown in Figure 6.3.

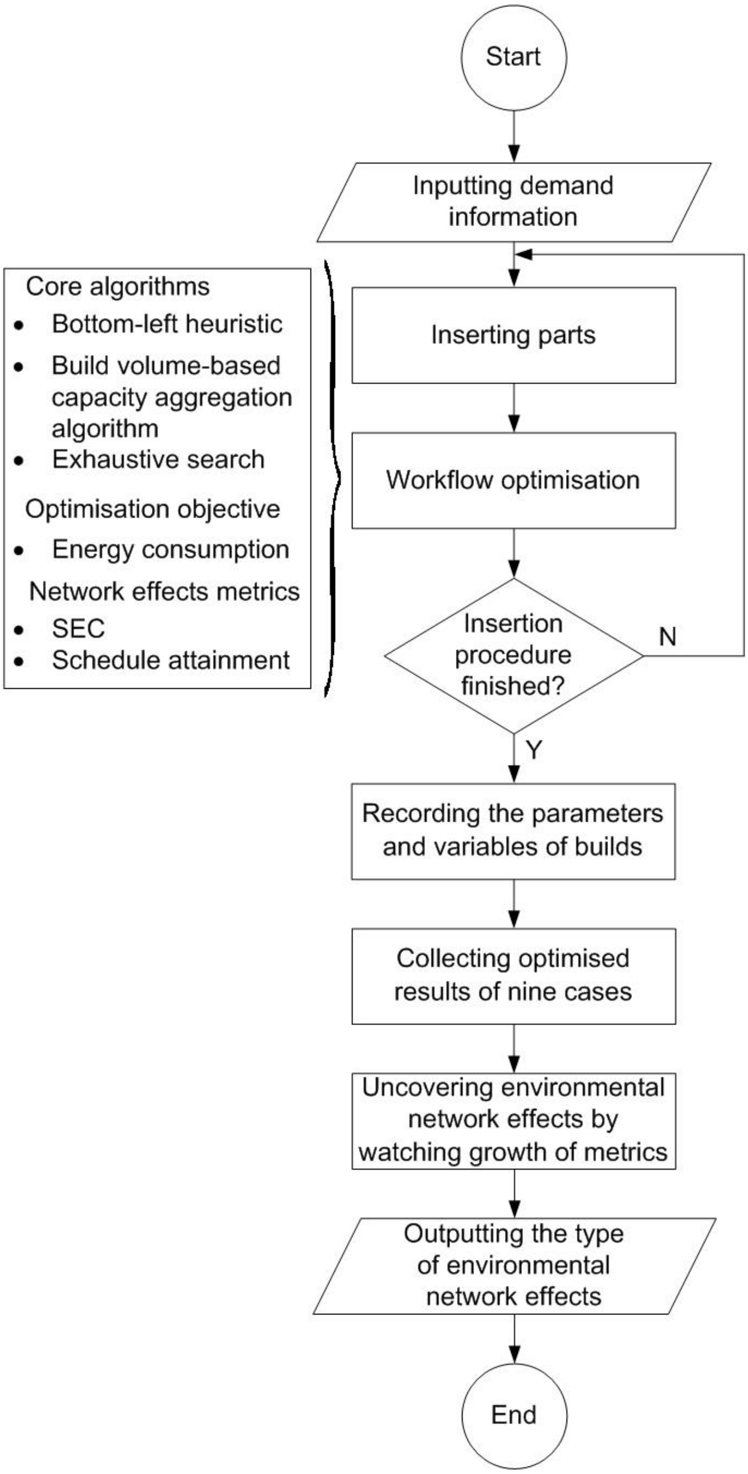


Figure 6.3: Flowchart of System 2 — Investigating environmental network effects

System 2 consists of three algorithms: BL heuristic, build volume-based capacity aggregation algorithm and exhaustive search. BL heuristic was used to pack parts on beds. A build volume-based capacity aggregation algorithm was developed to effectively use the available build space of each machine, supporting the exploration of environmental network effects. Compared to the capacity aggregation algorithm in System 1, the build volume-based capacity aggregation algorithm just focuses on aggregating the capacity of multiple AM machines without considering the capacity in terms of production days. Unlike the build volume packing for a single build (Calabrese et al., 2022, De Antón et al., 2022), the build volume-based capacity aggregation algorithm was designed to aggregate the capacity of a maximum of five builds, allowing to make use of capacity utilization of those AM machines (Baumers, 2012). The pseudo-code for the build volume-based capacity aggregation algorithm is shown in Appendix E.

The system was initialized by inputting the demand information of parts. Based on the BL heuristic, a set of parts can be packed on the bed. A build volume-based capacity aggregation algorithm was developed to maximize the capacity utilization of five builds. This study considered minimization of energy consumption as the optimisation objective, subject to the capacity of builds. To obtain the optimized results, an exhaustive search was adopted to search the solution space, which was generated by permutating all combinations of rotations. The solution space generation and solution searching processes were in line with the procedures in System 1 as presented in Section 5.3. Once the insertion procedure is finished, the system outputs the optimized results in terms of the layout of builds as well as the value of parameters and variables. To understand more details of this system, a flowchart presents the logical structure of the packing procedure shown in Appendix F.

6.4 Results of environmental network effects

As introduced at the beginning of this chapter, this investigation is based on the assumption that there are two groups in the AM platform in this study: machine operators and customers. Gaining insights from Baumers (2019), a three-dimensional column chart, also called a cube-based model, was selected to suitably present the resulting network effects along with the identified performance metrics in the AM platform. In this chart, the value of each indicator is reflected by the height of the column. There are thus nine cases in total, as shown in Figures 6.4 and 6.5, reflecting the different permutations of network growth.

Figure 6.4 and Figure 6.5 depict the SEC and SA value of the nine cases illustrated in Table 6.1 respectively. The vertical axis in Figure 6.4 represents the SEC of each instance. The results can be interpreted that the more SEC diminishes, the greater the benefit from environmental network effects for machine operators.

It is noted that the SEC value, overall, is much lower than the results in the published literature at full capacity configuration (Kellens et al., 2010, Luo et al., 1999, Baumers et al., 2015). Specifically, the energy efficiency can be improved by approximately, on average 33% at full capacity configuration through network effects investigation in the AM platform. This is explained through the use of a build volume-based capacity aggregation algorithm. In addition, the minimum SEC value (76.70 MJ/kg) is very close to or even lower than the result (77.40 MJ/kg) presented in Section 5.4. This reflects the performance of the developed algorithms (i.e., capacity aggregation algorithm and build volume-based capacity aggregation algorithm) functioning in conjunction to improve the energy efficiency of the additive process.

However, compared to the algorithm developed in System 1, adopting the build volume-based capacity aggregation algorithm tends to need more CPU time due to an increase in the size of the solution space, resulting from multiple loops of packing algorithms including the BL heuristic and the developed algorithms. It should be noted at this point that a feasible way to streamline the computing process would be to parallelize the computing process by executing many calculations or processes simultaneously (Skillicorn and Talia, 1998), noting that exhaustive search optimisation is readily parallelizable.

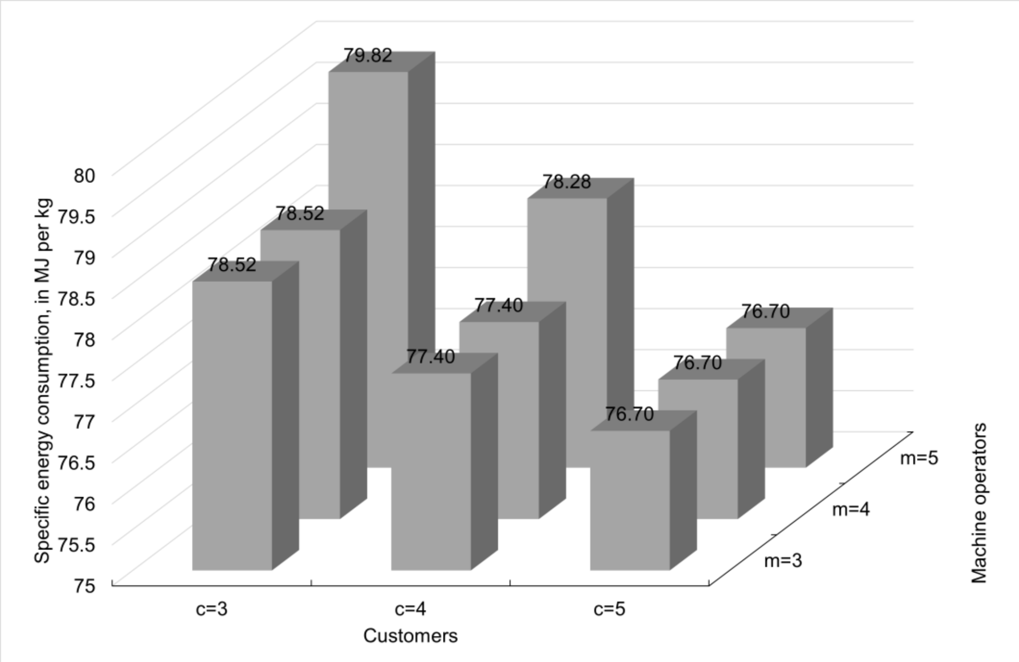


Figure 6.4: SEC with multiple machine operators and customers

As can be seen from Figure 6.4, network growth in terms of customer numbers improves SEC in all cases. This was to be expected as the developed workflow optimisation system is able to configure the work better as the volume and variety of products increases. In other words, more customers joining the AM platform helps each machine operator save energy consumption during production. Assuming that the machine operators are the group concerned with SEC and using the categories of network effects presented in Section 2.5.2, this points towards a cross-group network effect in which growth in the customer group results in benefits for the machine operators.

To reflect the impact of increasing customers on energy performance, the degree of mean SEC decline was calculated. As can be seen Table 6.2, the mean SEC of operator numbers was obtained by fixing customers and calculating the average SEC value. It shows that increasing one customer reduces 1-2% of energy consumption.

Table 6.2: Decline rate of mean SEC with increased customers

Specific Energy Consumption (SEC) (MJ/kg)		Machine operators			Mean SEC (MJ/kg)	Percentage decrease of mean SEC
		m=3	m=4	m=5		
Customers	c=3	78.52	78.52	79.82	78.95	1.60%
	c=4	77.40	77.40	78.28	77.69	1.28%
	c=5	76.70	76.70	76.70	76.70	

Growth in the number of machine operators appears to have a negative effect on SEC. This is explained by having more build capacity available, which results in the workflow optimisation system allocating products less efficiently. The result is not as clear as in the case of growth in the number of customers, however, with network growth in terms of machine operators decreasing energy efficiency in two of the nine cases.

Beyond energy consumption, using a workflow system that is able to allocate production over time allows an investigation of Schedule Attainment (SA), a metric to represent the operational performance of AM. As outlined in this chapter, this analysis makes the simplifying assumption that the customers primarily care about SA.

The vertical axis in Figure 6.5 represents the SA of each permutation of network growth. As can be seen, an increase in the number of machine operators increases SA in each instance. In other words, more machine operators joining results in more customers receiving their orders on time.

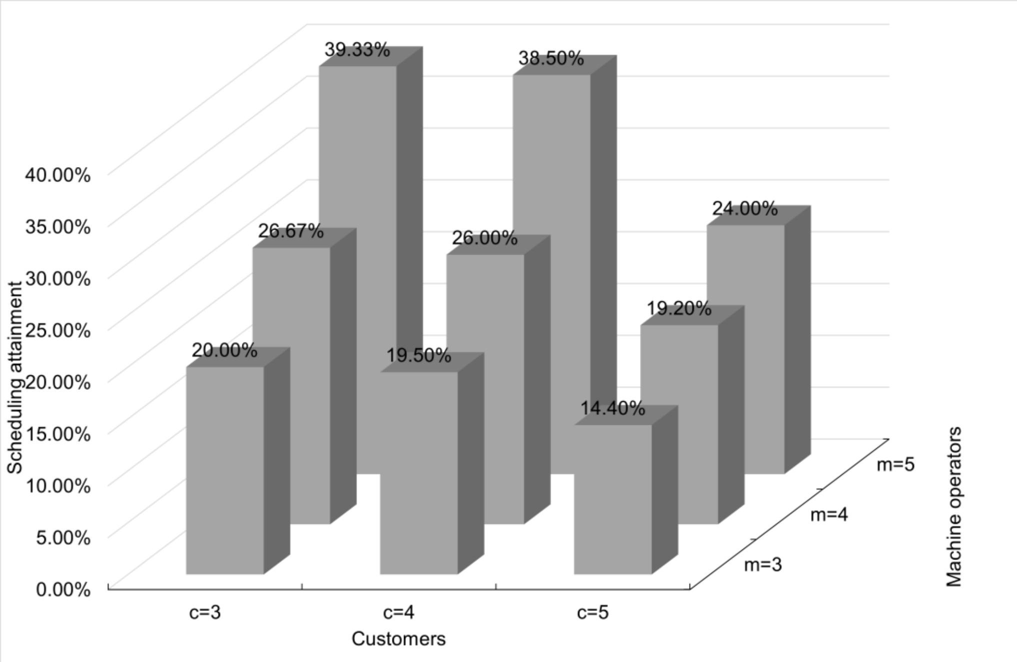


Figure 6.5: Schedule attainment under multiple machine operators and customers

In terms of the categories of network effects presented in Section 2.5.2, this again points towards a cross-group network effect in which growth in the group of the machine operators results in a benefit for the customers.

Analogous to the case of SEC, unilateral growth in the number of customers appears to have a negative effect on SA. This result can be explained by the fact that more customers are competing for the available machine capacity if the network grows in this way.

To reflect the impact of increasing machine operators on SA, the percentage increase of mean SA was used. As shown in Table 6.3, the mean SA of customers was obtained by fixing machine operators and calculating the mean SA value. It shows that increasing one machine operator increases approximately, on average 37.52% of schedule attainment.

Table 6.3: Growth rate of mean SA with increased machine operators

Schedule Attainment (SA)		Machine operators		
		m=3	m=4	m=5
Customers	c=3	20.00%	26.67%	39.33%
	c=4	19.50%	26.00%	38.50%
	c=5	14.40%	19.20%	24.00%
Mean SA		17.97%	23.96%	33.94%
Percentage increase of mean SA		33.34%		41.69%

The results of this exploratory investigation involving the application of the developed system to model the effects of a growing AM platform with two user groups thus point to the existence of network effects. At least one of these effects, leading to the reduction of SEC, suggests that the label of environmental network effects can be meaningfully applied. More specifically, the investigation suggests that there are indirect network effects. This forms a very interesting result due to the importance of this type of effect. The literature on network effects identifies indirect network effects as the most powerful due to their ability to generate positive feedback loops, in turn leading to rapid growth of networks (Gawer, 2014). Overall, this investigation thus combines the ideas of network effects with sustainability performance at the machine level.

It is important not to overplay the significance of these results since they originate from the use of a limited model with only three to five members in each group. Moreover, as the result of an exploratory simulation methodology, the model is also artificial and simplistic in its assumptions, for example suggesting that machine operators primarily care about SEC whereas customers primarily care about schedule attainment. Empirical research involving a more advanced conceptualization of network effects will be needed to establish these results more reliably. Ideally this would be done by subjecting a real-world dataset of AM platforms to statistical inference.

6.5 Summary

This chapter has applied an extended version of the workflow optimisation system to an investigation of the existence and magnitude of network effects in AM platforms. Despite being conceptually limited and based on an exploratory simulation method, it suggests that:

- A distinction should be made between customers and machine operators with respect to the performance of workflow optimisation methods.
- The use of SEC as a performance criterion in such an investigation leads to the concept of environmental network effects, which may be a meaningful and important conceptual tool in exploring the environmental impact of platforms and digitally networked industrial systems.
- Using the exploratory simulation method, it is possible to measure these network effects, albeit in a limited way and for a small AM platform.
- Increasing customers is beneficial to a 1-2% savings in energy consumption and increasing machine operators facilitates approximately 37.52% reduction of lead time.

Overall, the presented results serve as new indication that AM supply chains, in which multiple AM machines and multiple products are present, should be understood as networks. As shown, there is evidence for improvements in sustainability performance from network growth, which may form an important, so far unappreciated, additional benefit from participating in such networks.

This complements the current literature on platforms and network effects, which concentrates on profits and private value as a measure of the impacts of operating platforms. It may also produce a valuable new perspective on how digital information interchange systems can be leveraged to create sustainability benefits when operated together with manufacturing systems.

Chapter 7: Discussion

This chapter discusses the research results in five sections. Section 7.1 covers the impact of build failure on energy consumption in AM. Section 7.2 discusses the equilibrium of material consumption in AM including material deposited into parts, material waste, and material loss. A discussion of the new approach for optimizing scheduling and packing in AM is offered in Section 7.3. Section 7.4 discusses the implications of workflow optimisation on improving the sustainability of AM. A final discussion is conducted to understand the implications of investigating network effects in the AM platform in Section 7.5.

7.1 Impact of build failure on energy consumption in P-LPBF

The results presented in Chapter 4 demonstrate a realistic and practical way to model the energy footprint of P-LPBF, extending previous work on P-LPBF energy consumption by studying the energy embedded in the material, the effect of capacity utilization, and the expected impact of the risk of build failure.

The results can be compared with the literature by assessing SEC, which is the energy consumed by the P-LPBF process per unit mass of product geometry deposited (mostly measured in or convertible to MJ per kg).

In terms of energy consumption, this research also explored the effects of embedded energy on SEC of P-LPBF process by adding the energy embedded in the material E_{embed} into the numerator of SEC model, which is shown in Eq. (7.1). Table 7.1 provides an overview of SEC results.

$$SEC_{include} = \frac{E_{process}+E_{embed}}{M_{parts}} \tag{7.1}$$

Table 7.1: Specific energy consumption comparison for P-LPBF processes

Literature	Luo et al. (1999)	Kellens et al. (2010)	Baumers et al. (2010)	Baumers et al. (2015)	This research	
					Excl. embedded energy	Incl. embedded energy
AM variant	P-LPBF	P-LPBF	Metal LPBF	P-LPBF	P-LPBF	P-LPBF
Material used	Polymer	PA2200	SAE 316L	PA2200	PA2200	PA2200
SEC (Single part build) (MJ/kg)	N/A	N/A	139.50	1122.09	1304.10	6203.96
SEC (Full capacity build) (MJ/kg)	107.39; 144.32	130.12	111.60	113.66	161.42	542.45

The comparison in Table 7.1 shows that the energy consumption levels estimated in this research are higher than the available literature, suggesting that previous work has understated the energy consumption of AM. The results confirm, as expected, that the degree of capacity utilization has a significant effect on the energy consumption of the process (Baumers et al., 2017a), highlighting its importance for operating the process efficiently. However, the relationship between capacity utilization and efficiency gains in per-unit energy consumption is non-linear, the U-shaped pattern (models ***a*** and ***c***) in Figure 4.9, with the most energy-efficient builds occurring at intermediate levels of capacity utilization. This is due to the accumulating risk of build failure as the Z-height in the builds becomes large. Increasing the capacity utilization further, improved the amortization of fixed job energy consumption but this was insufficient to offset the increased risk of build failure and waste in embedded energy. Therefore, in practice, the risk of build failure and energy embedded in the material should not be overlooked when assessing the environmental performance of AM systems. This argument is analogous to existing research on the financial cost of AM (Baumers and Holweg, 2019).

It is also important to note that accounting for embedded energy is paramount for improving the degree of transparency in understanding the total energy consumption of the manufacturing process. AM already has an inherent advantage in this regard as it is possible to produce complex geometries in a single manufacturing step; this contrasts with conventional manufacturing, which often requires multiple operations spread across different sites (Baumers et al., 2013). This research expands the scope of the energy consumption analysis, using well-documented methods to offer an even more realistic picture of the true energy footprint of AM. These addressed objectives 1 and 2 as presented in Chapter 1.

Moreover, the results of this work underline the considerable impact of material waste streams on the environmental footprint of P-LPBF. Against the popular narrative, many AM processes create significant waste streams that need to be taken into account when evaluating the environmental performance of AM, for instance via life cycle assessment (Kellens et al., 2017a, Kellens et al., 2012, Faludi et al., 2015, Kellens et al., 2017b). Excluding the risk of the build failure, the SEC values for the single part build (5859.50 MJ/kg) and full capacity build (337.25 MJ/kg) are significantly different from the situation excluding waste streams (1231.69 MJ/kg vs. 107.80 MJ/kg, respectively). The comparison of SEC values in Table 7.1 suggests that waste streams have a bigger impact on environmental performance than the risk of build failure.

The difference in energy consumption behaviour between additive and conventional manufacturing processes, such as injection moulding, requires acknowledgement. In P-LPBF, since the build volume is fully packed at q=55, there is no improvement in the unit energy consumption in choosing to build a marginally higher quantity of parts. This is because producing one more part would need a new build cycle, resulting in a repeat of the full, fixed job energy consumption. Moreover, the minimum achievable energy consumption in P-LPBF is subject to the most energy-efficient operation for one build. Whereas the energy consumption curve in conventional manufacturing decreases asymptotically as the volume increases, continually improving the per-unit energy consumption.

Finally, sustainable AM requires greener supply chains, more efficient manufacturing processes and high-quality resource recycling (Huang et al., 2013, Despeisse et al., 2017, Kohtala, 2015, Allwood et al., 2022). Additionally, the impacts of build failure on the complexity of the supply chain structure should not be underestimated (Holmström et al., 2016, Li et al., 2017a). Moreover, the recycling and reuse of wasted material have a key role to play in improving resource efficiency in AM (Huang et al., 2013), while the combination of digitalization, interconnection, and automation is likely to facilitate resilient and efficient AM implementation.

7.2 The equilibrium of material consumption

This study established a model to study the equilibrium of material consumption during the additive process, as shown in Figure 4.4. This model assumes that the P-LPBF system operates in a steady state. Specifically, the mass of the virgin powder introduced into the system is in equilibrium with the mass of the material exiting the system. Therefore, the amount of fresh powder material introduced into the system equates to the mass of powder fused as parts, the powder waste due to degradation, and any other unaccounted-for powder losses.

Building on the steady state of the P-LPBF system, the established equilibrium model provides a theoretical way to understand the material consumption compositions and material flow as well as the measurement of material used in practice.

It has been identified that the measurement of material consumption during the additive process is difficult (Peng et al., 2018, Mukherjee et al., 2016). The proposed material consumption model offers a practical or even precise measurement method of material use during the additive process. This model tends to help operation managers accurately estimate the material consumption during the AM process, facilitating resource supply and management in production. Building on this, thanks to the localized feature of logistics in AM, the material suppliers are likely to gain benefits in terms of supply efficiency by interacting with manufacturers (Ben-Ner and Siemsen, 2017). A deep interaction or collaboration among manufacturers, customers, and suppliers is acknowledged to promote technology innovation in additive manufacturing (Ahuja et al., 2015, Zairi, 1998).

The constructed material consumption model affords a possibility of environmental sustainability improvement in P-LPBF. "If you can't measure it, you can't improve it", says Prince (2018). In other words, the measurement of material consumption has a significant role to play in improving the environmental sustainability of AM. The results in Section 4.4.2 have shown that the energy embedded in the raw material dominates the total energy consumption in both single-build and full-capacity configurations. The established model helps operations managers estimate the embedded impact of P-LPBF process, allowing them to adopt sustainability improvement measures/strategies. To do so, Monteiro et al. (2022) suggested an array of resource efficiency strategies in AM from four aspects: product design, materials extraction and production, processes, and end-of-life extension. Building on improving material efficiency, Girdwood et al. (2017) suggested that a better understanding of process parameters and efficient utilization of machine capacity would acknowledge further savings in material use during the additive process compared to conventional manufacturing. This puts stress on the significance of adopting optimisation approaches to improve resource efficiency, which would be discussed further in Section 7.3.

The proposed model may provide insight into environmental sustainability improvement in P-LPBF by estimating material waste. It is suggested to reuse waste material by converting material waste (e.g., support structure) into functional powder or wires in metal additive manufacturing (Monteiro et al., 2022). However, there are some uncertainties about the waste material, for example, volume and situation (Stieberova et al., 2022). A precise estimation of material waste is likely to facilitate recycling operations. Although it benefits resource efficiency, Ford and Despeisse (2016) stated that it is challenging to implement this conversion process into raw material for reuse in additive manufacturing. To this end, for polymer waste, Shanmugam et al. (2020) suggested that it is necessary to handle, and separate polymers based on their properties (e.g., physical and chemical) to support effective polymer waste management. These disposal methods include incineration, recycling, landfilling, and carbonization (Chen et al., 2020).

7.3 New approach for packing and scheduling optimisation

AM, as a parallel manufacturing process, enables the manufacture of different parts in a build volume simultaneously (Ruffo and Hague, 2007). This gives rise to the build volume packing problems during the machine setup stage. Such packing problems are classified as NP-hard (Kaaouache and Bouamama, 2015), which could be solved by adopting computational approaches (Hur et al., 2001).

This study considered all orientations of parts to support the generation of solution space, allowing the computer to exhaustively search all feasible packing solutions. However, as the parts increased, the optimisation process would be challenging because the problem instance size exponentially surged, resulting in a considerable amount of CPU time (Tao, 2004). Such computational challenges tend to occur particularly in the mass production of AM. To this end, it is necessary to choose specific mathematic models and algorithms that fit the problems (Jian and Wang, 2014).

A new framework was developed in this study to realize the integrated optimisation of scheduling and packing. It contains two main stages: solution space generation and optimal solution identification. Compared with the extant optimisation approaches regarding addressing production planning in AM, for example, metaheuristics (Tafakkori et al., 2022, Zhang et al., 2020), the optimisation method developed in this research supported a robust generation of optimized solutions. Specifically, a set of simplifications have been made in this study, for example bounding box adoption. Converting the part into a bounding box is usually used to implement 2D packing, which ensures productive packing in AM (Tafakkori et al., 2022). In addition, scheduling and packing were integrated at a part level in this study rather than at the production run level (job or batch) (Tafakkori et al., 2022). This has led to a higher level of capacity utilization particularly in multiple build volumes, allowing effective use of machine resources in AM. As a result, objective 3 was accomplished.

When considering business use, the developed system is likely to help operations managers rapidly generate a satisfied packing and scheduling solution with minimal energy consumption, gaining competitive advantages in terms of sustainability (Barreto et al., 2010). However, it requires further development to satisfy specific requirements for business use, for example, one system for all types of AM technologies use, the deployment of AM machines (e.g., quantity, model) and the kind of parts.

The established integrated optimisation system in this study may provide insight into the advancement of digital manufacturing platforms in P-LPBF. It is noted that digital platforms for manufacturing have a significant role in improving product quality, reducing prototyping costs, and reducing time to market (Chryssolouris et al., 2009). The developed system in this thesis allows a small scale of interconnections between P-LPBF machines through capacity aggregation, facilitating the efficient utilization of production resources including machines, material, and power. It is acknowledged that digital manufacturing platforms have a broad role in offering manufacturing services, for example, data collection, storage, processing, and delivery (EFFRA, 2023). However, it is challenging to enable manufacturing businesses, particularly small and medium-sized enterprises, to satisfy the requirements of evolving supply chains (Gerrikagoitia et al., 2019).

7.4 Implications for sustainable AM through integrated optimisation

Compared to conventional manufacturing, AM holds great potential in minimizing the carbon footprint in product and production development, and whole life cycle stages. Its capability to involve in sustainable manufacturing for example repair, upgrade, and remanufacture tooling shows an opportunity for significant savings in energy consumption, costs, and emissions (Morrow et al., 2007). Regarding integrated optimisation of scheduling and packing, the AM equipment is allowed to use interchangeable documents, i.e., CAD models in STL format. It may be profitable to pool demand to achieve capacity utilization (Baumers, 2012).

The results in Section 5.5 have shown that the integrated optimisation approach is likely to facilitate a more energy-efficient production, particularly in higher volume scenarios. This approach allows AM system to pack more parts on the bed compared to the separate optimisation method. This raises higher energy consumption and materials use. However, it has less environmental impact, measured using SEC when compared with separate optimisation.

To further assess the performance of the developed system, the SEC value of this study is compared with the literature. In a single build, the energy consumption levels (107.77 MJ/kg) estimated in this study are very close to the available literature (Luo et al., 1999, Baumers et al., 2015, Wang et al., 2022b), indicating the effectiveness of the developed system in SEC estimation. A notable point that should be mentioned is that, as estimated by this research, the SEC value is lower in full builds (i.e., four builds in this research) than in one build scenario (79.54 MJ/kg vs. 107.77 MJ/kg). This is due to that the higher degree of capacity utilization ratio has a positive effect on the SEC of additive process for example 107.80 MJ/kg vs. 1231.69 MJ/kg (Wang et al., 2022b).

This study extended the previous research on the integrated optimisation of scheduling and packing in AM (Ransikarbum et al., 2020, Tafakkori et al., 2022, Aloui and Hadj-Hamou, 2021, Zhang et al., 2020). This has been done by investigating the integrated optimisation mechanism and energy consumption predictive model. Specifically, the proposed optimisation approach allows multiple AM machines to efficiently utilize available build space. One reason is that the 2.5D packing allows AM systems to fill the build volume rather than pack a single floor of parts on the bed with 2D packing methods (Oh et al., 2018b). Another reason can be found that building on 2.5D packing, the capacity aggregation is capable of effectively employing the available build space of multiple AM machines rather than tightly packing parts in a single AM machine with a 3D packing approach (Araújo et al., 2020).

The adopted approach aims to improve the environmental sustainability of P-LPBF process from the production planning perspective. However, the effects of process parameters on sustainable manufacturing need to be concerned (Hao et al., 2010, Siva Rama Krishna and Srikanth, 2021). In Direct Laser Deposition (DLD), many process parameters have an effect on the microstructure, and residual stress of parts, for example, powder feed rate, laser power, and laser scanning strategy (Shamsaei et al., 2015). This would affect the quality of parts and the probability of build failure, resulting in extra consumption of energy and material. From the perspective of equipment utilization, the developed system would help to use P-LPBF machines environmentally friendly by making use of each machine and aggregating the capacity of all P-LPBF machines. To some extent, this would reduce waste of equipment utilization and therefore improve production efficiency as well as manufacturing sustainability (Ford and Despeisse, 2016).

The study provides a digital solution for production planning and scheduling in P-LPBF. In this system, the parts and additive process can be traced using data, laying a base for realizing digital transformation for companies. This offers opportunities for innovation by combining established logistics and supply chain management (Holmström and Partanen, 2014). Interacting real-time data with other equipment (e.g., robots) and the environment by embedding sensors, more benefits in terms of sustainability and cost reduction of AM can be gained further (Syafrudin et al., 2017).

7.5 Implications for investigating network effects in the AM platform

The network effects in terms of environmental impacts in the AM platform were investigated in this study. Considering specific energy consumption and schedule attainment as metrics, the network effects in the AM platform were identified, addressing objective 4.

The results in Section 6.4 indicate that network effects do exist in the AM platform — indirect network effects. This means that more customers joining the network allow lower environmental impacts for each machine operator. More machine operators joining the network helps less waiting time for each customer. This is due to the mechanism of capacity aggregation embedded in the developed computational tool. In addition, it is partially because of the economics of scale, i.e., cost advantages companies experience when production becomes efficient (Baumers and Holweg, 2019). However, it cannot be completely attributed to the economics of scale because, as suggested by Petrick and Simpson (2013) and Weller et al. (2015), the economics of AM are fundamentally different to conventional manufacturing. The tool-free manufacturing allows an elimination of temporal and monetary investment in designing and fabricating the necessary tooling and fixtures, featuring AM as an enabler to produce individual parts in small batches without any set-up time concerning the resources (Atzeni and Salmi, 2012). Instead of capital-intensive and machine-intensive production locations, AM is able to manufacture based on demand. This allows the possibility of separating product design and production, providing new business models that relies either on product services or manufacturing resources (Thiesse et al., 2015).

Investigating network effects in the AM platform may offer a view of understanding the relationship between the demand side and supply side as well as improving the sustainability of AM, i.e., adopting the economic theory to study environmental behaviour in the AM platform. Indeed, AM is capable of design freedom, on-demand production for tooling, and remanufacturing of metal parts (Knofius et al., 2019, Rahito et al., 2019, Yi et al., 2019). These features allow AM an enabler for redistributed manufacturing and a technological facilitator in the fourth industrial revolution (Arifin et al., 2022, Turner et al., 2019). The investigation of environmental network effects is exploratory and tentative, and this adds in a number of new concepts and framework to the study of workflow optimisation systems in AM.

Taking into account the potential of environmental benefits via exploiting network effects, AM tends to contribute to the construction of Smart Manufacturing Systems (SMSs). This will offer much more effective production, sustainability, agility, globalization, and mass customization and give a glimpse into the future of how AM technology will be operated in the industry (Qu et al., 2019).

Chapter 8: Conclusions and recommendations for further work

8.1 Conclusions

A workflow optimisation approach was developed to improve the environmental sustainability of P-LPBF. This has been done by establishing an environmental sustainability model and using exploratory simulation. Using this model, the basic elements of environmental sustainability were studied. In addition, the impact of the risk of build failure and capacity utilization on energy consumption was quantified. In the exploratory simulation, two computational tools were developed to realize the integrated optimisation of scheduling and packing as well as to uncover environmental network effects in the AM platform respectively. Detailed conclusions are presented below.

8.1.1 Factoring build failure into energy consumption

The effects of the risk of build failure on the energy consumption of P-LPBF were investigated in this thesis. This has been achieved by modelling the expected energy consumption per unit across the entire range of build capacity utilization. Embedded energy was also considered as part of the total energy consumption to assess the overall energy footprint of P-LPBF.

In many existing AM studies, the effects of the risk of build failure on AM energy consumption are ignored. The model proposed in this study allows researchers and manufacturers to obtain the expected energy and material consumption information and shows how more realistic models can be constructed. It can thus facilitate further research to mitigate the environmental impacts of AM through product and process design (Baumers et al., 2013). Without consideration of build failure, process energy consumption estimates may not be realistic and resource consumption may be underestimated, resulting in overly optimistic assessments of energy demands and the environmental impacts of P-LPBF.

The results also show that, for the investigated P-LPBF system, the energy embedded in the material has a greater impact on the total energy consumption than the AM process itself. Moreover, the impacts of waste streams have an outsized effect on the ecological impact of AM compared to the risk of build failure.

8.1.2 Integrated optimisation of scheduling and packing

A manufacturing execution system (or a computational tool) has been developed to achieve minimal energy additive manufacturing through integrated optimisation. Overall, this system provides a new optimization framework and new integrated optimization algorithms to address integrated optimization problems in P-LPBF. The energy consumption estimator was embedded into this system. In addition, a capacity aggregation algorithm was developed. BL heuristic and exhaustive search algorithms were adopted in this system. The existing studies have not yet investigated the integrated optimisation of scheduling and packing through aggregating the capacity of multiple builds in P-LPBF. The developed system provided a precise resource estimation (e.g., energy consumption and material use) under minimal-energy configurations and optimized layout of build(s). This would help further research to identify the resource consumption of additive processes and support sustainability-related considerations in the design (e.g., product and process) (Diegel et al., 2010).

An emphasis is placed on the integrated optimisation approach that was developed at a part level in this study, which is different from the integration methods in extant literature (Tafakkori et al., 2022, Zhang et al., 2020). Furthermore, aggregating the capacity of builds has a positive effect on improving the capacity utilization ratio and energy efficiency at a high level of demand profiles during the additive process. This helps a tighter and more realistic integration of scheduling and packing in AM, leading to the improvement of environmental sustainability in terms of energy consumption, material consumption, and equipment utilization (Ford and Despeisse, 2016). Without a deep understanding and implementation of integrated optimisation, the additive process is unlikely to be environmentally friendly, resulting in equipment utilization waste, higher energy consumption and more material use, as discussed in Sections 7.3 and 7.4.

8.1.3 Environmental network effects

The purpose of the environmental network effects study is to uncover the network effects between machine operators and customers in the AM platform. This has been realized by establishing another computational tool to estimate the specific energy consumption and schedule attainment under a set of demand profiles.

This thesis has investigated environmental network effects from the economics perspective, i.e., taking the AM platform as a market and creating value based on the economies of scope in demand (Gawer, 2014). Building on the main framework of System 1 shown in Section 5.3, a new build volume-based capacity aggregation algorithm was developed in System 2. This contributed to the maximum capacity utilization ratio across multiple AM machines and minimal energy consumption for each specific demand profile as well as the optimized layout of builds.

Specific energy consumption and schedule attainment were regarded as indicators to characterize the environmental network effects in AM. Results indicated that there are indirect network effects between machine operators and customers in the AM platform. In other words, increasing customers allows each machine operator to gain environmental competitiveness during the additive process. Increasing machine operators facilitates each customer less waiting time for product delivery.

AM holds great potential for improving sustainability, for example, energy efficiency and complete time. Without such an investigation, this potential cannot be fulfilled further. This study offered an understanding of the mutual impacts between the supply and demand sides in the AM platform, affording an opportunity for the improvement of product services (e.g., rapid product delivery) and manufacturing resources (e.g., aggregation, sharing, and allocation) in business via the AM platform (Thiesse et al., 2015). Furthermore, due to its performance in improving the energy efficiency of AM as presented in Section 6.4, the developed system may provide a way of investigating environmental sustainability improvement by discovering the effects that are existed in manufacturing systems.

8.2 Limitations and recommendations for further work

8.2.1 Limitations

There are three main aspects of limitations for this study: risk of build failure, integrated optimisation, and environmental network effects.

In terms of build failure, this study investigated the effects of risk of build failure based on single-machine cases only. When considering mass production using AM, process failure on individual AM machines is likely to affect the operation of other machines and the overall resource consumption. Operating multiple AM machines allows further optimisation. For example, when operating two machines, the production time of splitting jobs equally into two builds tends to be shorter than filling one and running another at lower capacity, therefore, influencing appropriate job scheduling. In addition, build failure is explored in the context of build configurations containing identical parts in the form of a fixed probabilistic value for each layer. This might not be reflective of common practice for the technology as mixed-part builds are often used (Ruffo and Hague, 2007, Baumers et al., 2017b). The effect of shape complexity, design complexity, process parameters, and parts orientation may, in reality, affect the probability of build failure.

The second main limitation is to do with the integrated optimisation investigated in this study. This thesis only focused on identical AM machines, and the number of machines used as well as the number of production days are relatively small. To satisfy the needs of customers, real production may involve various AM machines. In addition, some unexpected events, for example, breakdowns and rush orders may occur. These would make integrated optimisation more challenging. As the problem instance size increases, more CPU time will be required (Tao, 2004). When the problem instance size is fixed, many factors have impacts on the computational efficiency and solution quality, for example, algorithms/heuristics used and the way of formulating the problem. Baumers (2012) argued that the user's capability of filling the build volume is the major determinant of cost and energy efficiency in AM. In other words, the heuristics applied for addressing build volume packing issues have an effect on the benefits of AM. This thesis developed a 2.5D packing framework, a simplification of 3D irregular packing but an upgrade of 2D packing. Computational efficiency may be ensured in complex and large problem instance size situations. However, there is still room to improve performance, for example, specific energy consumption and capacity utilization in this study, through formulating 3D irregular packing problems and developing algorithms for 3D irregular packing.

The environmental network effects from an engineering design perspective are not investigated, which constitutes the third limitation of this study. Taking the AM platform as the two-sided market, this thesis studied network effects based on the economies of scope in demand. This offers a static and demand-side view of platform competition but does not solve the issues of platform evolution and innovation by investigating technological architectures. Considering the technological aspects of AM platform, it is likely to contribute more opportunities for sustainability improvements in AM through a comprehensive combination of production planning optimisation and platform innovation.

8.2.2 Recommendations for further work

To address the above limitations in terms of the build failure, further research could expand the presented energy consumption model. One important consideration would be to systematically consider the role of product geometry and other layer-based characteristics. Such an investigation could be done in the context of part design, multiple machines, mixed part geometries, build volume packing and production scheduling. Although energy accounts for only a small portion of total production costs (Ruffo et al., 2006, Baumers et al., 2013), the energy-efficient operation of AM is crucial to improve its environmental friendliness. It is shown that the total expected energy consumption of AM is reduced by operating AM at intermediate levels of capacity utilization. Monitoring manufacturing processes is conducive to reducing parts scrappage (Rao et al., 2015, Wuest et al., 2014). Moreover, this thesis suggests that processes and product designs should be leveraged to minimize the Z-height of builds, to decrease the possibility of build failure and its adverse impact on the environmental performance of additive processes.

In terms of integrated optimisation, three aspects for further research have been identified: (1) deep integration of information technology, for example, AI, machine learning, cloud computing, and digital twin. To deal with large-scale production optimisation problems in AM, adopting information technology would facilitate less computational time and high-quality solutions; (2) self-adaptive optimisation on processing parameters based on production tasks and conditions of AM machine. Depending on various production tasks and conditions of the machine, the processing parameters of AM machine may be different. Printing parameters optimisation is one of the main factors affecting the accuracy of 3D printing (Feng et al., 2019, Lyu et al., 2021). There is a need to adjust the parameters during the production planning stage to ensure the best performance of printing; and (3) intelligent decision-making of algorithms based on the attributes of packing problems in AM. The capability of algorithms has an impact on the searching efficiency and solution quality in addressing the build volume packing problems (Hopper and Turton, 2001). Considering the attributes of packing problems, intelligent decision-making of packing algorithms could be investigated.

When considering business use, further work could be done by developing a deployable system based on the optimisation framework developed in this study. This may require high-performance computing technologies to support large-scale computation of workflow optimisation as well as a large memory to record and save the value of parameters and variables, and optimized results. In addition, other objectives (e.g., production costs, and production time) could also be included to support multiple production choices for operations managers. Furthermore, it is promising to establish a deep connection between the developed system with some modelling software, for example, AutoCAD, facilitating the conversion of digital models of objects into data required by the developed system. Further work could be done by developing a system fits all categories of AM technologies, which may be beneficial to its commercialization.

Environmental network effects have just been studied from an economics perspective. Such effects allow the understanding of environmental impact in AM from the demand side. Further research could be done to investigate environmental network effects from an engineering design perspective, taking the AM platform as a technological architecture. This would be complementary research of this study by considering the engineering aspect of environmental network effects, helping to understand the mutual effects between supply innovation (i.e., machine operators) and demand competition (i.e., customers) in the AM platform (Gawer and Cusumano, 2014). This research investigated network efforts in small-scale scenarios using exploratory simulation. When considering a large-scale scenario or even business use, it is necessary to consider some other important functions (e.g., interaction among machine operators, customers, and platform owners) and computational requirements (e.g., usage of high-performance computing, cloud computing). In addition, choosing the level of openness of the platform has an effect on the adoption of complementary developers, and diversity of complementary applications by platform owners (Soto Setzke et al., 2019). In this sense, further research could be investigated by studying how the degree of platform openness drives AM platform evolution over time and its consequences (Gawer, 2014).

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Appendices

Appendix A Pseudo-code for the layer-based estimators

This pseudo-code presents the sequence of estimation procedures including build time, energy, and material consumption.

1. Begin program.
2. Begin build time estimation.
   2.1 Start build time estimation loop assessing each build.
      2.1.1 If the packing of the build is finished, then:
         2.1.1.1 Add layer-dependent time contribution, based on total number of layers and fixed time per layer.
         2.1.1.2 Add geometry-dependent time contribution, based on total cross-sectional area in a build and fixed time per mm^2.
   2.2 Move on to energy estimation.
3. Begin energy estimation.
   3.1 Start energy estimation loop assessing each build.
      3.1.1 If the packing of the build is finished, then:
         3.1.1.1 Add fixed job-dependent energy contribution including energy use during warm up and cool down stages.
         3.1.1.2 Add time-dependent energy contribution, based on build time and fixed minimum power consumption.
         3.1.1.3 Add layer-dependent energy contribution, based on total number of layers and fixed energy per layer.
         3.1.1.4 Add geometry-dependent energy contribution, based on total cross-sectional area in a build and fixed energy per mm^2.
   3.2 Move on to material estimation.
4. Begin material estimation.
   4.1 Start material estimation loop assessing each build.

4.1.1 If the packing of the build is finished, then:

4.1.1.1 Obtain total material based on the number and geometric volume of each type of parts inserted in a build.

5. Output and record the build time, energy, and material consumption estimates in each build.
6. End program.

Appendix B: Pseudo-code for an integrated optimisation of scheduling and packing algorithm

The below pseudo-code expresses the structure and logic of implementing integrated optimization of scheduling and packing in P-LPBF.

1. Begin program.
2. Obtain input from user on instantaneous demand profile on Day One and Day Two to contract a demand matrix.
3. Create a precedence vector based on the geometric volume of parts.
4. Generate an insertion precedence based on the demand matrix, dimension of parts and precedence vector.
5. Start inserting procedure loop based on the insertion precedence using bottom-left heuristic.

5.1 If choose Day One, then:

5.1.1 If the inserted parts on Day One within the capacity of machines, then:

5.1.1.1 Record the parameters of parts.

5.1.2 Move the excess parts from Day One to Day Two and update demand on Day Two.

5.1.3 If the inserted parts on Day Two are within the capacity of machines under the updated demand, then:

5.1.3.1 Record the parameters of parts.

5.1.4 Output out of capacity and record the parameters.

5.2 If choose Day Two, then:

5.2.1 If the inserted parts on Day Two within the capacity of machines, then:

5.2.1.1 Record the parameters of parts.

5.2.2 Move the excess parts from Day Two to Day One and update demand on Day One.

5.2.3 If the inserted parts on Day One are within the capacity of machines under the updated demand, then:

5.2.3.1 Record the parameters of parts.

5.2.4 Output out of capacity and record the parameters.

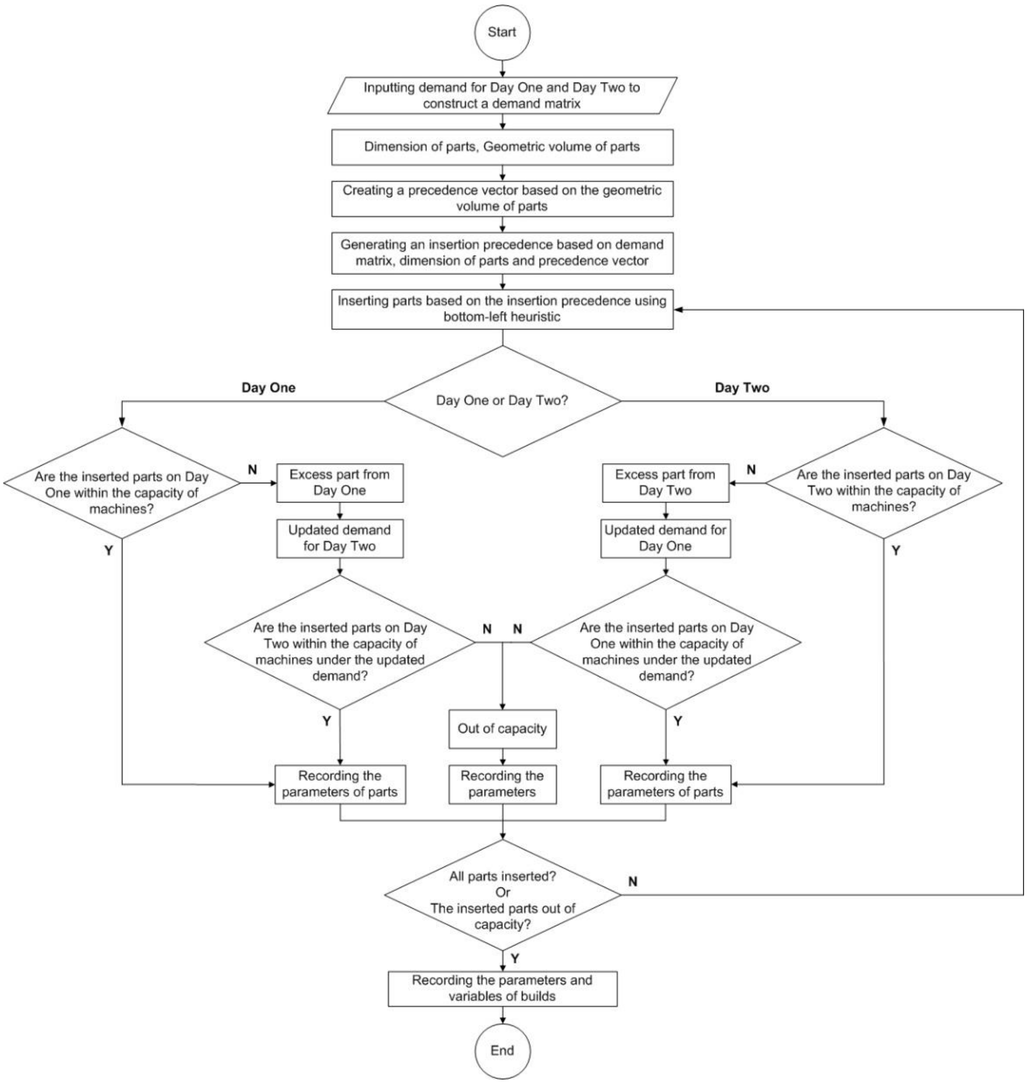
5.3 If all parts are inserted or the inserted parts are out of capacity, then:

5.3.1 Record the parameters of builds.

6. End program.

Appendix C: Flowchart of Integrated optimisation of scheduling and packing

This flowchart reflects a detailed procedure the exploratory simulation adopted in this thesis to address the integrated optimization of scheduling and packing problem. This approach contains the Bottom-Left heuristic, capacity aggregation algorithm and exhaustive search algorithm.



Appendix D: Pseudo-code for the solution space generation

This pseudo-code describes the procedure of solution space generation, supporting the generation of optimized solution and layout of builds.

1. Begin program.
2. Start solution generation loop
   2.1 Obtain input from user on instantaneous demand profile on Day One and Day Two.
   2.2 Adopt precedence vector, dimensions of parts and insertion precedence.

2.3 Create a solution space based on the permutations of rotating operations for parts.

2.4 Insert parts based on the insertion precedence with capacity aggregation algorithm and bottom-left heuristic.

2.5 Record the parameters of builds.

2.6 If the generation of the solution space is completed, then:

3. Exhaustive search of the solution space.
4. Output the optimum result and layout of builds.

Appendix E: Pseudo-code for a build volume-based capacity aggregation algorithm

The pseudo-code for build volume packing algorithm presents the flow of investigating environmental network effects.

1. Begin program.
2. Obtain input from user on instantaneous demand profile to contract a demand matrix.
3. Create a precedence vector based on the geometric volume of parts.
4. Generate an insertion precedence based on the demand matrix, dimension of parts and precedence vector.
5. Start inserting procedure loop based on the insertion precedence using bottom-left heuristic.

   5.1 If the inserted parts are within two machines' capacity, then:

      5.1.1 Input the demands of parts again.

   5.2 If the inserted parts are over two machines of but within three AM machines' capacity, then:

      5.2.1 Record the parameters of parts within three builds.

   5.3 If the inserted parts are over three machines but less than four machines' capacity, then:

      5.3.1 Record the parameters of parts within four builds.

5.4 If the inserted parts over four machines but less than five machines’ capacity, then:

5.4.1 Record the parameters of parts within five builds.

5.5 If the inserted parts are over five machines’ capacity, then:

5.5.1 Record the parameters of parts with five builds.

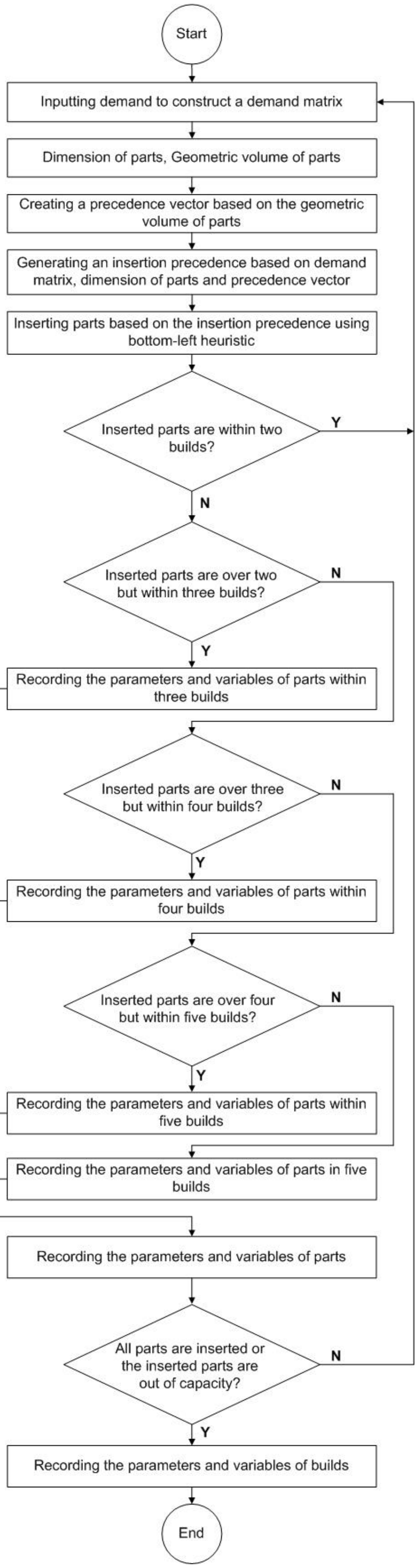
5.6 If all parts are inserted or the inserted parts are out of capacity, then:

5.6.1 Record the parameters of builds.

6. End program.

Appendix F: Flowchart of packing procedure for investigating the environmental network effects

This flowchart illustrates a detailed process of build volume packing across multiple machines and multiple parts for the investigation of environmental network effects in the AM platform. This tool is consisted of Bottom-left heuristic, a build volume-based capacity aggregation algorithm and exhaustive search algorithm.


Start
Inputting demand to construct a demand matrix
Dimension of parts, Geometric volume of parts
Creating a precedence vector based on the geometric volume of parts
Generating an insertion precedence based on demand matrix, dimension of parts and precedence vector
Inserting parts based on the insertion precedence using bottom-left heuristic
Inserted parts are within two builds?
Y
N
Inserted parts are over two but within three builds?
N
Y
Recording the parameters and variables of parts within three builds
Inserted parts are over three but within four builds?
N
Y
Recording the parameters and variables of parts within four builds
Inserted parts are over four but within five builds?
N
Y
Recording the parameters and variables of parts within five builds
Recording the parameters and variables of parts in five builds
Recording the parameters and variables of parts
All parts are inserted or the inserted parts are out of capacity?
N
Y
Recording the parameters and variables of builds
End