The Impact of Process Planning on Cost and Production Losses in Additive Manufacturing

By

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I would like to dedicate this thesis to my two grandmothers, who were two of the strongest women I ever had the privilege of knowing.

For my Amma and Dida.

Abstract

Additive Manufacturing (AM) is a class of manufacturing techniques that relies on joining material, layer-upon-layer, to create the final object. With significantly lower barriers to manufacturing-on-demand and fulfilling product variety, AM is predicted to cause a disruptive revolution in manufacturing and product-service industries. However, mainstream adoption of AM, particularly at scale, is hindered by a lack of suitable operations management understanding, exacerbating issues related to productivity and high cost. Therefore, this thesis attempts to provide a path towards efficient AM operations at scale. This is done by addressing key process efficiency concerns via operations management interventions and thus developing best practice recommendations for AM users.

The methodological approach in this research is quantitative exploratory simulation of process planning in the AM system, spanning decisions at the build level-of-abstraction through to the whole production facility. Relevant metrics are developed to capture the impact of process planning on production losses and production cost, and evaluate the underlying mechanisms of efficient, effective production using the example of polymer laser sintering.

The results of this work provide guidelines for AM users that centre on three overarching themes. First, production losses at the AM machine are reduced, and thus value-adding capacity is increased, by maximising the use of machine capacity in each build. Second, integrated optimisation of part allocation, packing and build scheduling leads to more cost-effective and cost-consistent AM workflows, driven by a trade-off between capacity-, failure-, and schedule adherence-related costs. Third, the implementation of manufacturing cells in AM production facilities can significantly reduce non-value-adding time in the AM workflow, at the expense of poorer flexibility in expanding the facility as the production scale increases. Overall, this thesis argues that process planning can be successfully leveraged to improve process efficiency and, thus, attractiveness of AM for future adopters.

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Throughout my PhD journey, I have met many fellow researchers who have just as many reasons for pursuing a doctoral degree, from following a keen interest in a particular topic of research, to starting on an entirely new career path. In my case, I simply felt that I wasn't done with university, and that I wanted to continue learning in an expert, academic setting. A few years on, it is safe to say that I have learned far more than I could have imagined, both about my research and about myself; and, while learning is a lifelong endeavour, I am finally ready to leave the "student" tag behind! To those who have been part of this journey, I owe a big "thank you"…

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Shreeja Basak

Table of Contents

1 Introduction

Additive Manufacturing (AM) is a class of manufacturing techniques that relies on joining material, layer-upon-layer, to create the final object. This contrasts to subtractive manufacturing, which removes material from a block workpiece to achieve the final form, and formative manufacturing, which typically uses pressure and/or heat to manipulate the raw material into the final form.

A key characteristic of AM is the ability to produce objects directly from digital models, without the need for intermediate moulds or tooling. Consequently, the manufacturing process can be initiated easily and repeatedly, underpinning the history of AM use in prototyping applications. Furthermore, the economically-feasible batch size falls to one, and pre-existing design-for-manufacturing constraints are relaxed. This has led to significant interest in the adoption of AM for end-part production, or direct digital manufacturing (Holmström *et al.*, 2016).

Early hype suggested that AM would support limitless geometric freedom and widespread manufacture at the point-of-use, with the cost of production independent of the production scale (Garrett, 2014; Ben-Ner and Siemsen, 2017). It was claimed that AM would cause paradigm shifts in supply chains (e.g. decentralised and localised production), business models (e.g. prosumers), and production processes (e.g. print entire products in one step), among others (D'Aveni, 2015). However, as of 2022, the market share of AM is still less than 0.1% of the global manufacturing industry, at USD 15.2 billion out of USD 44.5 trillion (AMFG, 2020; Geiselman, 2022; Interact Analysis, 2022). This shows that the early, albeit optimistic, expectations of an AM revolution have not been met yet.

On the other hand, the Wohlers report found that the AM market has grown by 19.5% from 2021 to 2022, and more notably, the share of AM use for end-part production has risen to just over one third of all AM applications (Geiselman, 2022). Expanding further, Sculpteo's survey of AM users shows that the production of “end-use, functional parts” is the top use case among so-called “Power Users”, who have over five years of industrial experience with AM (Sculpteo, 2022). Therefore, there is demonstrable potential and interest in direct digital manufacturing using AM.

Bringing this together, the underlying rationale of this thesis is to help bridge the gap between expectation and reality for direct digital manufacturing. This will be achieved by investigating the role of operations management in overcoming the barriers to AM technology adoption to both unlock the potential for direct digital manufacturing and encourage wider use of AM. The remainder of this introductory chapter is organised as follows. Section 1.1 describes the background to the field of study and explains the significance of the operations management perspective in AM technology adoption. Section 1.2 summarises the research gap in the extant literature and explains how this motivates the doctoral research presented in this thesis. Section 1.3 outlines the research aims and objectives that arise, followed by a summary of the thesis structure in Section 1.4 and the published research outputs in Section 1.5.

1.1 Research Context

1.1.1 AM Use Case

Throughout this thesis, the use case for AM-based direct digital manufacturing is the fulfilment of an incoming order stream, containing different and unrelated parts, using polymer laser sintering. This is synonymous to the operations for an AM service bureau, who provide on-demand manufacturing-as-a-service to customers, but typically do not engage in design or product development themselves (Piller, Weller and Kleer, 2015).

In this particular use case, revenue is generated by exploiting the ability of AM to produce dissimilar parts concurrently, which then introduces the challenge of managing different product streams (Holmström *et al.*, 2016). Profitability also depends on both effective and efficient operations, in terms of both time and cost, which becomes a common theme in the research. Most importantly, AM bureaus are not limited in operations to low-volume production; and thus the question of scaling up AM adoption and operations can be adequately explored. To support this, a case study company that operates an AM service bureau is used to inform and inform part of the research conducted.

Laser sintering, which is a powder-bed fusion AM technique, is chosen as the reference AM process due to its applicability to industrial AM. A notable feature of laser sintering is the ability to stack parts in 3D to utilise the entire build volume (Baumers and Holweg, 2019), rather than being built on the base alone. Laser sintering is therefore often more resource-efficient than alternative polymer AM processes (Hopkinson and Dickens, 2003). The industrial applicability of laser sintering is further driven by two factors: the mechanical strength of parts produced, which are often similar to conventionally manufactured parts (Bourell *et al.*, 2014); and the potential to process a wide variety of materials, particular engineering polymers, which have favourable mechanical and thermal properties (Goodridge, Tuck and Hague, 2012; Tan, Zhu and Zhou, 2020). Thus, laser sintering is often a feasible alternative to conventional polymer manufacturing processes such as injection moulding.

While the scope and findings of this research are linked to the characteristics of laser sintering, generalisable insights will be drawn that apply to AM operations more widely. To support this, the wider AM context is explored first.

1.1.2 Technology Adoption of AM

A realistic re-interpretation of the early hype around an AM revolution is to describe AM as a potential "general purpose technology" (GPT). The term refers to technologies that have a transformative effect on businesses, households and entire economies through gains in productivity and onward innovations (Bresnahan and Trajtenberg, 1995; Jovanovic and Rousseau, 2005). AM confidently meets all three qualifying characteristics of GPTs: AM is used in a variety of industries already (e.g. medical devices, consumer goods, aerospace), demonstrating *pervasiveness*; AM equipment and technology have evolved and *improved* over time, improving accessibility and cost for users; and finally, a multitude of *complementary innovations* have arisen (and continue to emerge) based on AM, from applications with new functionality based on geometric and multi-material capabilities of AM to new manufacturing-as-a-service business models (Garrett, 2014; Choi, 2018). Therefore, the premise in this thesis is that higher adoption of AM will lead to wide-ranging benefits, as per GPTs.

The adoption of GPTs occurs over prolonged periods of time, upwards of 30 years, and consequent improvements in productivity are not immediately felt (Jovanovic and Rousseau, 2005). Given that AM was first developed in the 1980s, it follows that the journey of AM towards full GPT status is still ongoing. AM users and the wider market will encounter milestones along the way, underpinned by strategic imperatives of growth, innovation, and performance (Cotteleer and Joyce, 2014). From the product perspective, this will include faster innovation cycles and the development of new products with improved performance, thanks to AM capabilities. From the process and organisation perspective, there will be new fulfilment pathways based on the flexibility of AM operations, alongside new business models that exploit the economic characteristics of AM to deliver higher growth and innovation. Finally, beyond the organisation, new supply chains and market interactions will arise from the digital thread that supports AM, leading to better performance.

Like other GPTs, AM exists as part of a wider "ecosystem" of processes and value chains, which includes machines and materials in the physical realm, and design platforms in the digital realm (Piller, Weller and Kleer, 2015). For each firm within the AM ecosystem, there are multiple challenges to overcome while working towards the above milestones to successfully adopt AM and realise the associated benefits. Mellor et al. (2014) provide a comprehensive framework of the different aspects of technology implementation for AM, as seen in Figure 1.1. The research in this thesis focuses on the operations part of this framework, in particular the elements of process planning, cost accounting, and integration across the AM workflow. Therefore, the contribution of this thesis will be to examine the OM barriers to AM adoption and provide suitable tools for new or potential users of AM to overcome these.

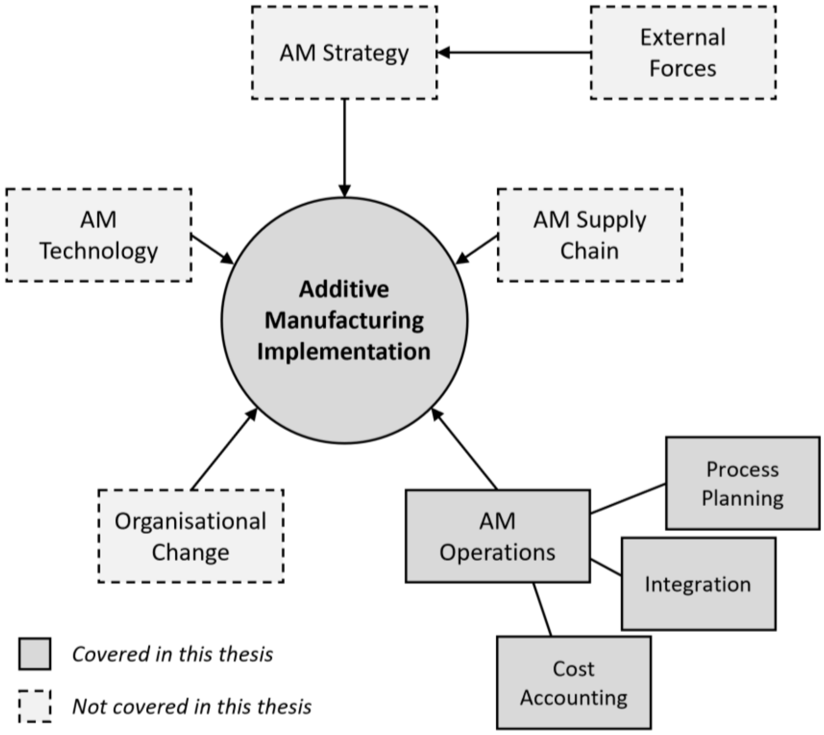


Figure 1.1: Areas contributing to successful AM technology implementation, adapted from Mellor et al. (2014)

1.1.3 Scaled-Up AM

In transitioning from a technology adoption mindset to an operations mindset, it is important to first clarify the current extent of AM adoption for direct digital manufacturing and the presumed path of forward adoption. This helps explain the scope for scaled-up AM and associated operations research in this thesis.

To date, AM has gained acceptance as a viable method for low volume applications, based on process economics (Baumers *et al.*, 2016). However, to tip the momentum of adoption towards GPT status, AM operations and process economics must improve for certain medium and high volume applications as well. It is expected that AM use can then spread, in terms of increasing both the number of companies using AM and the economically viable throughput quantity. In addition to the use case in this research (higher-throughput AM service bureaus), scaled-up AM may be seen in mass customisation or production workflows for high-value or complex parts in large quantities.

A key competitive advantage for AM in this scenario will be to deliver more responsive and flexible production at scale than subtractive and formative manufacturing processes (Additive Manufacturing UK, 2015). This supports meeting future trends of increasingly short product life cycles and customer demands for products that better fit their needs (Bohlmann *et al.*, 2013).

Increased scale in manufacturing systems can be achieved in two ways, through upgrade and through replication (Putnik *et al.*, 2013). Upgrade refers to upsizing the characteristics in individual elements of the manufacturing system, such as build volume dimensions or number of lasers in AM machines (Figure 1.2a). Given that AM machines have fixed volumetric capacity, increasing scale through upgrade is not currently possible without technological innovation. On the other hand, replication is to link together individual elements to form a network of scaled-up capacity (Figure 1.2b). Scaling up via replication can be achieved with existing AM equipment, requiring only the installation and operational integration of new machines into the AM workflow. Furthermore, it is suggested that replication offers better flexibility in AM operations, improving the responsiveness to demand and resilience of the manufacturing system to poor reliability (Eyers *et al.*, 2018). Therefore, this thesis focuses on replication as the more viable path towards medium-to-high volume direct digital manufacturing, and this is hereafter referred to as scaled-up AM.

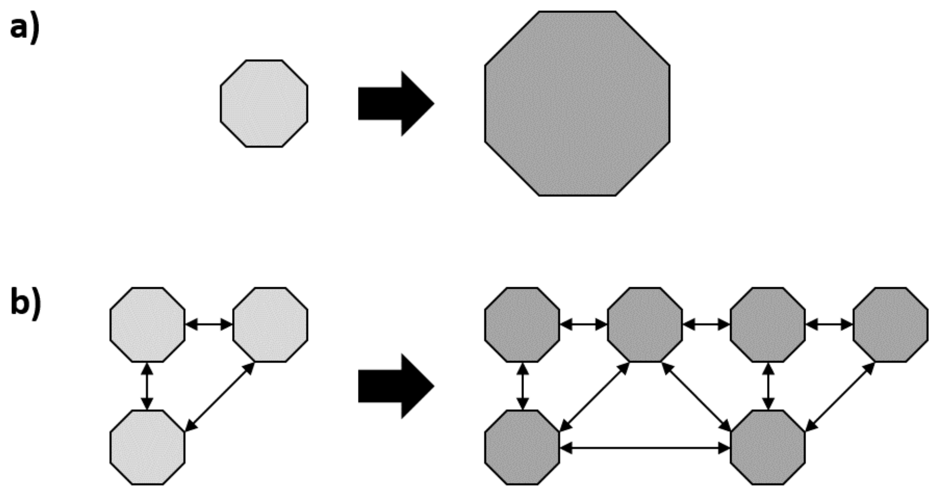


Figure 1.2: Increasing scale in manufacturing systems through a) upgrade or b) replication, adapted from Putnik et al. (2013)

1.1.4 Operations Management of Scaled-Up AM

To open with a definition, operations management is "managing inputs (resources) through transformation processes to deliver outputs (service or products)" (Rowbotham, Galloway and Azhashemi, 2007, p. 2). This can be split into two objectives for the transformation process: effectiveness, delivering products and services to meet the intended purpose; and efficiency, improving the ratio of the transformed outputs to the required inputs (Naylor, 2002, p. 7).

The effectiveness of AM in responsive and short lead time direct digital manufacturing is well-established. However, the bottleneck for further adoption and implementation at scale lies in the efficiency of AM operations. In particular, the efficient use of the equipment resources in the AM process remains an issue. Challenges such as slow process speed, high equipment cost, and variation in quality of the output increase the time, cost and labour required for production (Baumers *et al.*, 2016). Therefore, developing suitable AM operations systems to mitigate these issues is imperative to promote wider AM use, and this requires a holistic approach to operations management.

There are four interlinked areas that contribute to successful implementation of transformation processes: capacity management, scheduling, inventory management and control (Naylor, 2002, pp. 19–20); and these can be further described from a manufacturing perspective. The goal of capacity management is to design and manage the process to maintain desired levels of throughput; this concerns medium-to-long term equipment investment and work flow design decisions to achieve the required output in parts per time period. Moving to a short term perspective, scheduling entails the planning of activities and allocation of resources to optimise the process time, cost, and other relevant objectives. Inventory management supports the scheduling facet of operations by maintaining sufficient stocks of materials, work-in-progress (WIP), and finished goods to ensure smooth process activities and fulfilment of customer demand. Encompassing all three areas, control involves monitoring the process and taking corrective action, where necessary, to ensure that performance objectives are met in areas such as time, cost, quality, robustness to disturbances, and so on (Buffa, 1980). Figure 1.3 illustrates the relationship between these four elements of operations management.

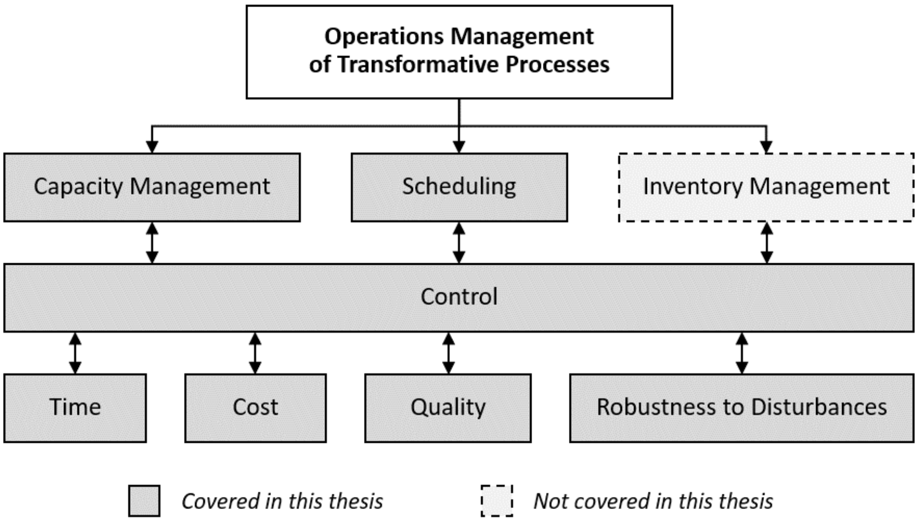


Figure 1.3: Facets of operations management for transformative processes

In manufacturing systems involving networks of dedicated equipment, as is the case for subtractive or formative manufacturing, the efficacy and efficiency of the process relies on integrating all four operations management areas. In particular, production relies on the inventory management of batches of similar products through multiple process steps across different equipment, and even different facilities. However, when using AM, the production flow for responsive direct digital manufacturing is better described as multiple streams of products aligned to customer demands, which combine at the general-purpose AM machine. The freedom to manufacture without intermediate tooling makes it possible to approach AM operations management from the perspective of flows of individual products, rather than an inventory-based perspective (Holmström *et al.*, 2016). This product-centric approach promotes greater alignment between the manufacturing system operations and the strategic aims of responsive and flexible manufacturing (Lyly-Yrjänäinen *et al.*, 2016). Therefore, this research focuses on product-centric AM fulfilment and the impact of the three remaining operations management facets (capacity management, scheduling, and control) therein.

A further, defining feature of scaled-up AM is the mutual interchangeability, or "fungibility", of capacity that exists both within and across AM machines (Baumers *et al.*, 2017). Fungibility allows individual products to be manufactured, subject to process constraints, in any part of any build space within the network of machines. This leads to both opportunities and challenges with respect to AM operations for process efficiency. Capacity management is simplified, to an extent, as build space can be allocated flexibly to demand both inside and outside the firm to achieve economically-efficient process operations (Ruffo and Hague, 2007; Hedenstierna *et al.*, 2019). This can temper the issue of matching investment in expensive AM equipment with unpredictable demand from customers (Eyers *et al.*, 2018). On the other hand, the increased freedom in routing individual parts through the manufacturing network makes it more challenging to find optimal configurations of part-position-build for cost-, material- and time-efficient production. Moreover, to ensure customer satisfaction and avoid waste, suitable control and monitoring tools must maintain required levels of process reliability whilst delivering product variety from build-to-build (D'Aveni and Venkatesh, 2020). A core theme therefore emerges for this thesis: the management of the AM process for efficient use of fungible, network-oriented capacity to provide product variety-driven value at scale.

1.1.5 Complementary Innovations in the AM Ecosystem

Process efficiency improvement is often associated with core innovation, which is primarily hardware or software changes to the technology, or "core product". In the case of AM, core innovation has indeed fomented transformations in the layer-wise manufacturing process (e.g. developing point-based photo-curing in stereolithography into plane-based photo-curing using "digital light processing"). However, innovation can also occur around the core product, known as complementary innovation. This is the development of products and/or services that create a more favourable ecosystem for the core product, which is the AM machine itself. Complementary innovations such as new materials with a wider processing window for polymer laser sintering, or software that adjusts process parameters in fused deposition modelling to mitigate against faults are also key to maximising the process efficiency of the AM machine and wider manufacturing system.

Taking a wider perspective, which includes the potential of AM as a GPT, it follows that complementary innovation plays an equally important, if not more important role in the AM ecosystem than core innovation alone. Complementary innovations increase the attractiveness of the core product, which in turn enhances technology adoption therein. This is achieved by improving the ease of use of, providing alternative routes of exposure to, or showcasing the potential new capabilities of the core product or technology for users. Manufacturing-as-a-service providers, or AM service bureaus, are an example of a business model-based complementary innovation in the AM ecosystem that encompass all three features. The service element provides support to those unfamiliar with the technological requirements of AM, and allows manufacturers to incorporate AM into their process as an outsourced step; while AM bureaus' operations demonstrate the potential to successfully shift from low-volume, high-variety production towards high-volume, high-variety production using AM.

Further complementary innovations are required, however, to help improve the viability of scaled-up AM in a wider range of direct digital manufacturing applications. The performance frontier theory supports this argument by explaining that the gap between the actual cost-performance trade-off for a given manufacturing system, known as the operating frontier, and the ultimate fixed asset frontier, determined by the core product, depends on the efficiency of processes and procedures therein (Schmenner and Swink, 1998). This relationship is illustrated in Figure 1.4. Consequently, the AM operations manager's challenge lies in understanding how to remove inefficiencies to *improve* performance to the current operating frontier, and establish suitable processes and procedures to *better* the operating frontier. This will help AM to reach its potential, and is the starting point for the research motivation.

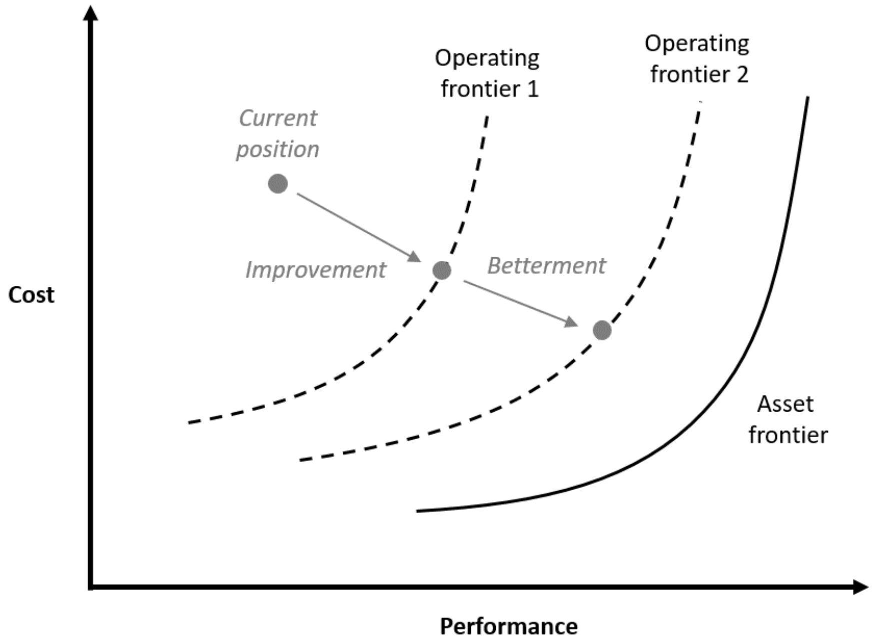


Figure 1.4: Operating and asset frontiers for manufacturing systems, adapted from Schmenner and Swink (1998)

1.2 Research Motivation

Following hype of an AM-driven revolution and concurrent high market growth a decade ago, the AM industry currently occupies a curious state of "slow revolution" with diverse use-cases and companies, but a lack of meaningful progress in further adoption or scaling up of production capabilities (Beltagui, Rosli and Candi, 2020; Davies, 2023). To overcome this, Milgrom and Roberts (1990) assert that complementary, organisational innovations are required to coordinate the different functions and operations within the firm to access and elevate the benefits of the value-adding technology (in this case, AM). In turn, improvements in the operations management of AM can lead to better performance of AM systems (Schmenner and Swink, 1998); and in particular, help overcome barriers of high production cost and poor productivity, which inhibit the mainstream uptake of AM (Baumers *et al.*, 2016). Therefore, this research aims to elucidate a path towards efficient AM operations at scale, such that this platform technology can be more widely adopted by manufacturers to respond to customers' needs en masse. In this section, the research motivation is further explained via three interconnected gaps in the extant literature.

The first gap relates to a lack of transparency about machine-level process efficiency and manufacturing performance in AM. To date, research studies have focused on narrow metrics of performance, such as the build time or throughput, which relate to the deposition process alone. However, these approaches to AM manufacturing performance do not capture or draw attention to sources of inefficiency elsewhere in the machine operations, for example, during machine setup or arising from poor reliability and repeatability (D'Aveni and Venkatesh, 2020). Eyers and Potter (2017) emphasise the need for a systems perspective of AM operations, particularly for industrial applications, and yet there is no suitable method for monitoring the process efficiency or use of AM capacity as a whole. Existing performance measurement frameworks from the realms of conventional manufacturing, such as value-added time and production losses, are based on repetitive production steps executed over predictable throughput (Hines and Rich, 1997; Muchiri and Pintelon, 2008). Yet, scaled-up AM is characterised by variation in both process and products; and so suitable manufacturing performance metrics must be developed to provide AM operations managers with clear insights about the current state of their machines and how best to use the operational capacity.

Extending this further, the concept of benchmarking the performance of AM systems against its potential has not been explored. This gap in the understanding of AM operations severely limits the ability to investigate and evaluate initiatives to improve the operating frontier of AM equipment relative to the asset frontier (Schmenner and Swink, 1998), and thus achieve cost and productivity improvements. Additionally, from a capital equipment investment perspective, poor clarity about AM machine capabilities hides the relative advantage of AM and diminishes performance expectations. Both of these are key factors for driving the intention to adopt AM (Schniederjans, 2017), and so poor understanding of AM performance and drivers of process efficiency acts as a direct barrier to its adoption in industry.

The second gap relates to the scheduling and control of production activities across a scaled-up network of machines operating in parallel, and how this impacts the cost-effective operations management of responsive direct digital manufacturing. Within individual machines, the relationship between high utilisation of machine capacity and improved process economics is well-accepted (Ruffo, Tuck and Hague, 2006a; Baumers *et al.*, 2016). However, suitable approaches for scheduling production across multiple machines to achieve this degree of process efficiency are not well understood. Hedenstierna et al. (2019) show that networks of capacity can be leveraged to improve machine utilisation by trading fungible capacity on an intra-firm basis, but this does not provide practical direction for how to manage the allocation of capacity within the firm. In particular, responsive AM operations, as required for make-to-order fulfilment, must reconcile conflicting objectives of minimising the batch size for short production lead time and maximising the load on the machine for cost-effectiveness (Costabile *et al.*, 2017). Therefore, the trade-off between the different cost drivers across the network of machines requires close examination. In the production planning of make-to-order AM, this extends the existing computationally-complex challenge of packing parts for cost-effective production (Araújo *et al.*, 2018) into the time domain, with further dimensionality due to multi-machine operations.

The third gap relates to capacity management within the AM production facility. While AM supply chain literature postulates about reconfiguring production infrastructure to create new value streams and reduce sources of waste in the workflow, for example via decentralised and localised production and production on demand (Ben-Ner and Siemsen, 2017; Zhang *et al.*, 2019), little attention has been given to the capacity management within each production facility to meet the required throughput. Despite multiple observations of different facility layout approaches in AM operations studies, the facility layout or workflow design itself is always considered a foregone conclusion. Therefore, consideration of the facility layout choices for AM is absent from the discourse.

The choice of facility layout is typically driven by the trade-off between production volume and variety in conventional manufacturing, using general purpose or dedicated equipment as appropriate. However, the flexibility of direct digital manufacturing (Lyly-Yrjänäinen *et al.*, 2016) alongside the fungibility of AM equipment capacity (Baumers *et al.*, 2017) has the scope to completely alter this balance point. Additionally, Huang et al. (2021) note that the facility layout requirements in particular change as the scale of AM production increases, and that capacity management decisions in this scaled-up AM context must focus on the efficiency of the production workflow. To this end, a thorough examination of the process efficiency drivers and ancillary motivators for different facility layout approaches for AM workflows, as the scale of production increases, is missing in the extant literature.

1.3 Aims and Objectives

The aim of this research is to investigate how to manage AM operations to improve production cost and losses in the context of scaled-up, make-to-order manufacturing. This advances understanding of the process efficiency of AM, and particularly, the transparency of AM operations for direct digital manufacturing and other industrial applications. The following research objectives, which contribute to this research aim, are addressed in this thesis:

1. To evaluate the effect of process planning on the production losses in AM, at the machine level of abstraction.
2. To evaluate the effect of process planning on the total cost for make-to-order fulfilment using scaled-up AM, at the manufacturing system level of abstraction.
3. To investigate suitable facility layouts for scaled-up AM production, and their effect on process efficiency in terms of cost and production losses.

The primary research objectives above contribute to a final, ancillary objective in this research: to establish the mechanisms by which process planning affects the costs and benefits assessment of AM operations from a technology adoption perspective. Therefore, a complete chain of understanding is formed between the process planning step in the AM workflow, the operational performance of the entire AM system, and the strategic fit of scaled-up AM within a firm. All of the research objectives above will be addressed using polymer laser sintering as the exemplar AM process, given its widespread use in industrial AM contexts.

Summarising the aims and objectives of this thesis in one question, this research will attempt to answer the question: how should scaled-up AM be implemented and why?

1.4 Thesis Structure

This thesis follows the conventional order of chapters focusing on the prior literature, research methodology, results obtained, and discussion of results. The purpose of this structure is to present a clear research funnel, progressing from reviewing the broad, overarching challenges of scaled-up AM (Chapters 2 – 3); to developing and testing specific operations management interventions (Chapters 3 – 6), and finally to exploring the wider implications for future implementation and adoption of AM (Chapters 7 – 8).

Throughout the sequence of chapters, the three key themes of this research are addressed in a consistent order, in alignment with the three research objectives. In the literature review (Chapter 2), methodology (Chapter 3) and discussion (Chapter 7), the subdivision of the chapters focuses on the production losses, production cost and facility layout for AM in turn; and the corresponding results are presented in separate chapters (4 – 6). The chosen structure is intended to guide the reader through the different aspects of scaled-up AM operations explored in this research, as shown in Figure 1.5.

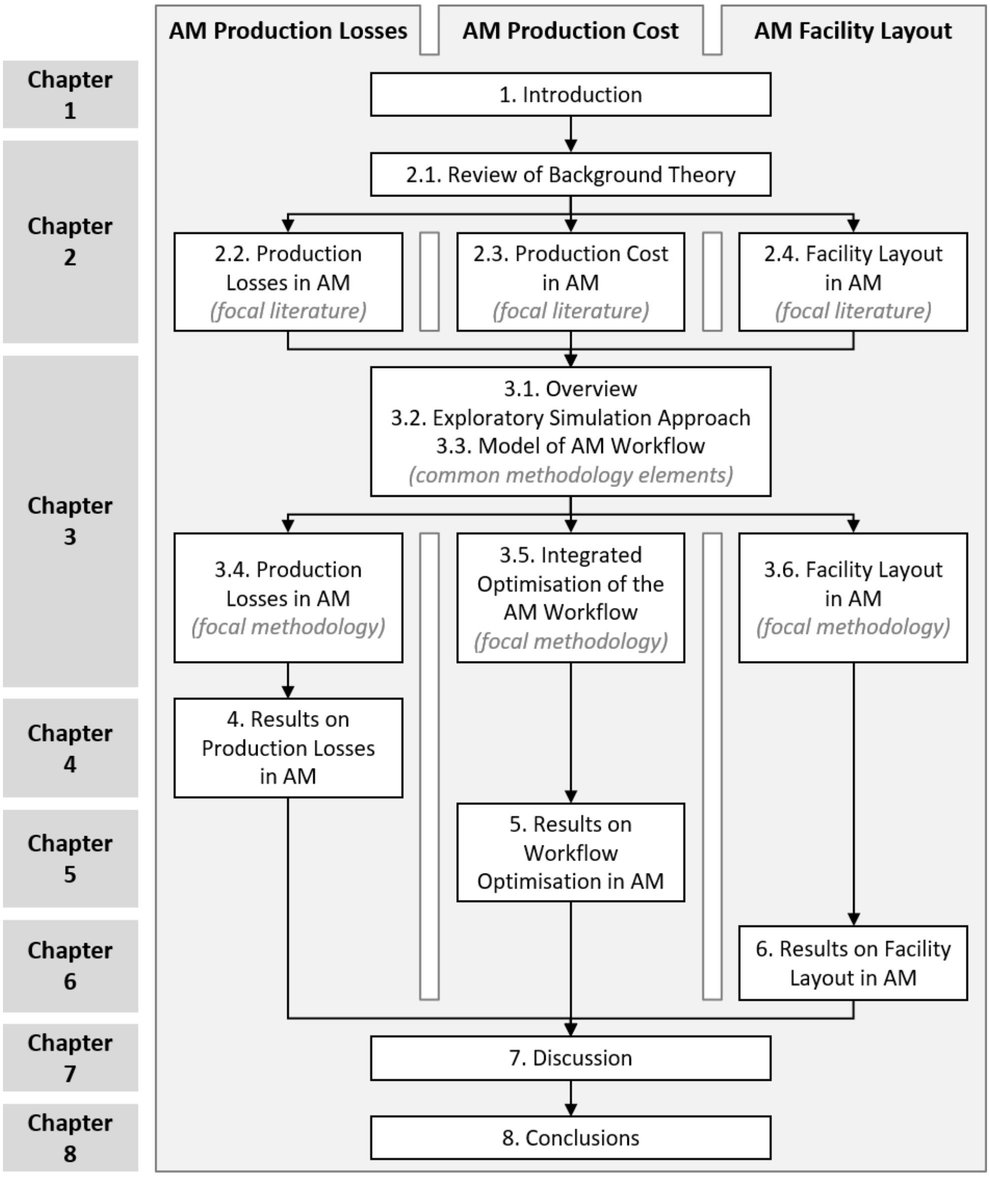


Figure 1.5: Overview of thesis structure

1.5 Published Work

A publication strategy was devised to support this doctoral research by means of structured dissemination and peer review. This consists of four separate publications: one of which has been published, and two further publications in the manuscript preparation stage.

The published journal article:

1. The first journal publication explains the role of production losses in AM, introduces Overall Equipment Effectiveness (OEE) for AM and examines

the effect of process planning on the OEE for polymer laser sintering. It is titled "Reducing production losses in additive manufacturing using Overall Equipment Effectiveness" (Basak *et al.*, 2022), and is published in the Additive Manufacturing journal.

The manuscripts under development:

2. The second journal publication proposes a research agenda to extend the work on production losses, and reflects on contributions from industry and academic experts about future challenges in operations management for scaled-up AM. The planned title is "Towards Industrial and Scaled-Up Additive Manufacturing: A Research Agenda". This work is currently undergoing additional preparation.
3. The third journal publication investigates the role of process planning on production cost across a network of AM machines. The planned title is "Integrated Workflow Optimisation to Improve Production Cost Consistency in Laser Sintering". This work is currently undergoing additional preparation.

The planned, final publication:

4. The fourth journal publication explores how scaled-up AM facilities should be organised, by examining the impact of facility layout on the setup investment and operational performance. The planned title is "A Comparative Study of Additive Manufacturing Facility Layout to Reduce Production Losses and Cost". This work is currently undergoing additional preparation.

Alongside this, concerted efforts have been made to engage with AM practitioners to share insights with industry. The research in this thesis has been presented at two conferences and one self-organised knowledge exchange workshop; and discussions are ongoing for a tailored workshop for the company that contributed data for the third research objective.

2 Literature Review

This chapter presents a review of the literature that indirectly affects or directly contributes to this research. To this end, the chapter is divided into two sections: the first part (Section 2.1) addresses the background theory, while the second part (spanning Sections 2.2 – 2.4) discusses the focal literature that underpins the research studies in this thesis.

The background theory explores relevant concepts in manufacturing operations, process economics and adoption of technology, and importantly, their influence on scaled-up AM. Following this, the focal literature covers the three areas of AM operations: production losses and process inefficiency, cost modelling, and facility layout design. Finally, the chapter closes with a summary of the gaps identified in the literature and how these relate to the research objectives, thus grounding this research in the discourse.

2.1 Review of Background Theory

2.1.1 Overview of the AM Process

2.1.1.1 General Workflow

To support the review of the background theory in the context of AM, this section provides a primer on the AM process workflow. While different AM techniques use distinct material mediums and physical processes, the general workflow is common (Gibson, Rosen and Stucker, 2015, pp. 4–6; Gardan, 2016).

The starting point is a digital 3D model of the part to be produced. This is typically a computer-aided design (CAD) or engineering (CAE) model, and any design optimisation occurs at this stage. The model is then converted to an STL (acronym for "stereolithography") file, which is a surface mesh file format that is common to all AM processes. The STL file(s) are grouped into a build file, corresponding to a single AM build; at this stage, the file(s) are scaled, oriented, and positioned as required, and any support structures are added. The build file is subsequently transferred to the AM machine, where it is "sliced" using machine-specific software and the machine code for the build is generated. Shifting to physical production tasks, the AM machine is set up next by replenishing consumables and setting process parameters. The automated build process is then started, with intermittent operator supervision to check for any errors. Once the build is complete, part(s) are removed from the machine and cleaned in the post-processing stage. The parts are then either ready for use, or undergo additional finishing steps.

Contrary to the perception of AM as a fully automated, one-step process (Ben-Ner and Siemsen, 2017), Figure 2.1 illustrates that the majority of steps in the overall AM workflow are either semi-automated or entirely manual.

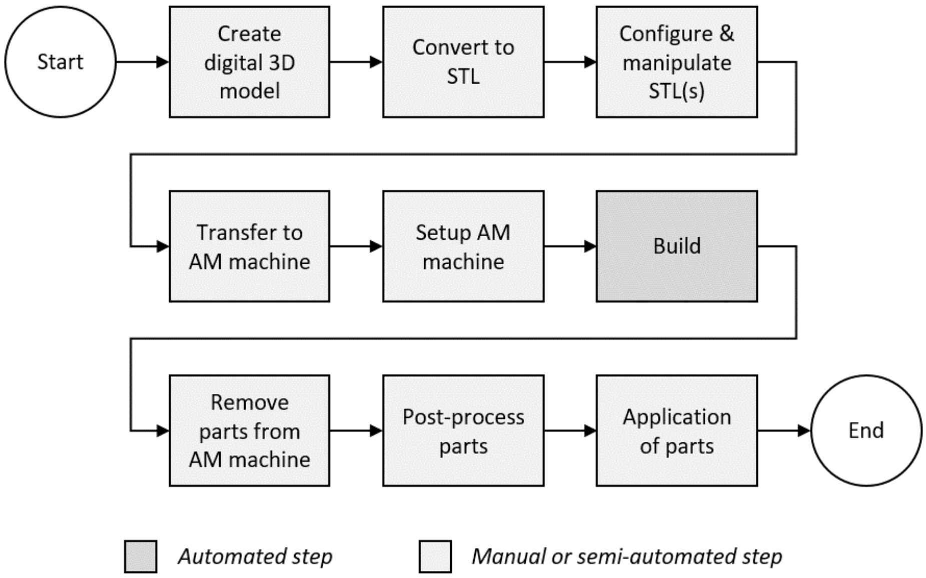


Figure 2.1: General AM workflow, inspired by Gibson, Rosen and Stucker (2015, p. 5) and Gardan (2016)

2.1.1.2 Polymer Laser Sintering

Polymer laser sintering is used in this research as an example of an industrial AM process, and so its physical process requires explanation. Referring to the schematic in Figure 2.2, laser sintering relies on repeatedly filling the powder-bed (also known as the build volume) with a layer of pre-heated powder before selectively fusing regions using a laser beam (Goodridge, Tuck and Hague, 2012). First, a thin layer of powder from the feed is spread evenly over the build volume, and any excess is collected in overflow containers. Within the build volume, the computer-controlled laser(s) then sinters the powder area(s) corresponding to the part(s) geometry in the cross-sectional slice of the build file. The platform in the build volume is then lowered a distance corresponding to the layer height, and the process repeats until all layers are deposited. An example physical machine, the EOS Formiga P100, is shown in Figure 2.3.

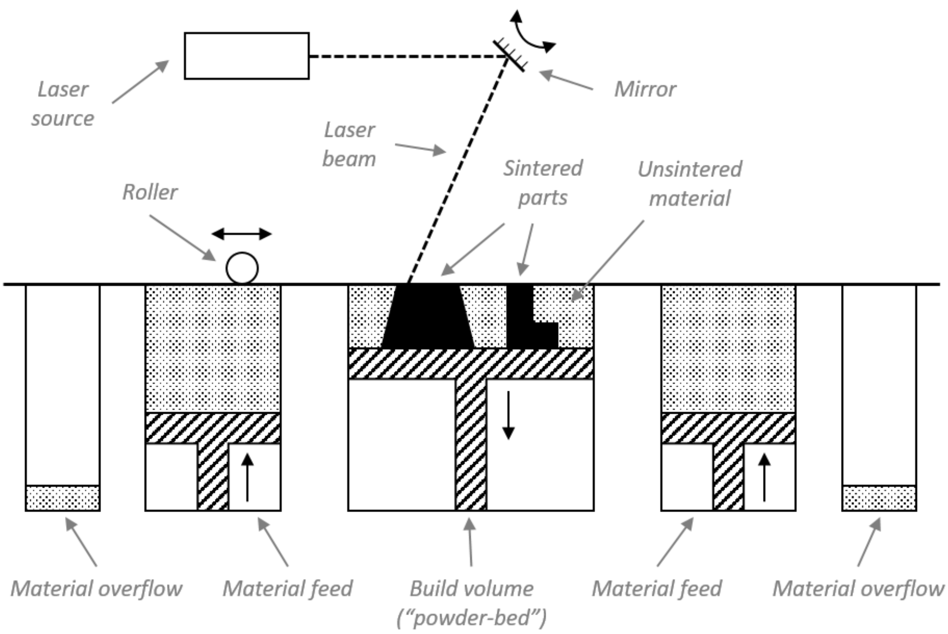


Figure 2.2: Schematic of the laser sintering process, inspired by Lohfeld and McHugh (2012)

Figure 2.3: EOS Formiga P100 laser sintering machine in research laboratory

2.1.2 Operations Management and Operations Research

The inter-related but distinct fields of operations management and operations research underpin this research, and form a helpful starting point for the review of managing AM processes.

Operations management (OM) relates to "creating, operating and controlling a transformation system" of input resources to outputs that meet customer needs (Naylor, 2002, p. 5), with a purview of performance and decision-making over operational, tactical and strategic levels. Alongside this, operations research (OR) concerns "how to conduct and coordinate the activities within an organisation", using a scientific or mathematical approach to help decide upon an optimal course of action (Hillier and Lieberman, 2010, pp. 2–3).

The remit of OM extends across all activities within the boundaries of the organisation, whereas OR typically focuses on a well-defined problem as a subset of the chain of activities (Naylor, 2002, pp. 6–7; Hillier and Lieberman, 2010, p. 3); and this distinction is shown in Figure 2.4. Thus, while both OM and OR provide objective insights for decision support, OM is more aligned to strategic growth and competitiveness (Fuller and Mansour, 2003) as it includes the broad, cross-functional trade-offs in decision-making for transformation systems (Buffa, 1980). Nevertheless, a systems approach involving both OM and OR can lead to a more holistic view of the processes, and as a result, and improved operations in manufacturing systems (Mingers and White, 2010).

Novel OM and OR perspectives are required for AM operations, which centre on the general purpose nature of AM equipment (Framinan, Perez-Gonzalez and Fernandez-Viagas, 2023) and ability to replace process-driven flows with product-driven flows (Holmström *et al.*, 2016). For make-to-order AM in particular, new structures emerge for organising and controlling fulfilment of varied product streams, from efficiently packing parts in a single build (Oh *et al.*, 2020) to sharing AM capacity across firms (Hedenstierna *et al.*, 2019). Thus, the focus of this review is to explore OM and OR with respect to product variety at scale, and the impetus to maximise time- and cost-efficiency in the workflow.

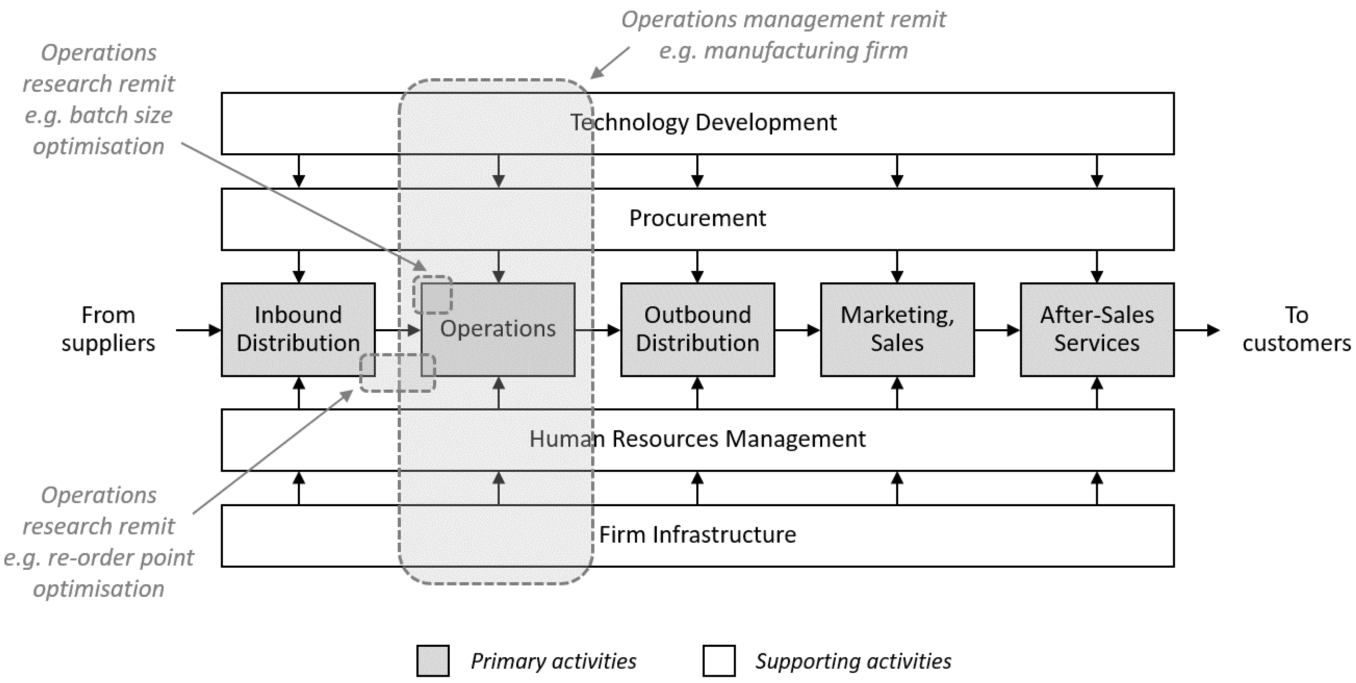


Figure 2.4: Remit of operations management and operations research with respect to organisational activities, adapted from Naylor (2002, p. 22)

2.1.2.1 Product Volume and Variety

The competitive objectives of the firm and its market lead to different product strategies based on volume and variety, which in turn influences the manufacturing process structures and operations (Naylor, 2002, p. 71). The Hayes and Wheelwright model, also known as the “product-process matrix”, is a widely recognised representation of these different OM systems (Hayes and Wheelwright, 1979). Shown in Figure 2.5, the model shows four key types of manufacturing operations, spanning from jumbled process flows to fulfil low-volume and high-variety products (top left quadrant) to continuous process flows to manufacture commodity products at high-volume and low-variety.

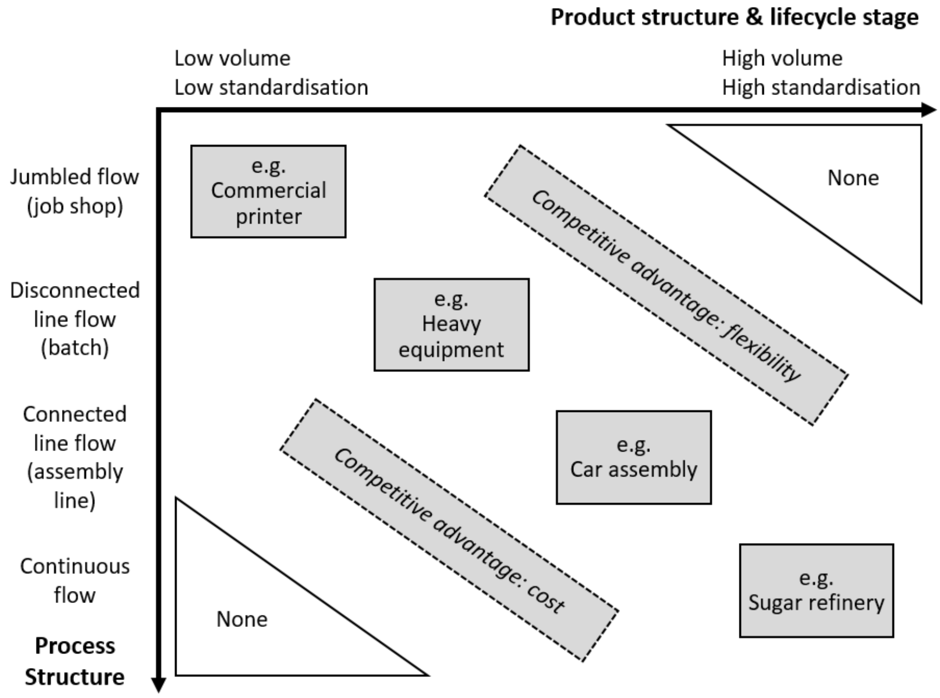


Figure 2.5: Product-process matrix, adapted from Hayes and Wheelwright (1979)

Hayes and Wheelwright (1979) argue that OM systems typically align with the diagonal of the matrix to minimise the risk of mismatch between organisational strategy and competencies. This suggests that the process structure for a given product strategy is fixed, or vice versa. However, subsequent industry surveys note the importance of catering more closely to customers’ needs; and this is pushing firms away from the diagonal, particularly in the top left quadrant of the matrix (Ahmad and Schroeder, 2002).

Continuing this theme, AM can improve the ability to meet customer needs, through variety at scale. Inverting the product-process matrix (as in Figure 2.6) illustrates how AM decouples product volume and variety, thanks to minimal marginal costs for added variety in AM (Baumers and Holweg, 2019). In this case, moving away from the matrix diagonal introduces new value streams, such as mass customisation. Digital manufacturing approaches, such as automated geometry personalisation and digital kit preparation, are also leveraged to deliver variety efficiently at higher volumes of production (Tuck *et al.*, 2008; Khajavi *et al.*, 2018; Baumers and Dominy, 2022).

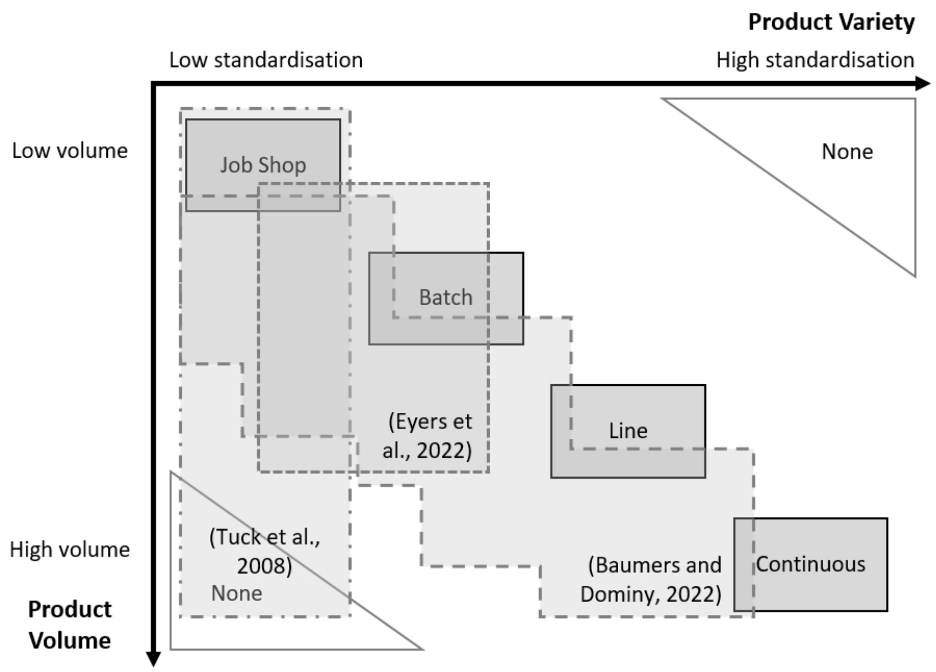


Figure 2.6: Effect of digital manufacturing and AM on the product-process matrix

Unlike conventional manufacturing, the process structures and standardisation of activities in AM depend on the quantity, quality, and customer co-creation requirements of specific products, rather than the volume and variety alone (Tuck *et al.*, 2008; Eyers and Potter, 2017; Eyers *et al.*, 2022). For example, mass customisation uses batch processes and high standardisation, whereas product co-design with customers inevitably requires low process standardisation and job shop operations (Eyers *et al.*, 2022).

While the freedom exists to operate the general purpose AM equipment in flexible or dedicated configurations (Tuck *et al.*, 2008), AM processes are presently limited to disconnected process flows as each build job is a discrete batch (Baumers and Holweg, 2019). This means that job shop and batch operations dominate in AM use cases (Eyers *et al.*, 2022). Although, research efforts towards continuous flows in AM are active, for example using angled print beds (Günther *et al.*, 2014) and volumetric deposition (Kelly *et al.*, 2019).

Overall, the traditional product volume-variety relationship is disrupted by AM, whereby variety can be delivered at higher volumes and thus the operations systems must adapt to support this. In the case of make-to-order fulfilment, a balance must be found between responsive and product-centric workflows, and the efficiencies that arise from process-centric management (Holmström *et al.*, 2016) for the presently-batch AM process (Baumers and Holweg, 2019).

2.1.3 Economies of Scale and Scope

Two complementary factors, economies of scale and economies of scope, govern cost efficiency in production for volume and variety.

Economies of scale are defined as "a small proportional increase in the levels of all input factors [leading] to more than proportional increases in the levels of outputs produced" (Panzar and Willig, 1977). In other words, economies of scale lead to increased resource efficiency for larger production volumes. Haldi and Whitcomb (1967) provide a generic cost-quantity relationship, given by:

$$C = aX^b \tag{2.1}$$

where:

C – total cost of production
X – total quantity of output
a – constant, depends on organisation, processes and outputs
b – constant, known as "coefficient of scale"

Where economies of scale are present for a particular product and process combination, the coefficient of scale, b, is less than one.

Economies of scope is a slightly newer concept, developed by Panzar and Willig (1977, 1981) while assessing multi-product firms in the 1970s and 1980s. It is defined as the cost savings that arise from combining production of two or more outputs, as compared to producing them separately (Teece, 1980; Panzar and Willig, 1981). Thus, economies of scope see increased resource efficiency where the product variety is higher. For an arbitrary set of outputs, economies of scale are present if the following inequality, adapted by Teece (1980), holds:

$$F_C(X_1, \dots, X_n) < F_C(X_1, 0, \dots, 0) + \cdots + F_C(0, \dots, 0, X_n) \qquad (2.2)$$

where:

F_C – total cost function for products in brackets
$X_1 \dots X_n$ – quantity of different products, denoted by subscript

If the cost functions reverse the inequality, then diseconomies of scope exist and each product should be fulfilled separately (Panzar and Willig, 1981).

In manufacturing operations, economies of scale and scope both arise from efficiently amortising input resources over a range of outputs. Economies of scale are found by sharing indivisible assets, such as equipment and specialist knowhow, and other common inputs, such as facility space and utilities, across the production quantity (Haldi and Whitcomb, 1967). To access economies of scope, the shared resources should be somewhat specialised to the firm, such that it is economically inefficient to access those resources from elsewhere in the market (Panzar and Willig, 1981). Teece (1980) further clarifies that indivisible but organisation-specific assets can satisfy both economies of scale and scope where they are inputs to the production of more than one product.

As a result, economies of scale typically affect the process structure (Naylor, 2002, p. 71), as per the product-process matrix in Figure 2.5. Higher economies of scale justify efficient dedicated equipment, and this is represented by a shift towards the bottom right quadrant of the product-process matrix. On the other hand, economies of scope influence the use of programmable and flexible production systems to shift operations towards the bottom left quadrant of the product-process matrix for reduced cost of variety (Goldhar and Jelenik, 1983).

The use of AM for direct digital manufacturing is widely considered to be re-writing existing practice around economies of scale and scope. The absence of tooling and consequent reduction in the setup cost and time for manufacturing new products leads to "economies of one", which focus on the economically feasible production of unique goods (Petrick and Simpson, 2013; Cotteleer and Joyce, 2014; Pour and Zanoni, 2015; Weller, Kleer and Piller, 2015).

In this part of the AM operations discourse, it is often suggested that economies of scale either do not exist or are redundant in the AM process (Pour and Zanoni, 2015; Weller, Kleer and Piller, 2015; Ben-Ner and Siemsen, 2017). Instead, individualisation and immediacy of production are prioritised, and it is suggested that economies of scale and scope are dichotomous. However, a detailed assessment of AM workflow resource consumption reveals fixed process elements (e.g. machine setup time and fixed machine capacity) that can be amortised over the contents of each build job (Ruffo, Tuck and Hague, 2006a; Baumers and Holweg, 2019; Khorram Niaki *et al.*, 2022). These are sources of economies of scale and affect the cost-effectiveness of AM, as further examined in Section 2.3. While no estimate of the scale coefficient, b, from equation (2.1) has been offered for AM, it is asserted that economies of scale are stronger in conventional manufacturing than AM (Ruffo, Tuck and Hague, 2006a). Thus, AM cannot compete from a cost perspective with conventional manufacturing at high volumes of production, exceeding tens of thousands in quantity. Although, this trade-off may shift in the future as the synergy of AM product and process design increases (Huang *et al.*, 2021), and AM machine productivity and other cost drivers improve (Baumers *et al.*, 2016).

Unlike the case for economies of scale, there is broad consensus that AM exhibits economies of scope in multiple forms. Combining the production of unrelated items in a single build leads to better utilisation of the volumetric machine capacity in various AM processes (Ruffo and Hague, 2007; di Angelo and di Stefano, 2010; Rickenbacher, Spierings and Wegener, 2013; Baumers *et al.*, 2017). This is generalised via the concept of fungibility of the build space, introduced in Section 1.1.3, which provides complete geometric freedom to pursue product variety and associated economies of scope within a build job (Baumers *et al.*, 2017). Furthermore, Hedenstierna et al. (2019) show that build space fungibility enables both economies of scale and scope to be extended beyond the boundaries of the firm: this gives rise to unique "economies of collaboration", whereby capacity in AM machines is dynamically shared between firms to improve uniformity of utilisation and process cost.

To summarise, Table 2.1 outlines the economies of scale and scope that arise in AM operations, as compared to conventional manufacturing.

Table 2.1: Comparison of economies of scale and scope in AM and conventional manufacturing operations

Element	**Description**	**Source**
Economies of Scale		
Similarities	Amortisation of fixed/shared inputs in AM and conventional manufacturing workflows	(Ruffo, Tuck and Hague, 2006a)
	Standardised AM and conventional manufacturing workflows to increase amortisation of shared inputs as quantity of (similar) products increases	(Tuck *et al.*, 2008)
Differences	Higher amortisation of fixed inputs in conventional manufacturing leads to better economies of scale at quantities >10,000	(Ruffo, Tuck and Hague, 2006a)
	Continuous AM workflows are not found in industry practice, limiting amortisation of assets due to batch process structure	(Baumers and Holweg, 2019)
Economies of scope		
Similarities	General purpose AM extends concept of flexible, programmable machines for low cost of variety	(Goldhar and Jelenik, 1983)
Differences	Fungibility of build space leads to minimal marginal cost for variety in AM	(Baumers and Holweg, 2019)
	Direct digital manufacturing method and fungibility of machine capacity enable "economies of collaboration" between AM firms	(Hedenstierna *et al.*, 2019)

2.1.4 Adoption of Technology

An innovation is of little benefit and has no impact on organisations and wider society unless it is adopted by willing users. Adoption of technology is therefore an area of interest, studying the motivators and decision-making that leads to individuals and organisations accepting or rejecting new innovations (Straub, 2009). Complementing, but separate to, technology adoption is the concept of technology diffusion, which relates to the spread of an innovation through a population of potential adopters, and provides an aggregated view of the individual adoption decisions (Straub, 2009). Treating diffusion as a managed process of sharing knowledge and information about a new innovation, higher diffusion of technology corresponds to higher awareness and external peer influence on the average member of the population, who then becomes more inclined to adopt the new technology (Rogers, 1983, p. 234). This link between diffusion and adoption leads to an S-shaped cumulative relationship, as shown in Figure 2.7. While adoption and diffusion are inextricably linked, given the relative immaturity of scaled-up AM, this section focuses primarily on adoption.

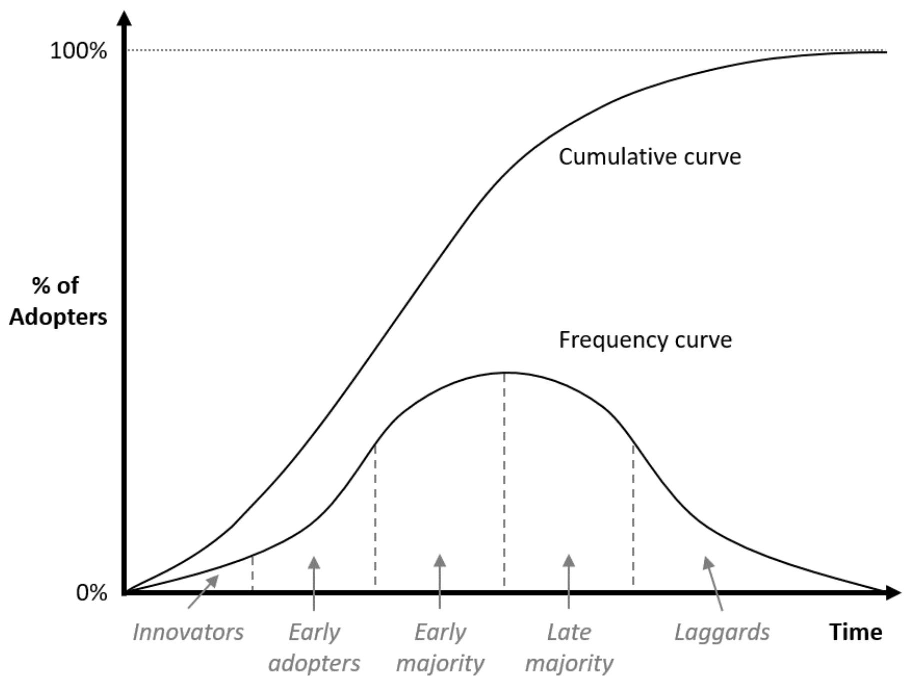


Figure 2.7: S-shaped cumulative curve of adoption and normally-distributed frequency curve, adapted from Rogers (1983, pp. 243, 247)

Various theories have been developed to ascertain and evaluate the attributes of an innovation that affect its likelihood of adoption. Often, these theories are specific to a given sector, such as the Concerns-Based Approach Model for innovation in education (Hall, 1979), or heavily focus on the psychology and motivations of individual actors, rather than organisational decision-making, as for the Technology Acceptance Model for information technology (Davis, 1989). In contrast, the Innovation Diffusion Theory (Rogers, 1983) stands out as an influential model for evaluating innovations in a wide variety of application contexts (Straub, 2009; Handfield *et al.*, 2022).

The Innovation Diffusion Theory focuses on generalised traits that influence the adopter's perception of the innovation, and thus should predict future rates of adoption (Rogers, 1983, p. 212). Summarised in Table 2.2, the five innovation attributes that arise are: relative advantage, compatibility, complexity, trialability, and observability (Rogers, 1983, pp. 213–232). Together, these attributes cover the capabilities of the innovation as well as its impact on current practice and wider potential for diffusion.

Table 2.2: Attributes of innovations that affect adoption rate, as per Rogers (1983)

Determinant of Adoption	**Description**	**Effect on Adoption**
Relative advantage	Perception of the innovation as better (economically, or status-wise) than previous options	Positive correlation
Compatibility	Perception of the innovation's consistency with the adopter's existing systems and experience	Positive correlation
Complexity	Perception of difficulty in use and understanding of the innovation	Negative correlation
Trialability	Extent to which the innovation can be experimented with, to reduce the adopter's uncertainty	Positive correlation
Observability	Extent to which the innovation and its impacts can be observed and communicated by the adopter	Positive correlation

In their AM-specific application of this theory, Oettmeier and Hofmann (2017) further categorise and expand the innovation attributes into technology-related, firm-related, market structure-related, and supply-chain related factors that affect adoption rates. The resulting eight determinants of adoption rate are outlined in Table 2.3. Notably, this model for adoption emphasises the view of AM as part of a wider ecosystem, rather than just an isolated novel manufacturing process (Mellor, Hao and Zhang, 2014; Piller, Weller and Kleer, 2015). Indeed, the eight determinants of adoption align very closely with the six factors for AM implementation, proposed by Mellor et al. (2014); this is illustrated in Figure 2.8.

Table 2.3: Determinants of adoption rate, as per Oettmeier and Hofmann (2017)

Determinant of Adoption	**Description**	**Effect on Adoption**	**Category**
Relative advantage	Benefits of the innovation with respect to its costs	Positive correlation	Technology
Complexity	Perception of difficulty in use and understanding of the innovation	Negative correlation	
Absorptive capacity	Ability of the firm to develop, evaluate, and apply relevant new knowledge	Positive correlation	Firm
Compatibility	Perception of the innovation's consistency with the firm's existing systems and experience	Positive correlation	
External pressure	Influence of regulation, competition, and customer needs on the firm	Positive correlation	Market Structure
Perceived outside support	Training, knowledge, and support to reduce uncertainty about the innovation	Positive correlation	
Supply-side benefits	Simplification of the upstream supply chain	Positive correlation	Supply Chain
Demand-side benefits	Increased customer collaboration and agility in the downstream supply chain	Positive correlation	

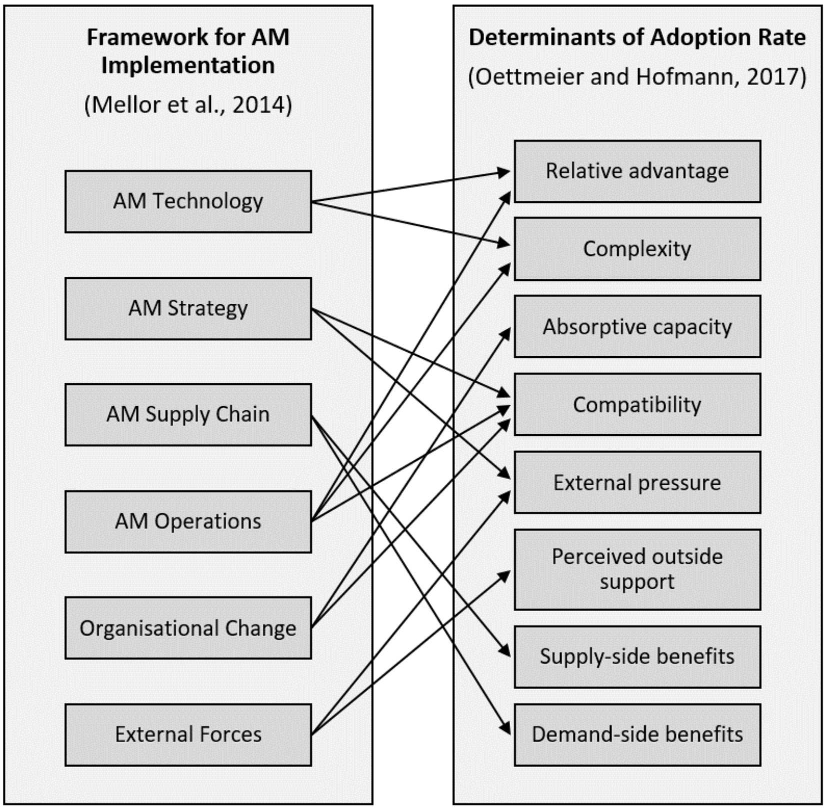


Figure 2.8: Influence of Mellor et al.'s (2014) framework for AM implementation on Oettmeier and Hofmann's (2017) determinants of adoption rate

Across various assessments of AM against the determinants for adoption, there is a strong consensus about the relative advantages of AM, indicating that these are well-understood and accepted by both current and potential adopters. The commonly mentioned advantages are: capability for complex and customisable products, increased production responsiveness, and ability to deploy customer-centric business models (Mellor, Hao and Zhang, 2014; Schniederjans, 2017; Khorram Niaki, Torabi and Nonino, 2019; Handfield *et al.*, 2022). However, in contrast, the influence of wider process-related, firm-related, and market-related attributes are much less clear. The findings from a number of case study and survey analyses are presented in Table 2.4, showing the inconsistencies regarding which individual attributes are deemed significant for AM adoption.

Table 2.4: Assessment of AM against determinants of innovation, as per Rogers (1983) and Oettmeier and Hofmann (2017)

Determinant of Adoption	**Assessment of effect on AM adoption, as per…**			
	(Oettmeier and Hofmann, 2017)	(Schniederjans, 2017)	(Khorram Niaki, Torabi and Nonino, 2019)	(Handfield *et al.*, 2022)
Relative advantage	✓	✓	✓	✓
Compatibility	✓	✓	× (“Technology adaptability)	×
Complexity	✓	×	× (“Technology adaptability)	✓
Trialability	-	×	-	×
Observability	-	×	× (“Customer expectations”)	✓
Absorptive capacity	✓	-	-	✓
External pressure	×	× (“Social pressure”)	× (“Business and market expansion”)	×
Perceived outside support	✓	✓ (“Facilitating conditions”)	-	✓

Note: ✓and × denote determinants that affect or do not affect AM adoption, respectively	
White fill denotes explicit assessment	Grey fill denotes implied assessment, with the related term quoted in brackets

When considering multiple adoption attributes together, Oettmeier and Hofmann (2017) note that positive perceptions of AM compatibility with existing systems in the firm amplifies the assessment of benefits, or relative advantage, of AM. Looking beyond the firm, there is little discussion of trialability or observability among the studies. Although Handfield et al. (2022) argue that the acquisition of specialist knowledge from experts and setting honest expectations about AM quality are imperative to building trust about AM capabilities within the company and among customers to support adoption. It should be noted that insights about firm-related and market-related determinants are either taken from the broader discussion (Handfield *et al.*, 2022) or from comparable attributes in alternative frameworks adopted by the studies (Schniederjans, 2017; Khorram Niaki, Torabi and Nonino, 2019).

Overall, the inconsistencies in the assessment of AM against the various determinants of adoption simply highlight the multi-faceted and complex nature of decision-making in technology adoption. Even among the relatively consistent factor of relative advantage, views on the cost-benefit relationship of the technology itself differ between adoptees and non-adoptees (Oettmeier and Hofmann, 2017), as expected; but they also depend on whether organisations approach the adoption decision early or late in the innovation's life-cycle (Schniederjans, 2017) – as labelled in Figure 2.7. Moreover, once a decision to adopt is made, implementing AM is an interdisciplinary, multi-step journey that relies on selecting the best options to realise the identified competitive advantages for the given product-process-organisation combination (Achillas *et al.*, 2015; Khorram Niaki *et al.*, 2022). This leads to a number of strategic and operational pathways for AM adoption, ranging from product evolution to full business model evolution (Cotteleer and Joyce, 2014).

2.1.4.1 Barriers to AM Adoption

The reasons for individual firms to adopt or reject AM can be aggregated into two opposing views of the future trajectory for AM: either as merely another option among the processes available to incumbent manufacturers, or as the underpinning technology for a disruptive manufacturing industry revolution (Holmström *et al.*, 2016). In either case, the importance of appropriate process management tools for AM is underlined by the barriers to AM adoption. Despite the progress made to date, overall industry perspectives on the key challenges for implementing AM at scale primarily focus on three areas: process productivity and efficiency, equipment reliability and stability, and integration of hardware with supporting software systems (Additive Manufacturing UK, 2015; Proff and Staffen, 2019; D'Aveni and Venkatesh, 2020).

Although academic perspectives often identify a much wider range of barriers, these typically vary according to the scope and industry. In the context of high-value, engineering part production, Thomas-Seale et al. (2018) add cost and material availability to the aforementioned barriers; whereas, small-to-medium enterprises often face more difficulties in educating and convincing customers to embrace AM processes for their parts, which must then be redesigned appropriately (Luomaranta and Martinsuo, 2022). A lack of suitable standards, common certification processes, and industry-specific guidance for AM implementation leads to poor confidence, particularly in safety-critical applications (Ford and Despeisse, 2016; Khorram Niaki, Torabi and Nonino, 2019), and an over-reliance on individual champions to spearhead AM adoption rather than systematic strategies (Luomaranta and Martinsuo, 2022).

To further complicate matters, AM adoptees must also account for likely increases in business and operations complexity, due to the data flows and systems required to support increased product variety and more responsive fulfilment processes (Handfield *et al.*, 2022). With this in mind, operations management and operations research are considered tools to overcome some of the AM adoption barriers, with a particular focus on areas such as optimising the process workflow to minimise sources of uncertainty, improving cost-effectiveness and resource efficiency in the workflow, and creating suitable assessment criteria and metrics for manufacturing performance (Ford and Despeisse, 2016; Luomaranta and Martinsuo, 2022). These principles motivate the focused literature review in the remainder of this chapter.

2.2 Production Losses in AM

2.2.1 Process Inefficiency Frameworks

Production wastes in a manufacturing flow centre on the notion of maximising the resources spent on delivering value, as per the customer's expectations. Known as lean manufacturing, the underlying argument is that any resources consumed by processes that are not wanted or needed by the customer are wasted (Ohno, 1988). These are summarised in seven wastes during production and one additional workforce-related waste (see Table 2.5). Importantly, all resources consumed in these wastes must either be paid for by the customer, or erode the profit margin for the product sold; in either case, the revenue generation potential of the process and, by extension, the competitiveness of the business are diminished. Therefore, the process effectiveness and efficiency are achieved by understanding what the customer wants, and eliminating wastes from the resulting process. This requires an external, customer-centric view of value, as well as an internal, organisation-centric view of the process and operations for delivering the product that embodies the value, known as the value stream (Womack and Jones, 2003).

Table 2.5: Wastes in lean manufacturing, adapted from Wahab et al. (2013)

Lean Waste	**Description**
Overproduction	Manufacturing excess quantity, ahead of schedule, or "just in case"
Waiting	Products not progressing through the workflow
Transportation	Excess movement of materials during the workflow
Unnecessary motion	Excess movement of people during the workflow
Inappropriate processing	Manufacturing that does not meet quality requirements, match customer requirements, or over-complicated processes
Inventory	Holding stocks of material, work-in-progress, or finished goods
Defect	Internal scrap and rework, or external repairs and remedial servicing
Underutilised people	Lack of engagement, mismatch between tasks and skills, and poor balancing of workload

Bridging the internal and external perspectives, it is imperative to understand the contribution of each process step to the value of the end product. To this end, the time taken for each process step is divided into value-adding and non-value-adding components (Hines and Rich, 1997). The value-adding time covers the conversion of raw inputs into semi-finished or finished outputs, and non-value-adding time refers to unnecessary actions in the workflow, such as waiting time, that should be eliminated. An additional third component within this framework, necessary-but-non-value-adding time, includes actions that are "wasteful but necessary under the current operating procedures" (Hines and Rich, 1997), such as travel between equipment. The relationship between these time components is shown in Figure 2.9.

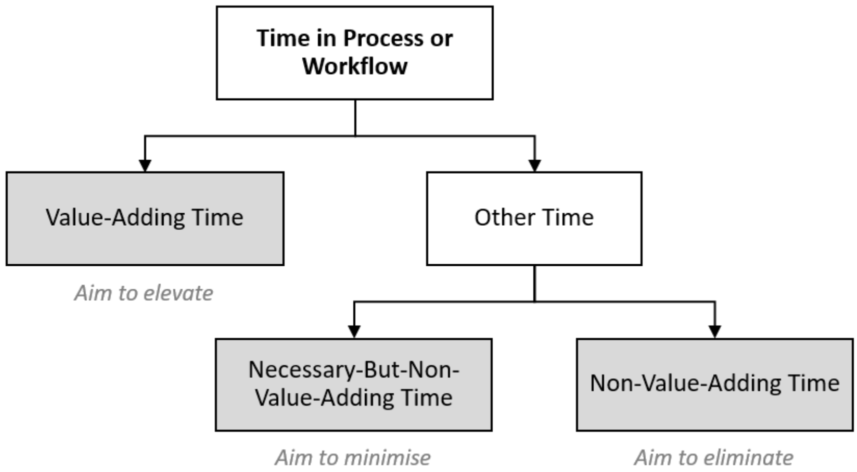


Figure 2.9: Relationship between time and value creation in a manufacturing workflow

A third framework for process inefficiency is the theory of the six production losses, which focuses on the equipment at the heart of the transformation process in manufacturing operations. Arising from the Total Productive Maintenance initiative (Nakajima, 1988), production losses capture different sources of equipment-related disturbance on the manufacturing process (Dal, Tugwell and Greatbanks, 2000). Table 2.6 summarises the production losses. This process inefficiency framework supports three of the four internal dimensions of lean manufacturing, related to the transformation process: quality in the manufacturing process and equipment, synchronisation of manufacturing planning with demand, and visibility of information flows about the manufacturing system to support feedback and corrective action (Wahab, Mukhtar and Sulaiman, 2013).

Table 2.6: Six production losses, adapted from Muchiri and Pintelon (2008)

Production Loss	**Description**
Breakdown	Equipment failure or breakdown
Setup & Adjustment	Changeover of equipment from one product to another
Idling & Minor Stops	Temporary interruptions or pauses during equipment operation
Reduced Speed	Difference between the designed and actual operating speed of equipment
Defects & Rework	Damage and lost output due to equipment malfunction
Start-up Yield	Substandard output from equipment start-up until stabilisation

Despite its internal orientation, the six production losses offer an integrated view of process efficiency and value-adding time for each machine by complementing efficiency in the time-domain with a measure of production output, or productivity, and quality thereof (Muchiri and Pintelon, 2008). While this machine-centric approach breaks down the overall manufacturing system into discrete sub-system elements, it allows operations managers to clearly evaluate how efficiently each part of the production process is performing.

Before exploring process efficiency in AM in more detail, it is important to note the relationship between time and cost perspectives of manufacturing operations. Working in the time domain is helpful, as the same measurement procedure can be applied to different steps in the process workflow; this leads to a common benchmark across any given workflow, and the ability to easily compare alternative options for the same process step (Dal, Tugwell and Greatbanks, 2000). However, time alone cannot capture the relative loss incurred by different sources of non-value-adding time (Jauregui Becker, Borst and van der Veen, 2015), and so time-based metrics should also be complemented by cost-centric measures for a full understanding of production efficiency.

2.2.2 Drivers of Process Inefficiency

AM is widely considered to be beneficial for reducing lean wastes in the production flow, as compared to conventional processes (Ghobadian *et al.*, 2020; Lakshmanan *et al.*, 2023). This is achieved through better customisation to customers' needs and matching production precisely to demand, fitting the principle of manufacturing "the right amount at the right time" (Handal, 2017). Table 2.7 expands on the impact of AM on lean wastes from a supply chain and strategic operations perspective.

Table 2.7: Impact of AM on lean wastes

Lean Waste	**Impact of AM**	**Sources**
Overproduction	Shortening supply chains Production on demand	(Ford, 2014; Holmström and Partanen, 2014; Ford and Despeisse, 2016)
Waiting	Condensing process steps to single print (and post-process)	(Baumers *et al.*, 2013; Ford and Despeisse, 2016)
Transportation	Distributed and localised production	(Holmström and Partanen, 2014; Ford and Despeisse, 2016; Ben-Ner and Siemsen, 2017)
Unnecessary motion	Condensing process steps to single print (and post-process)	(Baumers *et al.*, 2013; Ford and Despeisse, 2016)
Inappropriate processing	Use of digital manufacturing tools e.g. process simulation, digital testing	(Oettmeier and Hofmann, 2016; Lakshmanan *et al.*, 2023)
Inventory	Production on demand Replacing physical inventory with digital inventory	(Mashhadi, Esmaeilian and Behdad, 2015; Ford and Despeisse, 2016; Handal, 2017)
Defect	In-situ repair of high value products Manufacture of complex parts	(Holmström and Partanen, 2014; Ford and Despeisse, 2016; Ghobadian *et al.*, 2020)
Underutilised people	Standardisation of tasks Uniform training requirements for different products	(Oettmeier and Hofmann, 2016; Handal, 2017)

However, there is less consensus in the understanding of value-adding time in the AM process. Totah et al. (2017) deem the automatic printing and cool down time to be non-value adding in the AM workflow. Although the reasoning for this choice is not discussed, it can be assumed that the authors have taken an operator-centric perspective of the workload and seek to compare the labour input into different processes. In contrast, lead time and cost optimisation studies categorise the printing time at the machine as value-adding, relegating setup, waiting and ancillary manual tasks to non-value-adding time (Pushparaj *et al.*, 2019; Kurdve *et al.*, 2020). The latter position aligns more closely with assessments of AM value generation from a customer and organisational competitiveness perspective (Thompson *et al.*, 2016). Furthermore, treating part production as the value-adding step drives efforts to maximise the productivity of manufacturing systems, for example, using automation to reduce non-value-adding changeover time (Becker *et al.*, 2019).

Expanding upon the notion of productivity in the AM operations literature, the process planning and the productivity of AM equipment are demonstrably interconnected (Gopsill and Hicks, 2018; Stittgen and Schleifenbaum, 2021). Focusing on the utilisation of equipment in the time domain, the objective in both studies is to minimise changeovers and thus maximise the time that the AM machine is running by controlling the contents of each build. This can be achieved by altering the scheduling algorithm for converting incoming orders into build jobs (Gopsill and Hicks, 2018). Similarly, Stittgen and Schleifenbaum (2021) use the release rate of orders and the target output of each build to control the production time, referred to as the "work content", and gaps between builds to increase the utilisation of AM machines. The studies agree on the presence of an optimal level of throughput, which matches the capacity and work rate of the AM machine. Combining perspectives from process economics, production losses, and production system management: this optimal level of throughput corresponds to "technically efficient" operations, where production losses due to under- or over-loading are minimised and so the manufactured output is maximised for the given inputs (De Ron and Rooda, 2006; Baumers *et al.*, 2013; Stittgen and Schleifenbaum, 2020).

Nevertheless, conflating high equipment uptime with efficient use of equipment and other inputs provides an incomplete assessment of process inefficiency. Referencing the value-adding time framework, the efficiency and stability of value-adding steps require both capable and available processes (Womack, 2006). In other words, processes must be designed and operated such that equipment can be deployed when needed (available) and can produce good outputs (capable). The utilisation-centric perspective assumes ideal operating conditions, neglecting aspects such as maintenance, idling, process interruptions and defective output (Gopsill and Hicks, 2018; Stittgen and Schleifenbaum, 2020, 2021). Moreover, Framinan et al. (2023) note that the different facets of process planning (including orientation and packing of parts, and sequencing and scheduling of build jobs) affect the performance of AM systems in an interconnected manner; while this argument is made with reference to revenue and customer value, it can be readily extended to process efficiency. Therefore, a holistic and overarching view of process efficiency is required. However, assessments of value-adding time and production losses are absent in the context of AM, which leads to a significant gap in the understanding of process efficiency.

Fera et al. (2017) acknowledge some differences between production losses in AM and conventional manufacturing, arguing that reduced speed and start-up yield losses do not apply in AM. However, these assumptions fail to account for sources of equipment wear and tear, and general instability in the thermal conditions across the build chamber that particularly affect the deposition of early layers in the build (Bourell *et al.*, 2014; Abdelrahman and Starr, 2015). Additionally, the omission of reduced speed losses assumes that the “optimum setup” for the machine is always chosen, with the process parameters and packing of the parts delivering the shortest theoretical build time. The computational complexity of part packing alone is too high to make this a feasible assumption (Araújo *et al.*, 2019), notwithstanding the added solution space dimensions from the process parameters. Therefore, in the absence of any quantitative assessment of these assumptions, it is important to establish the extent to which the current understanding of production losses applies to and fits with the characteristics of AM.

2.2.3 Overall Equipment Effectiveness

The Overall Equipment Effectiveness (OEE) is a well-established measure of equipment performance, originally developed by Seiichi Nakajima as part of the Total Productive Maintenance system of manufacturing control (1988). OEE quantifies the impact of the six production losses, already introduced in Section 2.2.1, via the product of three constituent metrics. The first, availability, focuses on equipment utilisation; the second, performance, measures the operational rate compared to the theoretical upper limit; and the third, quality, tracks whether the output meets specifications (Garza-Reyes *et al.*, 2010). The three metrics combine to provide an estimate of the fraction of the planned proportion time that results in good quality output, or in other words, can be classified as "value-adding". This is summarised in Figure 2.10; and Nakajima's (1988) original equations for the constituent metrics are given below.

$$\mathrm{OEE} = \mathrm{Availability} \times \mathrm{Performance} \times \mathrm{Quality} \tag{2.3}$$

$$\mathrm{Availability} = \frac{T_{PP} - T_D}{T_{PP}} \tag{2.4}$$

where:

T_{PP} – planned production time
T_D – machine downtime

$$\mathrm{Performance} = \frac{T_C \times Q_P}{T_{PP} - T_D} \tag{2.5}$$

where:

T_C – theoretical processing time for one unit of output
Q_P – total quantity of output

$$\text{Quality} = \frac{Q_P - Q_D}{Q_P} \tag{2.6}$$

where:

Q_D – quantity of output deemed defective

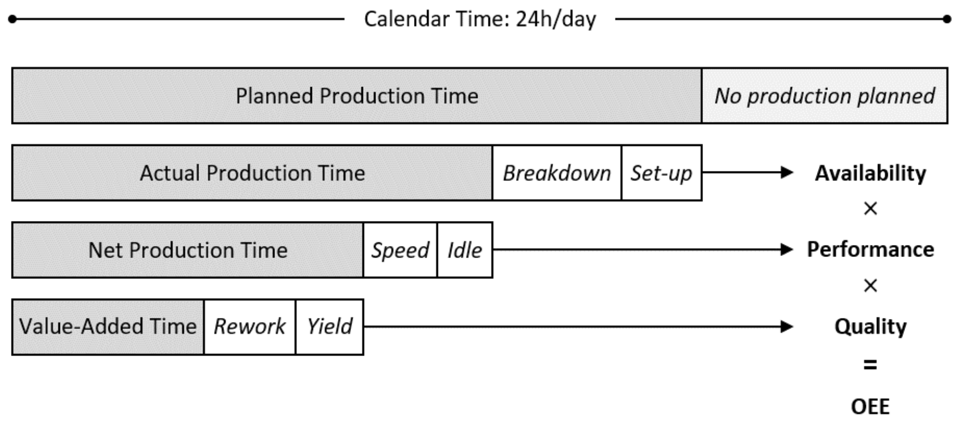


Figure 2.10: Schematic summary of the six production losses (white boxes), alongside the OEE and its constituent metrics

While the link to the six production losses is clear, there is some debate about the value that OEE provides as a key performance indicator in the operation manager's toolkit. Jonsson and Lesshammar (1999) identify four key areas to cover in manufacturing performance measurement: strategy, integration along the supply chain, customer satisfaction, and productivity. Given its machine-level focus, the authors note that OEE only covers the productivity aspect of performance. However, assuming that the product specifications match customer requirements, it can be argued that the quality metric in OEE implicitly capture the ability to produce the goods that customers demand (Bamber *et al.*, 2003; Jauregui Becker, Borst and van der Veen, 2015).

Nevertheless, within the remit of process efficiency, there is consensus that OEE can capture wide-ranging contributors to the effective use of equipment capacity, and condense this information into a succinct and easy to track metric (Jonsson and Lesshammar, 1999; Bamber *et al.*, 2003; Garza-Reyes *et al.*, 2010). This enables performance benchmarking and tracking over time for continuous improvement initiatives (Dal, Tugwell and Greatbanks, 2000; Garza-Reyes *et al.*, 2010; Kang *et al.*, 2016). Over time, these factors combine to indicate sources of hidden capacity within the system (Muchiri and Pintelon, 2008).

From the perspective of AM operations, the application of OEE towards measuring effective use of capacity is critical, as the cost of lost capacity in industrial AM processes is particularly high (Baumers *et al.*, 2016). The ability to compare the performance of different workflows using the same equipment (Dal, Tugwell and Greatbanks, 2000) allows the links between process planning and production losses to be probed; in this sense, OEE can almost be thought of as a learning tool to improve AM operations management. Although directed towards conventional manufacturing organised into dedicated production lines, the classification structure proposed by Pavnaskar et al. (2003) succinctly summarises the utility of OEE with respect to lean manufacturing: the metric identifies and measures machine-related inefficiency and unreliability factors that lead to wastes. Alongside this, the clear delineation in OEE between value-adding and non-value-adding steps within the process at the AM machine provides a gauge of return on investment for the equipment, which helps with equipment investment decisions.

2.2.3.1 Overall Equipment Effectiveness in AM

Despite assertions that the OEE is useful for providing a realistic estimate of production time-driven costs (Fera *et al.*, 2017) and for equipment improvement initiatives (Dirks and Schleifenbaum, 2020), OEE features very sparsely in the AM management discourse. The extant literature either provides cursory examples of sources of process inefficiency, such as lack of machine component synchronisation (Dirks and Schleifenbaum, 2020), or very limited, case study-specific examples of OEE formulations (Reid, 2019; Parshawanath Jain, 2022). This leads to a lack of both understanding and integration between qualitative, in-depth evaluation of production losses and quantitative analysis of the OEE in the aforementioned research.

The first of two studies that propose measurement frameworks for OEE in AM is the Overall Additive Manufacturing Effectiveness (OAME) metric (Reid, 2019). While based on the OEE metric, the distinguishing feature of OAME is to consider the time taken to detect and mitigate defects in-situ as a production loss that diminishes the AM machine running time, which affects the performance metric, rather than a loss of output due to quality. This leads to the OAME formulation as per equations (2.7) – (2.9).

$$\text{OAME} = \text{Availability} \times \text{Performance} \tag{2.7}$$

$$\text{Availability} = \frac{T_A}{T_{PP}} \tag{2.8}$$

where:

T_A – time that machine is available to run
T_{PP} – planned production time

$$\text{Performance} = \frac{T_R}{T_A} \tag{2.9}$$

where:

T_R – machine running time
T_A – time that machine is available to run

The inclusion of the in-situ defect mitigation process is a valuable step towards a more detailed and realistic account of necessary-but-non-value-adding time during the AM build process. However, a significant limitation of this work is assuming that all defects can be captured and corrected during the build, which leads to the omission of the quality metric from the definition of OAME. As a result, the OAME metric is incomplete as it completely neglects other quality issues at the part level, such as non-correctable part defects or unacceptable variation in material mechanical properties (Baumers and Holweg, 2019), and at the machine level, such as uncleanliness or unstable component performance (Fulga, Davidescu and Effenberger, 2017). It should also be noted that Reid's (2019) definition of the machine running time relies on the same assumption as Fera et al. (2017) that the actual build time is always equal to the minimum theoretical build time (see Section 2.2.2).

By contrast, the second study that applies OEE to AM (Parshawanath Jain, 2022) follows a more conservative approach by using the International Organisation for Standardization (ISO) definitions of availability, performance and quality, as per ISO 22400-2:2014 (The British Standards Institution, 2014). Probing the definitions of each metric further, a notable deviation from the original OEE formulation (equations (2.4) – (2.6)) is found. The actual production time in the availability metric (equation (2.11)) covers the time taken by "only the value-adding functions" (The British Standards Institution, 2014). This is equivalent to the ideal running time (Nakajima, 1988), rather than the intended definition, which is the total time that the machine is running (see Figure 2.11). As a result, the availability metric in this study gives the ratio of value-added time to planned production time, which is effectively analogous to the entire OEE metric, as per Nakajima's (1988) definition. By grouping together the production losses in this manner, the visibility of each source of production inefficiency is diminished.

$$\text{OEE} = \text{Availability} \times \text{Performance} \times \text{Quality} \tag{2.10}$$

$$\text{Availability} = \frac{T_{APT}}{T_{PBT}} \tag{2.11}$$

where:

T_{APT} – actual production time
T_{PBT} – planned busy time

$$\text{Performance} = \frac{T_{PRI}}{T_{APT}} \tag{2.12}$$

where:

T_{PRI} – planned run time
T_{APT} – actual production time

$$\text{Quality} = \frac{Q_G}{Q_P} \tag{2.13}$$

where:

Q_G – quantity of output deemed good
Q_P – total quantity of output

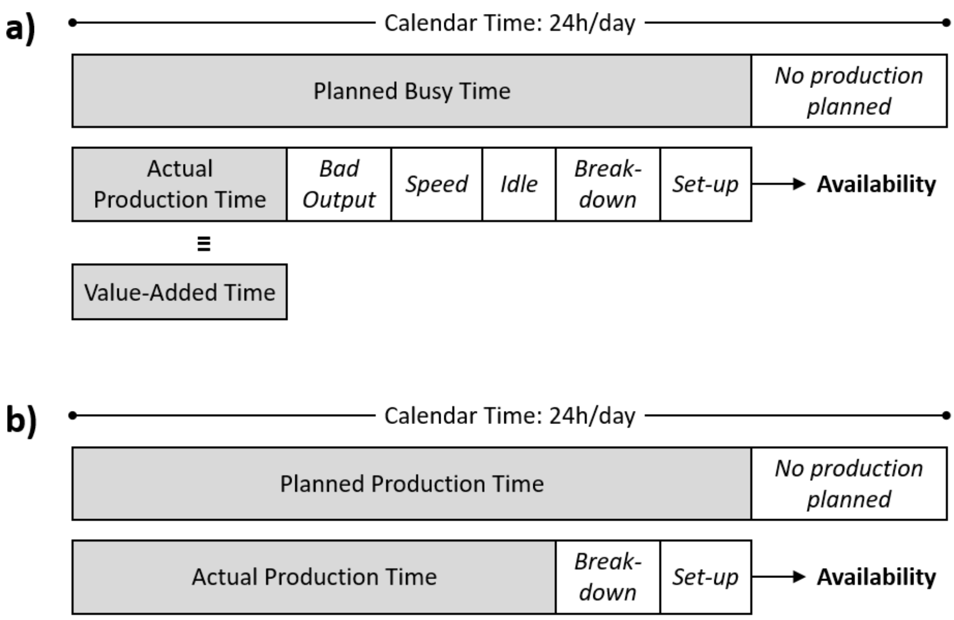


Figure 2.11: Comparison of "actual production time" definitions, as per a) ISO 22400-2:2014 (The British Standards Institution, 2014), and b) Nakajima (1988)

Shifting attention to the quality metric in equation (2.13), the use of a quantity-based measurement puts all sizes of output on par with one another. This does not align with the consensus that the resources and equipment capacity consumed by AM processes, and therefore wastes, in the case of rework, differ based on the geometry and size of the output (Ruffo and Hague, 2007; Baumers *et al.*, 2013; Rickenbacher, Spierings and Wegener, 2013). As a consequence, the quality-related losses of the AM machine may be under or overestimated, depending on the properties of the parts produced.

In all, a systematic assessment of the production losses in AM is missing. Given the prevalence of internal inefficiencies and complexity of the AM system, a thought-out interpretation of the OEE metric for AM is necessary to improve the transparency of process efficiency in AM. Moreover, the link between process planning and the production losses is not well-understood, as explained in Section 2.2.2, leading to missed opportunities to improve the operating frontier of AM.

2.3 Production Cost in AM

From a strategic perspective, the suitability of a chosen production process for adoption is informed by the balance between its benefits and costs. In this context, AM cost models aim to accurately capture the cost of resources consumed during the production of valuable outputs, helping to evaluate the net value creation (Thomas and Gilbert, 2014). Depending on the activities of interest, the scope of cost models can span the production process, the total fulfilment process including design and supply chain activities, and even the use phase of the product as well (Kadir, Yusof and Wahab, 2020). Given the focus of this research on AM operations within the manufacturing firm, the production process scope is a suitable level of abstraction for this review.

A thorough understanding of the underlying relationships between cost and the physical AM process is required to find the most cost-effective and feasible process planning options to maximise competitiveness (Chang, 2013, p. 239). Taking this a step further, AM cost models aim to both elucidate the cost drivers in the present, and highlight opportunities to broaden the economic applicability of AM in the future. Over time, this cycle of increasing depth of knowledge in AM process economics guides the development of impactful complementary innovations, pushing AM further towards GPT status.

2.3.1 Cost Model Approaches

The various different approaches for systematically estimating the contributors to production cost fall into two categories: qualitative or quantitative (Niazi *et al.*, 2006; Kadir, Yusof and Wahab, 2020). Qualitative approaches use prior knowledge and costing data from previous products and processes to infer the resources consumed for production of a new product. In contrast, quantitative approaches analyse features of the product and process to derive relationships based on the product parameters or process activities. While qualitative approaches are considered quicker to apply, the use of previous data can introduce bias and repeatability issues; and therefore, despite a higher level of complexity, quantitative approaches are considered more accurate (Niazi *et al.*, 2006). Importantly, quantitative approaches provide a clearer understanding of production cost drivers (Kadir, Yusof and Wahab, 2020). For reference, a non-exhaustive summary of the quantitative approaches is given in Table 2.8.

Table 2.8: Summary of quantitative cost model approaches for AM production

Cost model approach	**Basis**	**Techniques**	**Examples**
Parametric	Statistical regression of known or proposed cost drivers using available cost data (for early stages of product/ process design)	Regression	(di Angelo and di Stefano, 2010; Pacella and Grieco, 2010)
		Machine Learning	(Chan, Lu and Wang, 2018; Rudolph and Emmelmann, 2018)
Analytical	Decomposition of process into discrete operations or activities and summing relationships based on observable resources consumed therein (for late stages of product/ process design)	Engineering	(Schröder, Falk and Schmitt, 2015; Griffin, Hale and Jin, 2022)
		Breakdown	(Hopkinson and Dickens, 2003; Ruffo, Tuck and Hague, 2006a; Atzeni *et al.*, 2010; Atzeni and Salmi, 2012; Franchetti and Kress, 2017)
		Activity Based Costing	(Alexander, Allen and Dutta, 1998; Rickenbacher, Spierings and Wegener, 2013; Fera *et al.*, 2017; Baumers and Holweg, 2019; Šoškić *et al.*, 2019)

Among the quantitative techniques, activity based costing is the most suitable option for evaluating the cost of make-to-order AM, with the product variety this entails. Activity based costing focuses on the discrete activities in the workflow, and quantifies the corresponding resources consumed in each (Niazi *et al.*, 2006). This option is more adaptable than alternative techniques to changes in the AM workflow for different products and, importantly, the influence on pre-processing and post-process activities (Alexander, Allen and Dutta, 1998). In contrast, the more detailed cost estimation equations in the engineering approach are often limited in scope to the AM deposition step alone (Griffin, Hale and Jin, 2022), in order to limit the onerous data entry requirements for each product feature or process parameter (Schröder, Falk and Schmitt, 2015). Similarly, the activity based costing approach combines the mix of labour-intensive and highly-automated steps in the AM workflow in a more structured manner than the breakdown costing approach, which aggregates the different cost elements (e.g. labour, equipment) over the entire production process as if it were a single step (Hopkinson and Dickens, 2003; Ruffo, Tuck and Hague, 2006a; Atzeni *et al.*, 2010; Atzeni and Salmi, 2012).

An important feature of activity based costing is its application for comparing different process planning options, and their influence on the production cost drivers. The product feature-specific and process setup-specific cost formulations in parametric, breakdown and engineering approaches are less suited to this type of analysis (Niazi *et al.*, 2006; Kadir, Yusof and Wahab, 2020). The prevalence of the breakdown approach in cost models for break-even studies comparing AM with conventional manufacturing, as compared to the use of activity based costing in detailed analyses of AM operations and cost drivers (see references in Table 2.8) supports this assessment.

2.3.2 Drivers of Cost in Polymer Laser Sintering

The cost drivers correspond to the different resources consumed or utilised for a given manufacturing process, and their impact on the unit cost of production. Identifying the major cost drivers in AM is important for efforts to manage and reduce the production cost (Hopkinson and Dickens, 2003; Ruffo, Tuck and Hague, 2006a; Lindemann *et al.*, 2012). With this in mind, Table 2.9 provides a summary of the cost drivers for polymer laser sintering across a number of studies from the past 20 years.

While different cost drivers (and relative magnitudes thereof) are captured by each model, there is consensus that material and machine costs dominate the overall cost of production (Hopkinson and Dickens, 2003; Ruffo, Tuck and Hague, 2006a; Atzeni *et al.*, 2010; Baumers and Holweg, 2016). The joint contribution of these two cost drivers varies between 43% (Baumers and Holweg, 2016) and 98% (Hopkinson and Dickens, 2003) of the part cost. This is also corroborated by a recent survey of industry AM users, who note that 74% of the total investment into in-house AM capabilities is dedicated towards equipment and material costs (Sculpteo, 2022).

Atzeni et al. (2010) further show that reducing the cost of feedstock material and machine investment could improve production costs by 6% and 12%, respectively. The strategy for AM industrialisation also notes the importance of innovation in more affordable materials and machines (Additive Manufacturing UK, 2015); but in the meantime, these particular cost drivers are addressed via operations management, by maximising the efficiency of capital resources and material consumption during production, as examined in Section 2.3.3.

Focusing on the remaining cost drivers, the contribution of labour, energy, and overheads, such as facilities and software, are typically smaller in magnitude than the material and machine costs (see Table 2.9). The energy costs are so minor that Ruffo et al. (2006a) explicitly choose to omit them; a choice later affirmed by Baumers and Holweg (2016), who find that energy costs are less than 1% of the production cost. It is pertinent to note that sharp increases in the overall cost of energy, such as the 85% rise in average per-unit electricity price since 2021 (Department for Business, Energy & Industrial Strategy, 2023), would impact the energy, material and indirect costs to varying extents. Embedded energy in the material is 87% of the total energy demand in the AM workflow, as compared to 10% for process energy (i.e. electricity) consumption (Wiese *et al.*, 2021). Along with the increased costs for heating and lighting production facilities, it is therefore expected that the material and indirect costs have increased as a proportion of the total AM production cost, while process energy costs have been less affected.

Despite the touted benefits of AM to reduce reliance on labour during manufacturing, the majority of the AM workflow involves manual tasks (Baumers and Holweg, 2016), and the cost of skilled operators can exceed one eighth of the production cost (Ruffo, Tuck and Hague, 2006a) and one quarter of a company's investment in AM (Sculpteo, 2022).

Table 2.9: Summary of production cost drivers in polymer laser sintering

<table>
<tr><th rowspan="2">Cost Driver</th><th colspan="6">Contribution to Unit Cost of Production (%)</th><th rowspan="2">Type of Cost (Son, 1991)</th></tr>
<tr><th>(Hopkinson and Dickens, 2003)</th><th>(Ruffo, Tuck and Hague, 2006a)</th><th>(Atzeni et al., 2010)</th><th>(Schmid and Levy, 2012)</th><th>(Baumers and Holweg, 2016)</th><th>(Khajavi et al., 2018)</th></tr>
<tr><td>Material</td><td>74</td><td>33</td><td>30</td><td rowspan="4">86 – 89</td><td>27</td><td>-</td><td rowspan="5">Well-structured costs</td></tr>
<tr><td>Machine</td><td>24</td><td>38</td><td>59</td><td>16</td><td rowspan="2">86</td></tr>
<tr><td>Overheads (Indirect)</td><td>-</td><td>16</td><td>-</td><td>16</td></tr>
<tr><td>Labour</td><td>2</td><td>13</td><td>11</td><td>4</td><td>7</td></tr>
<tr><td>Energy</td><td>-</td><td>-</td><td>-</td><td>-</td><td><1</td><td>-</td></tr>
<tr><td>Risk of Failure</td><td>-</td><td>-</td><td>-</td><td>-</td><td>38</td><td>-</td><td rowspan="3">Ill-structured costs</td></tr>
<tr><td>Quality Control</td><td>-</td><td>-</td><td>-</td><td>11 – 14</td><td>-</td><td>-</td></tr>
<tr><td>Inventory</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>7</td></tr>
</table>

2.3.2.1 Ill-Structured Costs

As AM technology has matured, perspectives on the cost drivers in the extant literature have also evolved to include and quantify less tangible aspects of the production cost. The framework proposed by Son (1991) in Figure 2.12 includes quality and flexibility as such "relatively ill-structured costs" (hereafter simply "ill-structured costs"), complementing the "well-structured costs" explored in the previous section. Referring to the summary of cost drivers (see Table 2.9), the latter three studies each include individual ill-structured cost elements.

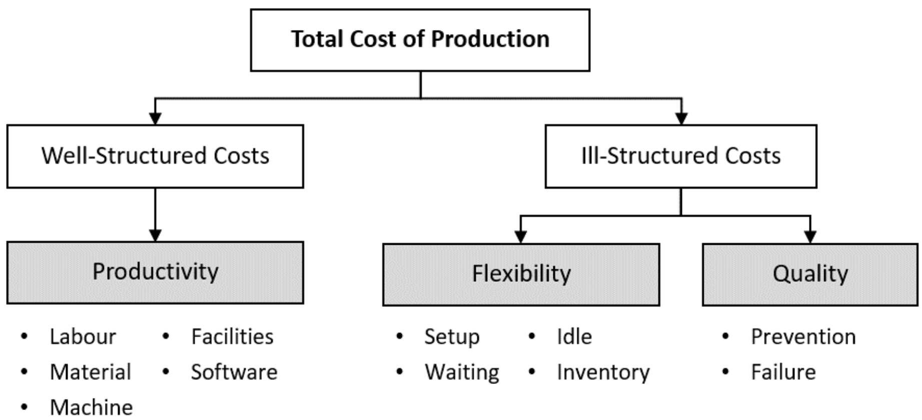


Figure 2.12: Framework of well-structured and ill-structured costs in production, adapted from Son (1991)

Exploring the quality-related costs first, the cost of failure arises from wasted resources expended on scrapped outputs (Ashby, 2011, p. 409). The extra resources consumed amplify the net cost by a given "scrap fraction", or likelihood of failure, as shown in equation (2.14). While Ashby (2011) assumes that only the direct material input into a generic manufacturing process would be lost in the case of failure, Son (1991) takes a more holistic approach that accounts for the cost of necessary rework or the total cost of scrapping an irreparable part. This delineation between failure modes that lead to recoverable versus irrecoverable scrap is carried forward in estimates of failure costs in polymer laser sintering (Baumers and Holweg, 2016, 2019), and also aligns with approaches followed in other advanced manufacturing processes (Jauregui Becker, Borst and van der Veen, 2015).

$$C_{total} = \frac{C_{net}}{(1-f)} \tag{2.14}$$

where:

C_{total} – total cost of production
C_{net} – net cost of production, before failure
f – scrap fraction

Furthermore, two different cost estimation schemes emerge for failure costs in laser sintering. The first follows a part-oriented approach with a fixed scrap fraction, as above, for each part in the build. This is applied to metal powder-bed fusion by Colosimo et al. (2019), and to laser sintering failures that arise from irreparable part defects by Baumers and Holweg (2016). The second scheme relates to an additional but distinct failure mode, whereby the entire build prematurely terminates due to an unforeseeable disruption (Baumers and Holweg, 2016, 2019). This scheme is layer-oriented, such that each layer during the build process is considered an independent step with its own likelihood of failure, as shown in Figure 2.13.

From a process economics perspective, both schemes are helpful for aggregating the many sources of quality issues in powder-bed fusion AM (Fulga, Davidescu and Effenberger, 2017) into a straightforward, outcome-based estimate of failure and its cost impact. However, the specific source of quality issues remains hidden in this way, which is not conducive to process improvement for cost reduction. Additionally, establishing the appropriate scrap fractions requires empirical observations of part rejections and build failures (Baumers and Holweg, 2016, 2019). While the process of gathering failure-related data may lead to additional costs, these empirical approaches avoid the need to rely on arbitrary estimates of part rejection or machine failure probabilities, as seen in Schröder et al. (2015) and Laureijs et al. (2017), respectively. This improves the validity of the failure cost calculations.

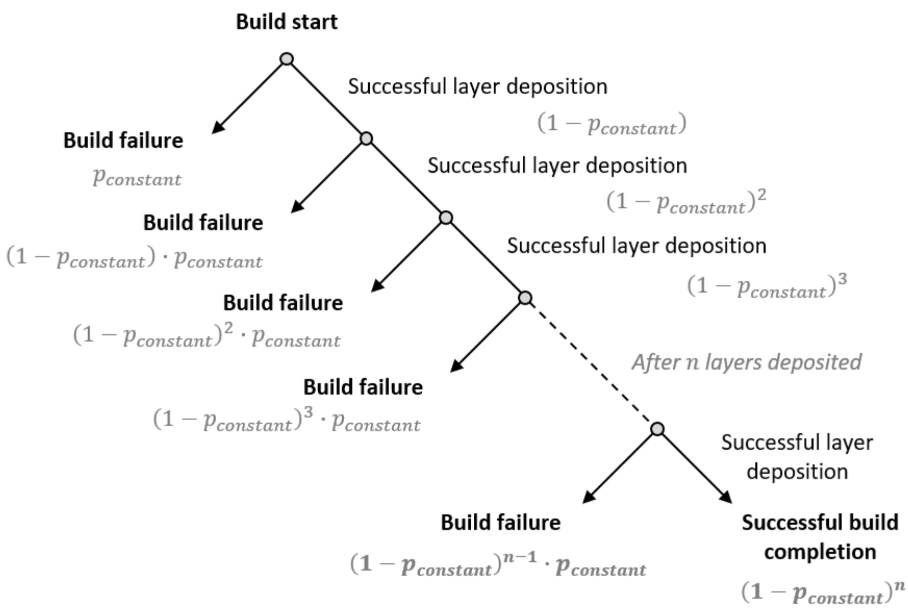


Figure 2.13: Discrete event probability tree for layer-wise calculation of build failure probability, adapted from Baumers et al. (2017)

Closely related to the cost of failure itself is the cost of preventative systems, designed to monitor and intervene in the manufacturing process in order to minimise failures (Son, 1991). Schmid and Levy (2012) find that the fixed and variable costs for preventative quality control systems account for between one tenth and one fifth of the annual revenue for medium-value parts, which are priced at EUR200. While this is not exorbitant, the importance of offsetting the additional cost with savings in time, resources and materials on defective output is emphasised.

Therefore, the cost-effectiveness of such preventative systems relies on their ability to alert operators to issues and, where possible, terminate the manufacturing process to avoid excess resource consumption. Colosimo et al. (2019) note that, in the case of metal powder-bed fusion, the reliability of the monitoring system itself affects its cost-effectiveness. If the error rates in the monitoring system are high, particularly if defects are erroneously detected in parts (false positive), then the part cost becomes inflated through unnecessary scrap and remanufacturing. Given the likely scrap fractions in the machine and error rates in monitoring systems, Colosimo et al. (2019) conclude that monitoring is economically beneficial only for medium-to-high value parts.

It is important to note that, while various preventative systems are emerging under research (Phillips, Fish and Beaman, 2018; Reiff *et al.*, 2018; Brion and Pattinson, 2022), fully functional closed-loop quality control systems with active process correction capabilities do not yet exist for laser sintering.

Shifting attention to the flexibility-related costs, a key cost contributor in any manufacturing process is the inventory of work-in-progress or finished parts. To this end, from a supply chain perspective, Alogla et al. (2021) note that manufacturing on demand using AM can entirely eliminate inventory costs, as compared to conventional manufacturing pathways. However, avoiding inventory relies on a minimum order quantity that is nearly eight times higher for AM than conventional manufacturing; and so responsive production of a varied mix of products is achieved, but at the expense of limited flexibility in the quantity to be delivered. On the other hand, Khajavi et al. (2018) show that inventory can arise within direct digital manufacturing operations due to a mismatch between the production fulfilment dates for different parts within an order. This points to an important link between appropriate management of the AM workflow and the production cost drivers, which can also be expanded to cover the flexibility costs of setup and waiting, as alluded to by the, albeit limited, sensitivity analysis conducted by Schröder et al. (2015). Therefore, the following section explores this in further detail.

To conclude the review of polymer laser sintering cost drivers, it is important to acknowledge the breadth of both well-structured and ill-structured costs that have emerged in the extant literature. The study of well-structured costs has been expanded to include different ill-structured cost drivers, from a quality perspective (Schmid and Levy, 2012; Baumers and Holweg, 2016; Colosimo, Cavalli and Grasso, 2019) and a flexibility perspective (Schröder, Falk and Schmitt, 2015; Khajavi *et al.*, 2018; Alogla *et al.*, 2021). However, with the exception of one study (Khajavi *et al.*, 2018), the examination of cost drivers is limited to the operation of individual machines; and so the context of operating multiple machines within a production facility or wider network that underpins scaled-up AM is as-yet unexplored. Moreover, a systematic assessment of different ill-structured costs together, and any trade-offs therein, is missing from the discourse. Given the dominance of ill-structured costs, particularly the risk of failure (Baumers and Holweg, 2016), this is a particularly significant omission from the study of AM cost and cost-effective operations.

2.3.3 Impact of Process Planning on Cost Drivers

This section explores how process planning affects the cost drivers, thus linking the operations management of the AM system to its cost-effectiveness. The various process planning factors fall into different categories, as per Framinan et al. (2023), and are outlined in Table 2.10. Assuming that the process choice is fixed, the following process planning and operating factors (from Table 2.10) affect all of the cost drivers: part allocation to machines, order acceptance and scheduling, part packing and orientation in the build. These can be explored in more detail with respect to the AM workflow and build process.

Within a build, minimising the build height is a common objective when orienting and packing parts (Oh *et al.*, 2020). The overarching aim is to reduce the build time and associated overheads or indirect costs. For laser sintering and other powder-bed fusion processes, the number of layers and build height contribute most significantly to the build time. Alongside this, the volume of unsintered powder that undergoes thermal cycling, ultimately leading to waste, increases with the number of layers deposited. Thus, minimising the build height also reduces the consumption of expensive feedstock material.

Table 2.10: Summary of different process planning factors, from Framinan et al. (2023), and links to cost drivers

<table>
<tr><th>Categories</th><th>Process Planning Element</th><th>Link to Cost Drivers</th></tr>
<tr><td rowspan="2">Designing AM Process</td><td>Number of AM and ancillary machines</td><td>Indirect costs, via machine depreciation and maintenance</td></tr>
<tr><td>Organisation of machines in workflow</td><td>As yet unexplored (see Section 2.4.2.1)</td></tr>
<tr><td rowspan="4">Planning AM Process</td><td>AM process choice</td><td>All cost drivers, via process design and consumption of materials and energy</td></tr>
<tr><td>Part allocation to machines/ facilities in distributed network</td><td rowspan="4">All cost drivers, via amortisation of machine capacity and labour, and consumption of materials and energy</td></tr>
<tr><td>Order acceptance and scheduling</td></tr>
<tr><td>Nesting (packing) of parts</td></tr>
<tr><td rowspan="2">Operating of AM</td><td>Orientation of parts in build</td></tr>
<tr><td>Process parameter settings</td><td>Material, energy, indirect costs; via time and resources consumed during the build</td></tr>
</table>

Considering the ill-structured cost drivers as well, the risk of build failure provides a further motivation to minimise the build height. Although it should be noted that this arises due to the layer-wise nature of the build failure probability model (Baumers and Holweg, 2016). Alternative models focus on part orientation to balance minimising height (for the aforementioned effect on build time and material consumption) with quality-centric factors such as surface roughness that affect the part value rather than the production cost.

There is also consensus that the volumetric capacity should be maximally filled for each build. This relates to achieving economies of scale by apportioning the fixed machine time and resources (labour, energy) for the setup, loading, warm-up, cool-down, and unloading across the largest possible output set. Ruffo et al. (2006a) first identify the scale economies in the relationship between cost and quantity, which Baumers and Holweg (2019) later formalise by accounting for failure modes and operator variation as well.

While the amortisation of fixed costs motivates process planning to maximise capacity utilisation in various cost studies, this also increases build failure-related costs due to the taller build height. Baumers and Holweg (2016) thus find a trade-off between well-structured and failure-related ill-structured costs.

In a similar vein, when managing an incoming order stream in make-to-order AM, the timeliness of delivery becomes an additional constraint to balance with capacity utilisation (Costabile *et al.*, 2017). Production of early orders must be delayed to allow demand to accumulate and fill machines for cost effective production, risking late delivery. In this case, process planning shifts from packing alone to the allocation of parts to a sequence of builds in a machine; and the objective often becomes minimum makespan rather than build height or machine utilisation (Oh *et al.*, 2020). Although, sophisticated approaches are required to avoid additional ill-structured costs, such as inventory holding of partially fulfilled orders from one build to the next (Khajavi *et al.*, 2018).

Expanding the perspective to include allocating parts and scheduling builds across multiple machines, the extant literature begins to disagree on appropriate process planning approaches. A key reason is the relative recency of the topic, with studies that explore multi-build and multi-machine scenarios only appearing in the discourse from 2015 onwards (Oh *et al.*, 2020). Studies vary in their focus on cost, makespan, tardiness, fraction of orders accepted, and other related factors; and importantly, the process planning solution, in terms of a sequence of packed builds, is different depending on the objective that is prioritised (Altekin and Bukchin, 2021).

This points to a unique challenge of both cost-effective and consistent-cost operation of multiple machines for make-to-order fulfilment. Estimating the cost of orders is a challenge when the contents of the builds is unknown, due to variety in the rate and contents of incoming orders (Rudolph and Emmelmann, 2018). Therefore, shifting the focus of process planning capabilities to generate both cost- and time-effective AM builds in a predictable manner could improve users' business competitiveness and ability to attend to process improvement rather than stability.

It is also important to acknowledge that process planning activities are often handled by skilled operators, who rely on tacit knowledge about the manufacturing process. To this end, Mandolini et al. (2020) note the importance of properly capturing both tacit and explicit understanding of manufacturing processes towards successful implementation of cost models.

2.3.3.1 Role of Workflow Optimisation

Thus far, this section has highlighted that AM process planning for cost-efficiency involves a multitude of contributory factors, which operate at different levels of abstraction in the manufacturing system: from the orientation of a single part, to the acceptance or rejection of entire orders (Framinan, Perez-Gonzalez and Fernandez-Viagas, 2023). Additionally, the solution space within each factor is often vast, if not infinite. A prime example of this is packing parts for a build job, which alone is a computationally complex, non-deterministic polynomial hard (i.e. NP-hard) optimisation problem (Araújo *et al.*, 2018), even before other factors are combined therewith. As a result, novel and powerful optimisation techniques are required to deliver cost-effective AM production; and more importantly, such optimisation techniques must consider multiple aspects of the AM workflow (Baumers, Özcan and Atkin, 2017), hereafter referred to as "workflow optimisation".

Given the computational complexity of AM process planning optimisation, heuristic approaches are often employed in this domain (Oh *et al.*, 2020), because they are able to find a "good enough" solution within a reasonable computational time and workload, as compared to analytical or brute force alternatives. However, a key trend that still prevails among process planning optimisation studies is the optimisation of different workflow steps, such as packing, order acceptance, and build time minimisation, in isolation (Freens *et al.*, 2015; Li, Kucukkoc and Zhang, 2017; Chergui, Hadj-Hamou and Vignat, 2018). While constraining the optimisation problem in this way can lead to simpler and faster solutions, potentially vast swathes of the design space for process planning are overlooked at the intersection between the different process planning factors (Framinan, Perez-Gonzalez and Fernandez-Viagas, 2023), and so cost-effective process planning choices could be missed.

To address this gap, studies are emerging that recognise the presence of trade-offs between different parts of AM process planning (Altekin and Bukchin, 2021; Kapadia *et al.*, 2021), and attempt to optimise these in a holistic manner, hereafter referred to as "integrated optimisation". Three process planning elements are of particular interest: the allocation of incoming orders to build jobs, the packing of parts therein, and the scheduling or sequencing of the build jobs; together, these are referred to as the "packing and scheduling problem". The packing and scheduling problem is pivotal for cost-effective AM because it directly affects the build properties and, by extension, the cost drivers (Baumers, Özcan and Atkin, 2017; Costabile *et al.*, 2017).

A limited set of AM operations research studies are found to explore integrated optimisation of the packing and scheduling problem (Gopsill and Hicks, 2018; Khajavi *et al.*, 2018; Kapadia *et al.*, 2021), of which only the latter two consider three-dimensional packing, as found in the polymer laser sintering process. However, both of these studies focus on other tools available in direct digital manufacturing to optimise the workflow: automatic kit generation (Khajavi *et al.*, 2018), and dynamic order acceptance or rejection (Kapadia *et al.*, 2021). As a result, while novel algorithmic solutions for integrated optimisation of the packing and scheduling problem are presented, the results do not explore the links between this workflow optimisation phenomenon and the underlying cost drivers. It is therefore difficult to evaluate the cost-effectiveness of employing integrated optimisation against alternative, simpler solutions.

In the wider context, Framinan et al. (2023) note that integrated optimisation will feature heavily in future AM operations management tools. This echoes the assertion that AM system-level integration is required to improve the performance frontier for flexibility and controllability in the workflow, leading to better profit and revenue (Thomas and Gilbert, 2014; Baumers, Özcan and Atkin, 2017). Hence, proving the benefits of integrated optimisation for the packing and scheduling problem is key to the wider AM workflow performance.

2.4 Facility Layout in AM

The facility layout refers to the arrangement and organisation of processes, and the required equipment, to fulfil production. Appropriate layout choices depend on the production scale, variety of products, process technologies, and links to the upstream and downstream supply chains (Naylor, 2002, p. 240). This aspect of capacity management affects the production output that can be achieved, the number and types of equipment in the workflow, and the time and resources (e.g. operator workload) consumed during production (Radford and Richardson, 1977, p. 132).

In other words, facility layout is significant because it has repercussions for the future production workflow and for the balance of process inputs and outputs therein, which is directly related to the process efficiency. Furthermore, it is very difficult to remediate issues arising from inappropriate facility layout once production operations have begun, even with significant re-investment in time, organisational change and cost (Kopf *et al.*, 2016). This is exacerbated by the high investment cost required for AM, in terms of both equipment and operator training (Khorram Niaki and Nonino, 2017).

Despite this, the extant literature severely lacks consideration of AM facility layout or infrastructure requirements at the strategic or operational level. One possible reason is the relatively poor maturity of AM use in industrial contexts, which motivates a general-purpose workshop-style layout when first adopting AM to improve the ability to pivot towards changing production requirements (Kopf *et al.*, 2016). For this reason, AM operations management and operations research frameworks have remained focused on issues relating to process capability and reliability (Mellor, Hao and Zhang, 2014), and timely and cost-efficient management of the production workflow (Framinan, Perez-Gonzalez and Fernandez-Viagas, 2023). Therefore, the remainder of this section outlines appropriate facility layout approaches and implications for the AM workflow.

2.4.1 Facility Layout Approaches

There are three key facility layout approaches that are related to batch production, which matches AM operations characteristics (Baumers and Holweg, 2019), and are also found in various AM production facility studies. First, the process layout (Figure 2.14a) organises the production floor into zones of general-purpose equipment of the same type, and products are flexibly routed between these zones as per their processing requirements (Yoo *et al.*, 2016; Kellner *et al.*, 2019). Second, the line layout (Figure 2.14b) sequences equipment in the order of operations for a given product or group of similar products, known as a product family (Avventuroso *et al.*, 2017; Avventuroso, Silvestri and Frazzon, 2018). The equipment is typically dedicated to the product family, and the pace of the product flow through the system is set by operator- or machine-driven tasks. The third layout is a hybrid between the preceding options: cellular layout (Figure 2.14c) has clusters (cells) of general-purpose or dedicated equipment that correspond to common sequences in the manufacturing workflow (Kang *et al.*, 2018). Products are routed flexibly across the cells, and often proceed in series inside the cells. The operational characteristics of each layout option is presented in Table 2.11, with reference to manufacturing processes in general (Radford and Richardson, 1977, pp. 133–134; Naylor, 2002, pp. 242–251).

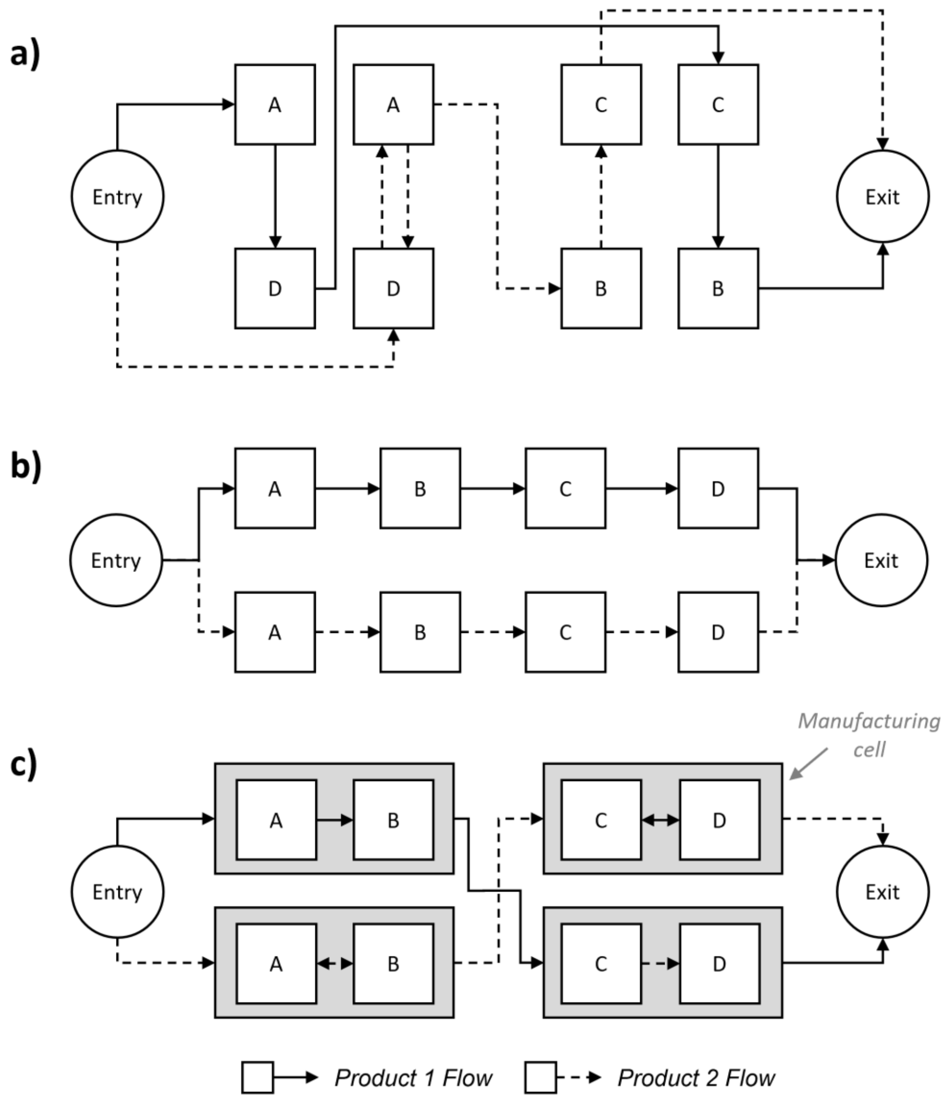


Figure 2.14: Example flows of different products through facility with a) process layout, b) line layout, and c) cellular layout

Table 2.11: Characteristics of facility layout approaches suitable for batch production

Characteristic	**Facility Layout Approach**		
	Process	**Line**	**Cellular**
Orientation	Equipment function	Product type	Hybrid
Product-Process Mix	High variety of products Generalised equipment	Low/no variety of products Dedicated equipment	Medium/high variety of products Generalised equipment in dedicated clusters
Advantages	Flexibility in scheduling Aligns with operator specialisation	No delay between processes Shorter throughput Higher control	No delay between processes within cells Higher scheduling flexibility than line layout Lower work-in-progress than process layout Higher task autonomy for operators
Disadvantages	Complex scheduling Higher quantity of work-in-progress Longer travel time between processes Products may loop back to the same part of the facility, depending on operations	Inflexible in scheduling Series flow vulnerable to disruption Synchronisation required along the line for a smooth flow Negligible task autonomy for operators	Low and/or uneven utilisation of some equipment in cells

2.4.2 Drivers of Facility Layout Choice

The suitability of each facility layout approach can be reviewed with reference to the scope of AM operations in this research, which is direct digital manufacturing to fulfil product variety.

In place of conventional manufacturing methods, AM can improve the economic feasibility of production variety when using the line layout, but the layout itself is oriented towards efficiency and therefore is not conducive to flexibility in production (Enrique *et al.*, 2022). Indeed, the two examples of an AM-based line layout involve identical parts (Avventuroso, Silvestri and Frazzon, 2018) or batches of parts differing in size only (Avventuroso *et al.*, 2017). Therefore, despite its focus on process efficiency, the line layout would not be suitable for the product variety orientation of this research.

On the other hand, the cellular layout is amenable to not only variety in production output (Kang *et al.*, 2018), but also variety in production processes involving hybrid-AM combinations (Boivie *et al.*, 2011; Lehmhus *et al.*, 2016) and even variety in workflow configurations (Arnarson *et al.*, 2022). Similarly, the product-agnostic configuration of equipment in the process layout facilitates easy re-orientation of the production facility to demonstrate a range of different applications of AM (Yoo *et al.*, 2016).

These examples of cellular and process layouts are presented as demonstrator facilities; and so there is no quantitative analysis of the available facility layout approaches to justify their choice, despite the opportunity to maximise value-adding time and minimise production cost (Ali Naqvi *et al.*, 2016). Few studies of facility layout offer an operations-oriented justification, and even fewer still seek to optimise the layout, once chosen. The following sub-sections therefore assess the limited extant literature for the potential impacts of the facility layout on process efficiency and scope for scaled-up AM.

2.4.2.1 Impact on Cost

The equipment requirements, or capacity within the manufacturing system, depends not only on the anticipated throughput of products but on the facility layout as well (Radford and Richardson, 1977, p. 132). This relationship is also influenced by factors such as the flexibility to introduce new products and the required redundancies against breakdown. Therefore, by extension, the facility layout choice affects the setup cost, as per the quantity of each equipment, of the production workflow. Kang et al. (2018) show that the equipment investment cost is a valid metric of comparison between different manufacturing system setups, albeit comparing conventional and AM systems within the same cellular layout.

The high costs of equipment, alongside necessary infrastructure and skilled labour, are an investment barrier to AM implementation and expansion, particularly for small and medium enterprises (Pour *et al.*, 2016; Khorram Niaki and Nonino, 2017). Referring to conventional manufacturing processes, the equipment requirements are higher in cellular manufacturing, as each cell should contain all the machines necessary for the process steps within to maintain the system advantages (Greene and Sadowski, 1984). However, it is not known whether the general purpose nature of AM machines can help other facility layout approaches achieve similar process efficiency advantages to the cellular layout. While consensus has built over the years that an AM production workflow is less costly to set up than a low-volume, flexibility-centric conventional manufacturing counterpart (Hopkinson and Dickens, 2003; Atzeni *et al.*, 2010; Kang *et al.*, 2018), no studies have been found to compare different layouts for AM production as the production scale increases. Therefore, the impetus to find cost-effective facility layouts also impacts the technology adoption and wider diffusion of AM.

2.4.2.2 Impact on Production Losses

Expanding on the links between facility layout and cost-efficiency of the workflow, the constraints on the workflow that arise from the layout choice impact the production time and quality.

The disparity in time taken for the AM production step compared to upstream and downstream parts of the AM workflow leads to production bottlenecks (Avventuroso *et al.*, 2017; Avventuroso, Silvestri and Frazzon, 2018; Kang *et al.*, 2018). This motivates parallelisation of the different steps, which is straightforward to implement in the process layout; optimisation of the number of machines in each step therefore leads to improved throughput and equipment utilisation (Kellner *et al.*, 2019). A similar approach is also feasible in the cellular and line layouts, but only where the manufacturing setup is modular (Lehmhus *et al.*, 2016; Avventuroso *et al.*, 2017; Avventuroso, Silvestri and Frazzon, 2018; Kang *et al.*, 2018). Given the footprint of industrial AM equipment, modularity is possible only with desktop-sized machines, as in the cited studies.

Focusing further on the process layout, Kellner et al. (2019) demonstrate that parts spend most of their time (82 – 86%) in storage or travel between machines. This corroborates weaknesses of the process layout relating to non-value-added time in the workflow, as identified in Table 2.11. On the other hand, Dutra et al. (2022) assert that the process layout improves production flexibility via concurrent manufacture of different products. However, this specific attribute is already available in AM (notwithstanding material requirements), independent to the facility layout (Pour *et al.*, 2016). Therefore, the trade-off between non-value-added time and parallelisation in AM workflows using the process layout is unclear and warrants further investigation.

Yoo et al. (2016) provide a different motivation for choosing the process layout, which is to control the production environment for the pre-process, process and post-process steps separately to improve safety and output quality.

Interestingly, a similar argument can be used for the cellular layout in high-value and industrial applications of AM (Nuclear AMRC News, 2015). For example, separate manufacturing cells can be reserved for different material flows, leveraging the ability to set up complete and independent workflows inside each cell, as demonstrated by Kang et al. (2018). However, separating and restrictively allocating resources introduces elements of the line layout by reducing the flexibility of the workflow and increasing its vulnerability to disruption (see Table 2.11). Given the vulnerability of powder-bed fusion systems to breakdown and outright build failure (Baumers and Holweg, 2016; Colosimo, Cavalli and Grasso, 2019), the organisation of the workflow with respect to this trade-off in quality factors is of pertinent interest.

2.4.2.3 Impact on Scaled-Up AM

Throughout this section, the use cases for cellular manufacturing are geared towards demonstrator (Boivie *et al.*, 2011; Lehmhus *et al.*, 2016) or standalone "micro-factories" (Kang *et al.*, 2018). This suggests better suitability towards low-scale AM or scaling up via distributed manufacturing, where each facility has a few cells that span the entire AM workflow and operate independently.

Shifting towards scaled-up AM, Ben-Ner and Siemsen (2017) make a valuable observation about the ability to invest in individual general-purpose machines to expand capacity in AM workflows, rather than investing in "lumpy increases in capacity", as would be found in conventional manufacturing. Extending this logic, the process layout would be more amenable to smoothly adjusting the capacity in the manufacturing workflow to the external demand. This is because there is greater freedom to expand capacity one function at a time by investing in individual machines. In contrast, the cellular layout aligns with expanding capacity by entire manufacturing cells at a time.

The scope to incorporate further digital manufacturing paradigms in the AM workflow also depends on the facility layout. The AM and hybrid cellular layouts each include automated transfer systems between stations in the cell, such as robotic arms and conveyor systems (Boivie *et al.*, 2011; Lehmhus *et al.*, 2016;

Kang *et al.*, 2018). The relative proximity of each process step facilitates the use of this readily-available technology to minimise the operator input between the steps in the AM workflow, which is conducive to operations at scale. In the process layout, alternative, albeit futuristic, solutions such as autonomous guided vehicles would have to be considered (EOS GmbH, 2023).

To sum up, the facility layout considerations for the AM workflow significantly change when operating at scale (Huang *et al.*, 2021). In particular, the focus must shift towards high process efficiency in the flow of products through the manufacturing system. Therefore, there is a need to establish the connections between the facility layout and the drivers of cost-effective and time-efficient production in order to support scaled-up AM.

2.5 Summary

The review of the background and focal literature can be summarised according to three themes that relate to each research objective, and their intersection with perspectives on operations management and technology adoption for AM. These are outlined below and in Table 2.12.

First, the technology adoption literature has shown the potential scope of AM to disrupt existing manufacturing and product-service businesses (Cotteleer and Joyce, 2014; Steenhuis and Pretorius, 2017; Maresch and Gartner, 2020), but emphasise that this is only possible if tools are available to AM users to reconcile the complexity of decision making in adopting and implementing AM (Oettmeier and Hofmann, 2017; Handfield *et al.*, 2022). To this end, the focal literature on production losses highlights that this key system for assessing the value-add of manufacturing processes has not been fully applied to AM (Fera *et al.*, 2017; Reid, 2019; Parshawanath Jain, 2022). An opportunity exists here to improve both the transparency of AM performance and direct AM users towards methods for achieving greater process efficiency.

Second, the literature pertaining to economies of scale and scope highlights the different sources of cost-effectiveness in AM (Rickenbacher, Spierings and

Wegener, 2013; Baumers *et al.*, 2017; Baumers and Holweg, 2019; Hedenstierna *et al.*, 2019). Relating this to AM operations management, the role of process planning (primarily the conversion of incoming orders to packed and scheduled build jobs) in realising economies of scale and scope has been explored in the aforementioned studies with respect to well-structured costs. However, the impact of ill-structured costs on cost-effectiveness in AM has largely been examined in isolation (Baumers and Holweg, 2016; Khajavi *et al.*, 2018; Alogla *et al.*, 2021), which misses any potential trade-offs therein. Therefore, there is scope to extend the understanding of both well-structured and ill-structured costs in tandem and, importantly, do so in the context of multi-machine operations as found in scaled-up AM.

Third, the operations management literature relating to process and facility design for product volume and variety (Radford and Richardson, 1977, pp. 133–134; Hayes and Wheelwright, 1979; Naylor, 2002, pp. 242–251) offers a strong framework for guiding the layout of facilities as the production scale increases. However, this perspective is almost entirely missing from the AM discourse, with limited examination of or justification provided for industrial AM users' choice of facility layout (Yoo *et al.*, 2016; Avventuroso *et al.*, 2017; Kang *et al.*, 2018). Moreover, there is no comparative assessment of the facility layout approaches with respect to AM, and evaluations of the process efficiency are limited to single paradigms (Avventuroso *et al.*, 2017; Kellner *et al.*, 2019). A gap therefore arises for developing a verifiable guide for AM users with respect to the appropriate facility layout, and underlying mechanisms for process efficiency, for different scales of production.

To close, the common thread throughout the research gaps, and subsequent design of this research, is the balance of efficiency with responsiveness and variety across the AM workflow. In short, this thesis aims to apply AM operations management principles in the pursuit of maximum cost-effectiveness, time-efficiency, and quality of output; while managing variety in both the production output, in terms of product mix and scale of production, and the process, from single machines to entire production facilities.

Table 2.12: Summary of literature gaps to be addressed by each research objective

Research Objective	**Identified Gaps in the Literature**
1. To evaluate the effect of process planning on the production losses in AM, at the machine level of abstraction.	• Poor transparency of AM process efficiency, particularly with reference to well-established theories (value-adding time, production losses) and metrics (OEE) that can support the AM business case (Pushparaj *et al.*, 2019; Kurdve *et al.*, 2020). • Absence of quantified estimates of production losses in the AM workflow, and evaluation of steps that can be taken to reduce these (Fera *et al.*, 2017; Reid, 2019; Parshawanath Jain, 2022). • Limited investigation of the link between AM process planning and production losses, despite studies that allude to its significance (Gopsill and Hicks, 2018; Stittgen and Schleifenbaum, 2020).
2. To evaluate the effect of process planning on the total cost for make-to-order fulfilment using scaled-up AM, at the manufacturing system level of abstraction.	• Studies into ill-structured costs are limited to individual machine operations (Schmid and Levy, 2012; Baumers and Holweg, 2016; Alogla *et al.*, 2021). Extension of this to multi-machine scenarios is required to reflect realistic industrial AM operations (Khajavi *et al.*, 2018). • Ill-structured costs have been evaluated in isolation in the extant literature, which neglects potential trade-offs therein (Baumers and Holweg, 2016, 2019; Khajavi *et al.*, 2018). • Similarly, process planning factors that influence both well-structured and ill-structured cost drivers are typically optimised sequentially, in isolation (Freens *et al.*, 2015). Integrated optimisation of these factors shows promise for improving cost-effectiveness of AM (Baumers, Özcan and Atkin, 2017), but the links to the cost drivers have not been explored.
3. To investigate suitable facility layouts for scaled-up AM production, and their effect on process efficiency in terms of cost and production losses.	• Within the limited discussion of equipment organisation for AM workflows (Yoo *et al.*, 2016; Avventuroso *et al.*, 2017; Kang *et al.*, 2018), the effect of different facility layout approaches on production efficiency from a time or cost perspective has not been explored. • While the relationship between facility layout and production scale (and variety) is well-established for conventional manufacturing (Radford and Richardson, 1977; Naylor, 2002), and could be significant for scaled-up AM (Huang *et al.*, 2021), both qualitative and quantitative investigation of this phenomenon is missing in the AM discourse.

3 Methodology

This chapter presents the research methodology, discussing the approaches and research design towards meeting the research objectives. The overall aim is to investigate the influence of operations management on AM process efficiency. The process efficiency is explored from two perspectives, production cost and production losses; and by systematically exploring patterns therein, this research will provide tools and insights to support the implementation of competitive scaled-up AM.

Similar to the preceding chapter, the structure of this chapter covers background elements and then aligns with the three research objectives. The first three sections explain the underlying principles to the methodology, including the modelling approach and its application to the AM workflow. Following this, Sections 3.4, 3.5 and 3.6 cover the development of models and metrics for investigating AM production losses, workflow optimisation, and facility layout, respectively.

3.1 Overview

The overarching methodological approach in this research is to deploy exploratory simulation to systematically investigate practical process planning interventions on different parts of the AM workflow. Exploratory simulation efficiently investigates how a complex system behaves under different conditions, often using discrete event simulation (DES) for operations-related studies. The generic method, and its application to AM make-to-order systems is shown in Figure 3.1, and explained further in the following section.

This approach is used to examine three OM and OR principles, and their intersection with AM operations. First, the theory of value-adding and non-value-adding time (Hines and Rich, 1997) and production losses (Nakajima, 1988) is systematically applied to the AM workflow to study the balance between flexibility and efficiency in the AM process. Second, the trend towards integrated optimisation in scheduling-related operations research (Framinan, Perez-Gonzalez and Fernandez-Viagas, 2023) is applied to AM, exploring the touted potential for improving AM cost-effectiveness (Baumers, Özcan and Atkin, 2017). Third, characteristics of the cellular and process facility layout approaches are contrasted in the AM context for the first time, exploring the influence on production losses and cost-effectiveness across the AM workflow.

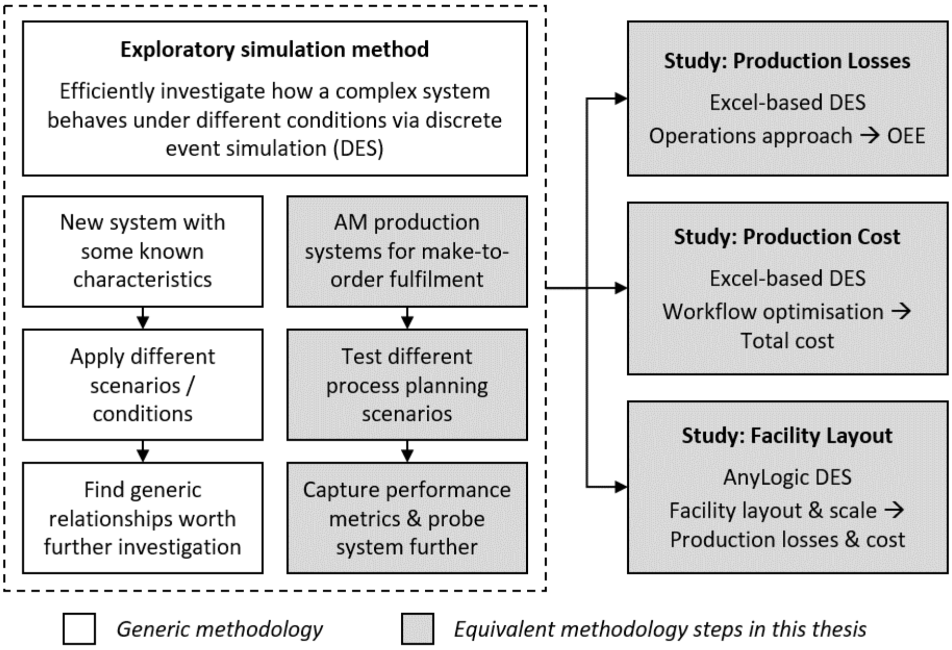


Figure 3.1: Summary of exploratory simulation methodology and its application to this research

3.2 Exploratory Simulation Approach

Exploratory simulation involves testing the effect of different scenarios (e.g. system structures, operating policies and future states) on a target system, in this case AM make-to-order production for direct digital manufacturing (Größler, 2010). This approach seeks to establish the generic, defining relationships and mechanisms within the system (Yilmaz, Ören and Hunt, 2011). In the context of investigating new systems, exploratory simulation sits between two extremes: the invention of novel conceptual models for a system, with proposed behaviours (generative simulation); and the use of simulation to refine systems to achieve target attributes (simulation experiment design). This is illustrated in Figure 3.2.

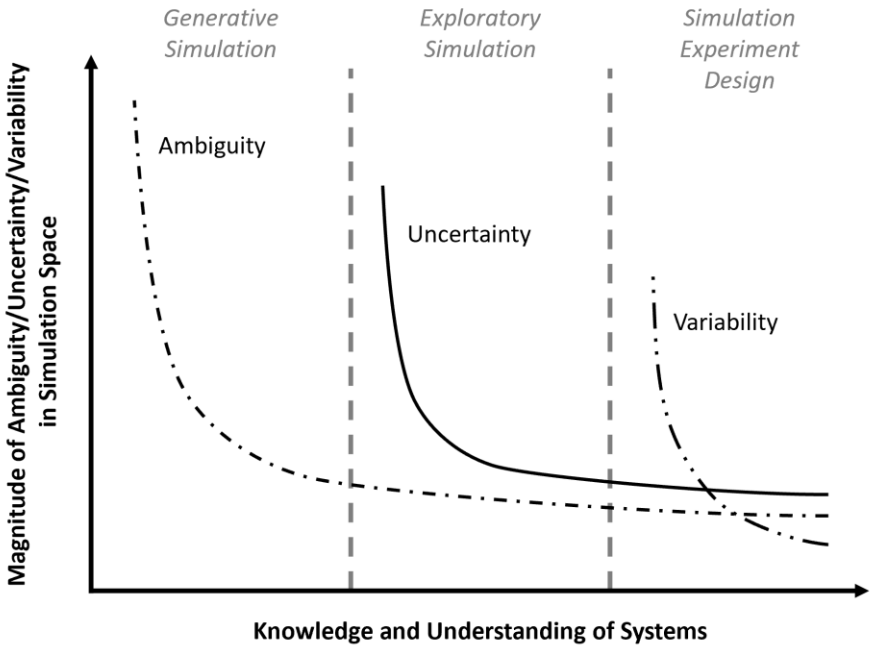


Figure 3.2: Types of simulation in the research of complex systems, adapted from (Yilmaz, Ören and Hunt, 2011)

A distinct strength of exploratory simulation is to explore novel systems in an efficient manner, highlighting areas of interest to be explored further via detailed models or empirical experiments (Ramasesh, Kulkarni and Jayakumar, 2001). This is achieved by examining the effects of different scenarios on the desired performance metrics, rather than attempting to capture the underlying causal relationships in the model itself (Größler, 2010). Therefore, exploratory simulation is well-suited to the investigation of operations management decision-making for scaled-up AM systems.

An alternative research approach is to derive qualitative and quantitative AM operations insights from empirical build experiments (see Ruffo et al. (2006a), Baumers and Holweg (2019)). While empirical studies offer the closest match to the real-world implementation of a given system, there are two major challenges to pursuing an empirical approach in this research. First, the multitude of build experiments required to obtain a statistically relevant sample of data for testing the different process planning experimental conditions would consume inordinate volumes of material, energy and machine time. For example, Khajavi et al. (2018) replace a mere 34 build experiments (across eight experimental conditions) with an alternative, simulated workflow; whereas the experiment design in this thesis exceeds 100 builds per research study. For the facility layout approaches, the second challenge is that it would be extremely cumbersome to physically re-arrange equipment within the research lab to replicate the required experimental conditions. An alternative option is to work with external organisations who already have the required facility layout setups. However, the requirement to commit extended time and resources to multiple build experiments still exists; and more importantly, it is not possible to test the effect of scaling up AM facilities in the real world, even with collaborating organisations, as this involves prohibitively expensive AM equipment investment and commissioning.

It is important to acknowledge that exploratory simulation has inherent limitations. While simulations are able to emulate stochastic processes, these are ultimately pseudorandom and based on probability distributions (Hillier and Lieberman, 2010, p. 935). Therefore, the random variation that occurs in the AM process (such as the build time or breakdown events) and the wider workflow (such as the inflow of customer orders) is not captured in its entirety. To mitigate this, the validity of simulation experiments is maintained by obtaining data from real-world sources, for example, via case studies (Chen and Tsai, 2008). Additionally, controlling factors that are both stochastic, i.e. random, and sporadic, i.e. scattered in time, ensures that they do not affect the experiments in a biased manner.

Overall, exploratory simulation makes it possible to develop new theories about the behaviour of complex systems from a combination of theory, intuition, and observations (Antunes, Coelho and Balsa, 2006). In this research, novel intuition about scaled-up AM is combined with existing operations management theory through targeted exploratory simulation to generate new understanding about AM operations efficiency that supports further adoption of the technology.

3.3 Model of AM Workflow

Prior to discussing the methodologies for the exploratory simulation studies, this section outlines the common model of the AM workflow that underpins each simulation and evaluation of the operations therein.

3.3.1 Process Steps for Polymer Laser Sintering

The research is grounded in a common understanding of the polymer laser sintering process steps. Figure 3.3 illustrates the laser sintering workflow for make-to-order direct digital manufacturing. This builds on and covers the latter seven steps from the generic AM workflow (see Figure 2.1), while specifying the various AM machine setup and post-build activities. The scope and detail here follows the AM management studies by Baumers and Holweg (2016, 2019).

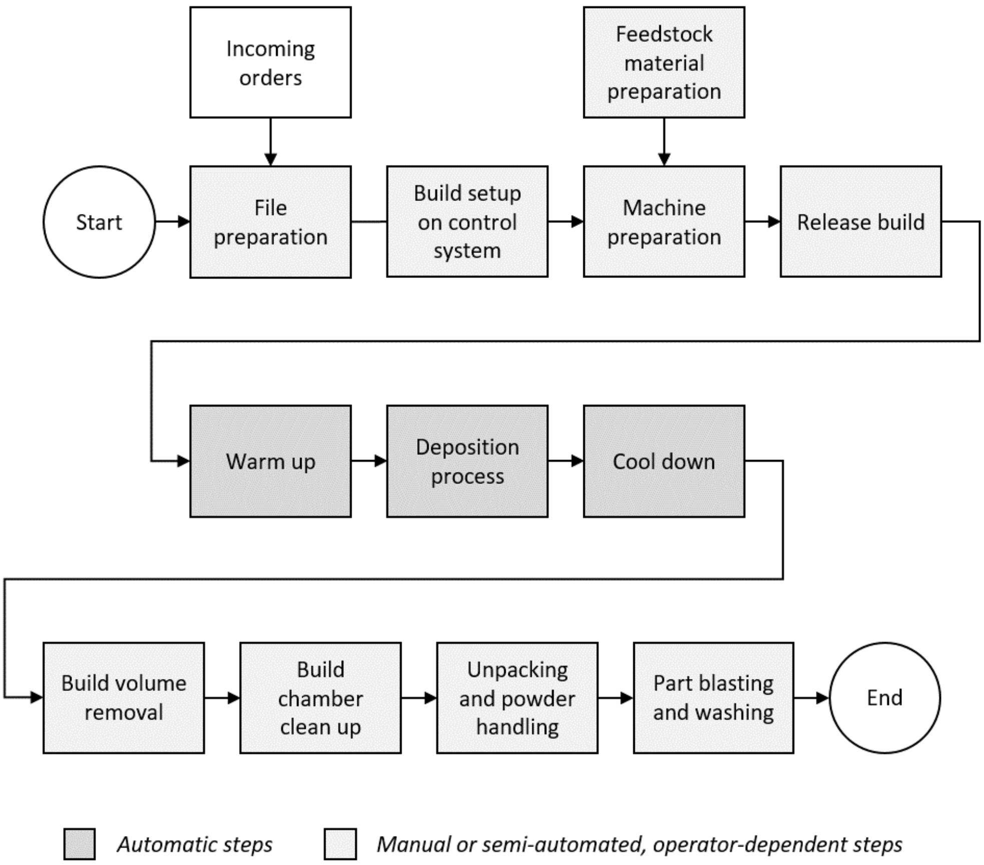


Figure 3.3: Polymer laser sintering workflow for make-to-order production

To aid the development of the simulations, a conceptual model of the AM workflow is formed by defining the inputs, outputs, and the scope and level of detail of the elements therein (Robinson, 2008). The inputs are the incoming orders, and process planning experimental conditions for the workflow. The outputs are the various metrics to describe the AM step, such as the build time, build height and capacity utilisation (see Section 3.3.3); the relevant cost- and production loss-related metrics are calculated from these outputs, as explained in Sections 3.4, 3.5, and 3.6. The scope includes the workflow steps from file preparation to readying parts for dispatch, as per Figure 3.3. The level of detail within the key model elements is outlined in Table 3.1, covering the incoming orders, the build jobs arising from the process planning approaches investigated, and the resulting effect on the AM workflow.

Table 3.1: Level of detail of elements included in the model of the AM workflow

Model element	**Level of Detail**	**Justification**
Orders	Quantity	Provides the space-related constraints on process planning in the simulations.
	Volume of parts	
	Arrival rate	Provides the time-related constraints on process planning in the simulations.
	Delivery due date	
AM Build Jobs	Packing of parts in the build	Affects process planning from the perspective of space-efficient use of capacity.
	Scheduling of builds in the workflow	Affects process planning from the perspective of time-efficient use of capacity.
AM Workflow	Equipment and arrangement	Determines the capacity available for process planning, and affects the progression of builds through the workflow.
	Time spent in each part of the workflow	Affected by process planning, the equipment characteristics, and scheduling of activities in the AM workflow. Determines the time-efficient use of available capacity.
	Resources consumed in each part of the workflow	Determines the cost-efficiency of capacity management and scheduling in the AM workflow.
	Disturbances e.g. build failure	Affects the time and resources consumed in the AM workflow.
Operators	Time to complete tasks	Affects the scheduling of the manual/semi-automatic activities in the AM workflow.
	Number of operators available	One operator per machine assumed or modelled, so that this does not influence the process planning.

3.3.2 Assumptions and Simplifications

Assumptions and simplifications arise during the process of translating a real-world process to the simulation domain. Assumptions account for uncertainties in or limited knowledge about the real-world domain, whereas simplifications aim to improve the speed and transparency of model development by appropriately limiting the scope and level of detail (Robinson, 2008). Key assumptions and simplifications for the AM workflow are outlined in Table 3.2.

Table 3.2: Assumptions and simplifications in the model of the AM workflow

	Description	Justification
Assumptions	Make-to-order fulfilment, unless specified	Make-to-order fulfilment is central to responsive direct digital manufacturing.
	One operator per AM machine	The number of operators should not unduly affect the time-efficiency of the manual/semi-automatic steps.
	Routine maintenance does not affect the AM workflow	The capacity management of a manufacturing system accounts for routine maintenance activities outside of productive time.
Simplifications	Order contents are populated using a set of test parts	Commercial sensitivity precludes the use of real, customer orders from companies. A set of dissimilar test parts are used instead.
	All orders are accepted	The scale of production is low enough to accept and fulfil all incoming orders without jeopardising competitiveness.
	All orders are for parts in the same material	All parts from orders can be grouped together, simplifying the build file preparation step.
	Part finishing (e.g. polishing) is excluded from the workflow	Part finishing is extraneous to the basic AM workflow, and not affected by the process planning scenarios explored in this research.
	Operator skill is uniform	Time taken by expert and novice operators overlap within one standard deviation (Baumers and Holweg, 2019); and so the difference in time is neglected.
	Only two failure modes (outright build failure, non-correctable part rejection) are considered	Remaining two failure modes for polymer laser sintering, correctable part failure and material-related failure (Baumers and Holweg, 2019), are not affected by the process planning scenarios explored in this research.

3.3.2.1 Failure Modes in Polymer Laser Sintering

Baumers and Holweg (2019) define four failure modes for polymer laser sintering: outright build failure, non-correctable part rejection, correctable part failure, and material-related failure. The latter two failure modes are not affected by the process planning scenarios. Correctable part rejection involves rework to bring defect parts up to standard, which is completed away from the AM machine and so the value-adding time of the AM machine is not diminished. Material-related failures are not connected to build file preparation, and it is assumed that the material preparation step is always completed successfully.

The first two failure modes are considered. Outright build failure refers to random faults (such as parts hitting the recoater, or sensor errors) that lead to irrecoverable early termination of the build. Part rejection refers to irreparable defects in the parts, often caused by contaminant-related disturbances or part slippage during production. To simplify the stochastic occurrence of these failure modes, rework is triggered by the mean time between failure (MTBF). The MTBF describes the average time between failure events, where the probability of failure at any given instance of time is constant (O’Connor and Kleyner, 2012, pp. 32–36). This reliability engineering metric therefore provides an estimate of how long the AM machine can be expected to run without interruption (Baumers and Holweg, 2019). The MTBF for the machine indicates the time to the next outright build failure; and the MTBF for the part triggers a non-correctable defect that leads to part rejection.

3.3.2.2 Set of Test Parts

Orders in the simulated AM workflows are populated with random quantities of test parts (Figure 3.4), rather than real, commercially sensitive customer parts. Each part is designed to emulate a product that could be ordered from an industrial AM bureau. The five parts in the set also display a range of sizes, shapes, and bounding-box aspect ratios, which makes the packing problem more challenging during process planning (Araújo *et al.*, 2018). A detailed description of each test part is provided in the Appendix.

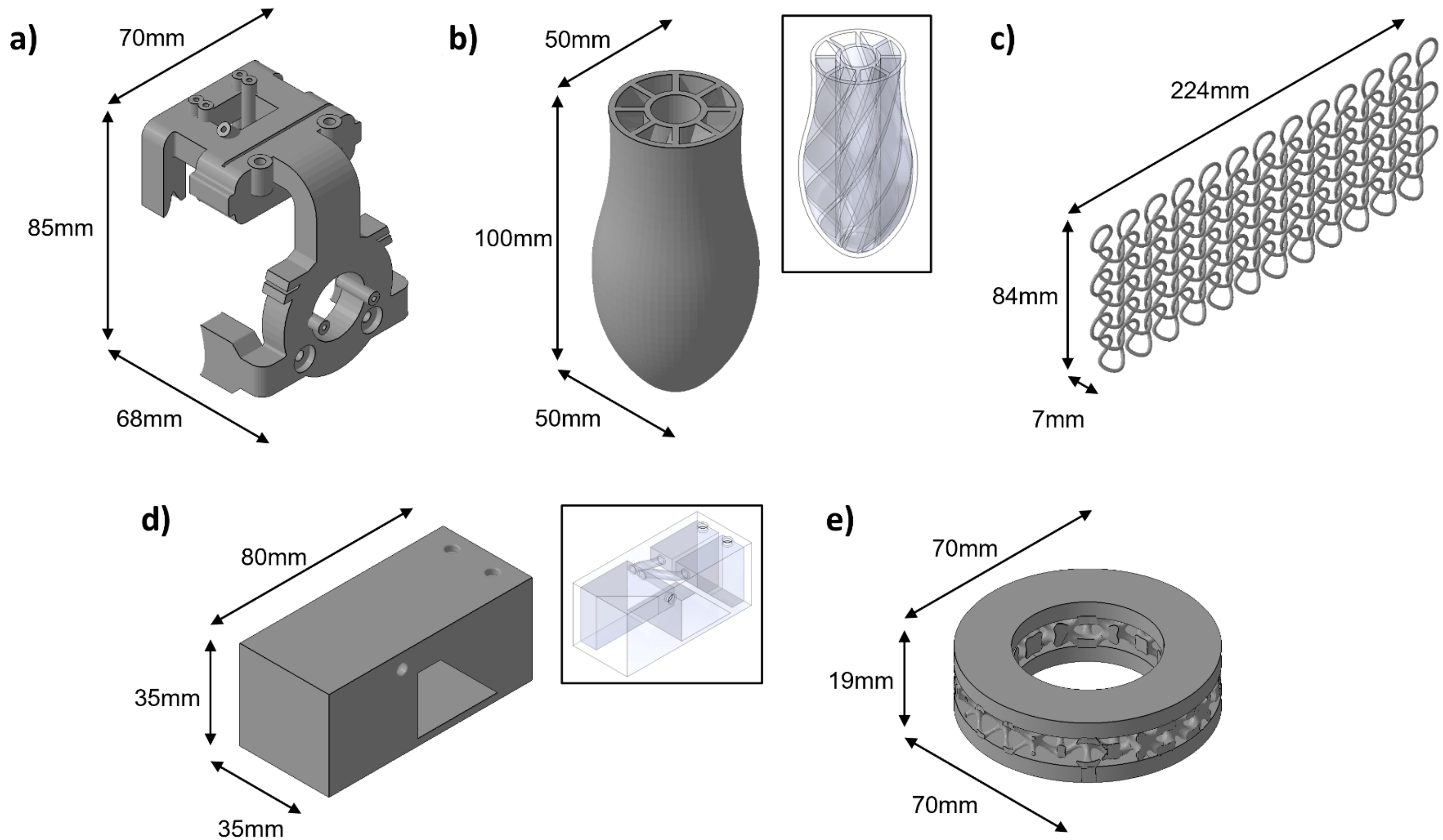


Figure 3.4: Test part designs – a) surgical guide, b) UAV body section, c) chainmail fabric, d) reaction device, and e) mechanical support

3.3.3 Process Metrics

A number of metrics are used in this research to characterise the build jobs and their relative use of the AM machine capacity. Remaining consistent with the laser sintering OM and OR literature, three key three metrics are defined below.

First, the build height is the vertical dimension of the build volume slice which contains the parts in the build job. Denoted as Z_{build}, it is measured from the base of the build volume to the topmost point of the packed parts (Figure 3.5). The build height is affected by the geometric properties and quantity of parts in the build, as well as their position and orientation in the build volume.

Second, the full build capacity utilisation is the fraction of the whole build volume that is occupied by parts. This is synonymous to measuring the use of the available physical capacity of the machine for productive output (Baumers *et al.*, 2013). As a result, the full build capacity utilisation indicates how efficiently the capital resource is being deployed during production. Referring to Figure 3.5, equation (3.1) defines the full build capacity utilisation, $U_{fullbuild}$:

$$U_{fullbuild} = \frac{V_{build}}{X \times Y \times Z} \tag{3.1}$$

where:

V_{build} – volume of parts in the build (mm^3)
X, Y, Z – dimensions of the full build volume (mm)

Third, the occupied cuboid capacity utilisation is the fraction of the build height-enclosed horizontal slice that is occupied by parts. The slight adjustment in the frame of reference, as compared to the full build capacity utilisation, allows this metric to focus on the packing efficiency within each build job. A high occupied cuboid capacity utilisation indicates that the committed build space is fully utilised, and that parts are packed to minimise the build height (Baumers and Holweg, 2019). Referring again to Figure 3.5, equation (3.2) defines the occupied cuboid capacity utilisation, $U_{occupiedcuboid}$:

$$U_{occupiedcuboid} = \frac{V_{build}}{X \times Y \times Z_{build}} \tag{3.2}$$

where:

V_{build} – volume of parts in the build (mm^3)
X, Y – in-plane dimensions of the full build volume (mm)
Z_{build} – vertical dimension of the occupied build volume (mm)

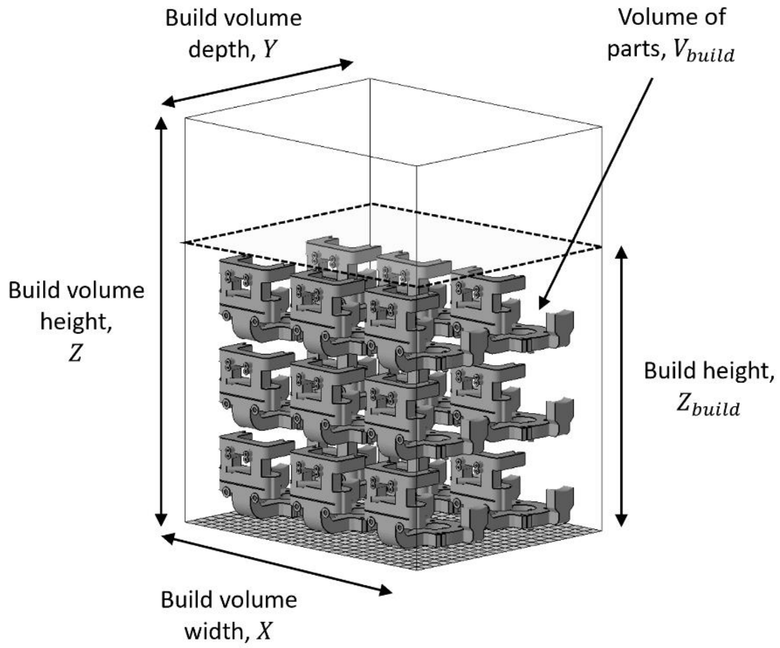


Figure 3.5: Generic build job with key parameters for process metrics

3.3.4 Build Time Model

Given that empirical build experiments are replaced with simulated builds, it is not possible to empirically observe the time taken for the AM build. Therefore, a build time model is proposed for this step. This model is based on the EOS Formiga P100, which has been used in previous empirical experiments for AM process economics (Baumers and Holweg, 2016, 2019).

The build time for powder-bed fusion AM can be split into contributions at the per-job, per-layer, and per-volume level (Baumers *et al.*, 2013). For each build job, there are fixed times for machine heat-up and cool-down. The part production time subsumes the layer-wise elements, such as the time to recoat a powder layer, and volume-wise elements, such as the laser scanning time.

The time for the three stages are then summed, and so the build time in hours, T_{build}, is given by:

$$T_{build} = T_{heatup} + T_{production} + T_{cooldown} \qquad (3.3)$$

where:

T_{heatup} – machine heat-up time (hours)
$T_{production}$ – part production time (hours)
$T_{cooldown}$ – machine cool-down time (hours)

Models of the part production time can include process parameters such as scan speed and laser scan distance, or detailed characterisation of the part geometry and position in the build volume (Pham and Wang, 2000; Choi and Samavedam, 2002; Ruffo, Tuck and Hague, 2006b). However, these approaches lead to cumbersome equations from a process economics and production loss perspective. Instead, this research continues with the method proposed by Baumers et al. (2013) to estimate the part production time with a multivariate linear regression model, using data from 14 previous build experiments for the same laser sintering machine (taken from Baumers and Holweg (2019)). The part production time in hours, $T_{production}$, is given by:

$$T_{production} = 0.54 + 0.0050 l_{build} + (4.9 \times 10^{-6}) V_{build} \qquad (3.4)$$

where:

l_{build} – number of layers in the build
V_{build} – volume of parts in the build (mm^3)

The model goodness of fit is estimated using the coefficient of determination, denoted R^2 and taking values between zero and one, which indicates the proportion of variance in the dependent variable that can be explained by the model (Navidi, 2011, pp. 531–533). The R^2 value for this model is 0.99. While providing confidence in the model utility, the very high goodness of fit could be due to overfitting to a limited number of observations. While a more complex data fitting technique, such as artificial neural networks (Munguía, Ciurana and Riba, 2009; Di Angelo and Di Stefano, 2011), may produce a more accurate model, the chosen approach is sufficient as the production time is only one tenth of the build time for this machine (Baumers and Holweg, 2016).

It is interesting to note that the manufacturer-quoted build rate for the Formiga P100 machine is up to 24mm/hour (EOS GmbH, 2008). In comparison, the model in equation (3.4) and build data from Baumers and Holweg (2019) suggest that the operational build rate is 51% lower, at 11.7mm/hour, where the average sintered area per layer is 4448mm^3. The discrepancy between the quoted and observed build rates highlights the often overly optimistic assessment of AM productivity, which is a challenge for industry adoption.

3.3.5 Build Volume Packing Tool

The simulation studies rely, in part, on specialist software to perform integrated optimisation of build volume packing and scheduling. The 3D Packing Research Application Tool (3DPackRAT), developed at the University of Nottingham, is used for this purpose.

Considered a black box system from an OM perspective, 3DPackRAT combines heuristic packing optimisation with scheduling algorithms to allocate and pack parts in order to efficiently use the available machine space and minimise the late delivery of parts (Baumers, Özcan and Atkin, 2017). In the web-based interface, part STL files are uploaded along with the quantity and target delivery date. Parts are then allocated and packed in the order that they are presented to the software, which is a necessary limitation to constrain the search space of the packing and scheduling problem. For illustration purposes, Figure 3.6 shows the packed configuration for a sample of 18 test parts using 3DPackRAT.

At the time of this research, 3DPackRAT is limited to packing and scheduling across a network of EOS Formiga P100 systems only. While 3DPackRAT can be applied as a packing-only tool for the P100 machine by ignoring the target delivery date input, it cannot be used for other laser sintering systems. Therefore, where the simulation studies include different machines, the "3D Scanline" packing tool within the commercial Autodesk Netfabb® Premium software is used instead. This packing tool is chosen because it prioritises build volume capacity utilisation for parts with a variety in size (Autodesk, 2021), matching the characteristics of the test parts in this research.

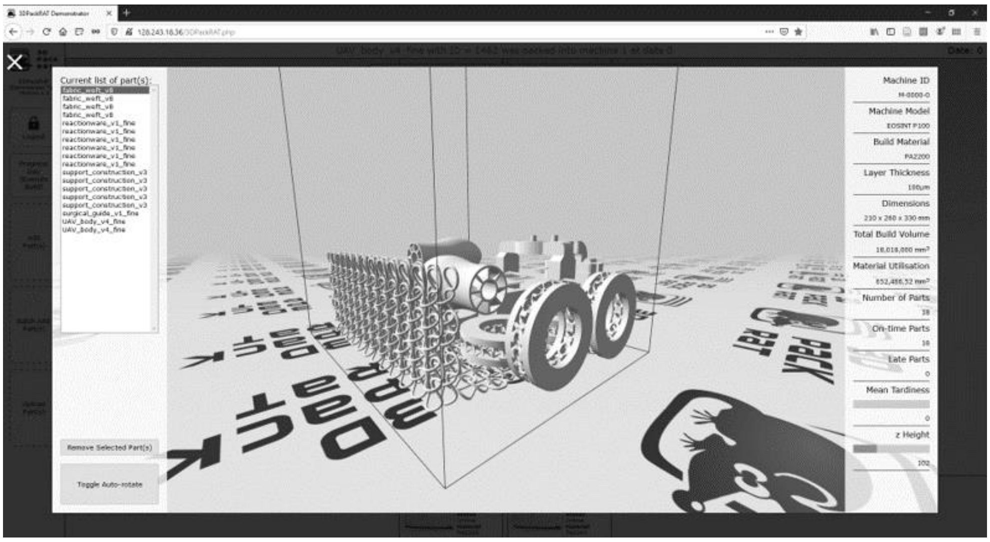


Figure 3.6: Build volume packing using 3DPackRAT

3.4 Production Losses in AM

3.4.1 Development of Overall Equipment Effectiveness for AM

A comprehensive understanding of the value-adding capabilities and sources of process inefficiency within a manufacturing process is central to it successful adoption and implementation. However, the existing methods for calculating and interpreting relevant manufacturing performance metrics such as OEE are not suitable for AM, owing to the reliance on identical, repetitive process steps and output (Nakajima, 1988; De Groote, 1995; Dal, Tugwell and Greatbanks, 2000; Huang *et al.*, 2003). Therefore, this section adapts and redevelops the OEE metric for the AM context, whilst maintaining the original intent and definition as per Nakajima (1988). This contributes to the first research objective by capturing the sources and extent of production losses in the AM machine, and the influence of process planning therein.

3.4.1.1 Scope of OEE within an AM Process Workflow

The scope of the OEE metric is defined by the system boundary for measuring planned production time and the production losses. Clarity is required with respect to the boundary of OEE measurements, as the AM workflow spans a number of different pieces of equipment and multiple steps at each.

The first step in setting the scope is straightforward, given that OEE is calculated with respect to specific equipment rather than the entire process workflow (De Groote, 1995; Garza-Reyes *et al.*, 2010). Therefore, only the steps at the AM machine are relevant for this metric (see Figure 3.7). To avoid inflow and outflow issues that may impact the OEE (De Ron and Rooda, 2006), it is assumed that equipment for upstream and downstream steps are available and the respective steps are completed correctly.

The second step involves appropriately categorising the different steps at the AM machine. In Figure 3.7, the pre-process, process, and post-process steps can be thought of as the machine setup, operational, and wrap-up phases of the AM machine operation. Machine setup is already one of the six production losses, and so the pre-process steps are classified accordingly during OEE measurements. However, the status of the post-process steps is less clear. Regular maintenance and cleaning of the machine are typically considered planned downtime in conventional manufacturing, and so excluded from the OEE calculation (Dal, Tugwell and Greatbanks, 2000; Garza-Reyes *et al.*, 2010). On the other hand, build chamber cleaning is mandatory between each build job, which erodes the machine’s availability. Moreover, the total time taken for this activity depends on the number of builds, and so is directly related to AM process planning decisions. Therefore, the definition of planned downtime is adjusted for AM such that post-process steps at the machine are classified as changeover losses (Basak *et al.*, 2022).

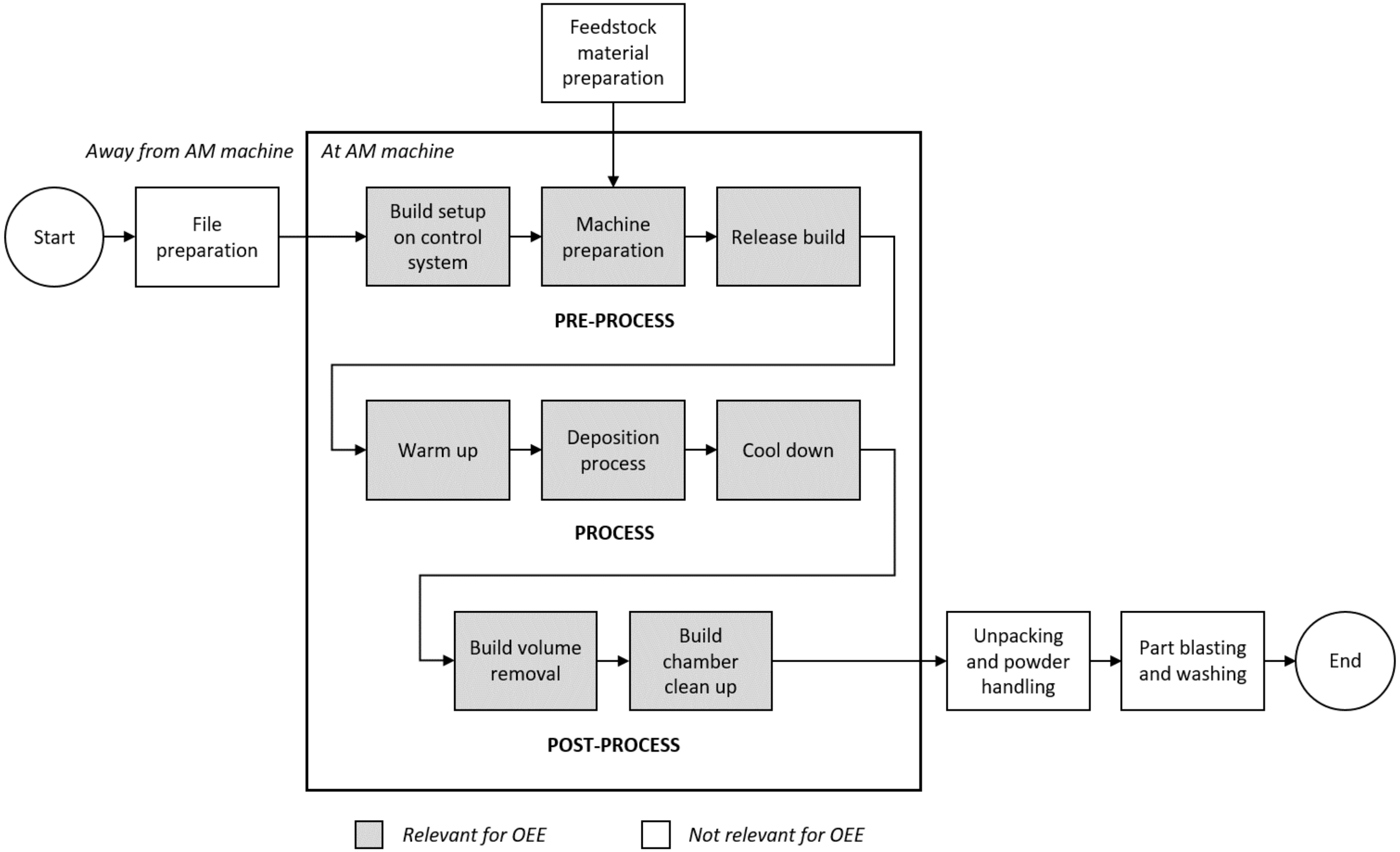


Figure 3.7: AM process workflow for polymer laser sintering and relevant steps for OEE

3.4.1.2 Adjusting OEE Equations for AM Processes

Appropriately defining the constituent metrics is central to adapting OEE for AM, to accurately quantify the production losses. Rather than altering the structure of the OEE calculation entirely as per Reid (2019), this research retains Nakajima's (1988) original OEE structure and modifies the equations of each metric to suit the operations characteristics of AM. Jauregui Becker et al. (2015) follow the same method in adapting OEE for high-mix low-volume machining.

Among existing OEE definitions, the availability is consistently measured in the time domain, whereas different approaches are proposed for the performance and quality. These include purely time-based measurement (Jauregui Becker, Borst and van der Veen, 2015; Reid, 2019), or monitoring output quantity alongside time (Nakajima, 1988; De Groote, 1995; Dal, Tugwell and Greatbanks, 2000; Huang *et al.*, 2003). Given that each AM build can produce dissimilar parts concurrently, neither quantity nor per-unit cycle times would be appropriate for the metrics in this research. Per-layer cycle times also would be difficult to measure as the production time changes depending on the contents of each layer in an AM build (Pham and Wang, 2000). To resolve these issues, the metrics are adapted by replacing the per-unit time and per-unit output calculations with cubic volume-based equations, as follows (Basak *et al.*, 2022):

Availability, A:

$$A = \frac{\text{planned production time} - \text{downtime}}{\text{planned production time}} \tag{3.5}$$

Performance, P:

$$P = \frac{\text{total cubic volume of parts}}{\text{actual production time} \times \text{theoretical volumetric process rate}} \tag{3.6}$$

Quality, Q:

$$Q = \frac{\text{total cubic volume of parts} - \text{cubic volume of defective parts}}{\text{total cubic volume of parts}} \tag{3.7}$$

By maintaining the structure of Nakajima's (1988) three constituent metrics, equations (3.5) – (3.7) avoid unnecessary deviation in what the OEE measures. Importantly, monitoring the cubic volume-based output succinctly captures how well the AM machine's build capacity is being used volumetrically (or physically) and over time. Also, the calculation is unaffected by part size or geometry and robust to different AM technology variants. As a result, this OEE metric can be used in a consistent manner to compare process efficiency and effectiveness across different products and processes in an AM factory.

3.4.2 Model and Simulation of Operations Approaches and Production Losses

The first simulation study explores the impact of operations approaches and other process planning factors on AM production losses, quantified by the OEE.

The "operations approach" describes the AM process planning objectives when converting incoming orders into build jobs. This arises from a trade-off in the build file preparation step between the cost efficiency of maximising capacity utilisation in each build versus the competitive advantage of fast delivery (Costabile *et al.*, 2017); and the relative importance of the lead time depends on the direct digital manufacturing application. An AM build may therefore contain a small quantity of varied parts (high-variety, low-volume), a large quantity of identical parts (low-variety, high-volume), or a combination that sits somewhere in between (Baumers and Holweg, 2019). To reflect the full spectrum of operations in the capacity-time trade-off, this research derives three distinct operations approaches from the extant literature.

The first operations approach is "Identical Batch Make-to-Stock AM" (IB-MtS), in which identical parts are made in fixed, standardised batches that each fill the machine space maximally to replenish inventory stock (Hopkinson and Dickens, 2003; Avventuroso *et al.*, 2017). The second operations approach is "Capacity Maximising Make-to-Order AM" (CM-MtO), in which mixed-part batches fill the available machine space up to a target build volume utilisation, prioritising high productivity when fulfilling incoming orders (Ruffo and Hague, 2007; Baumers *et al.*, 2016). The third operations approach is "Lead Time Minimising Make-to-Order AM" (LTM-MtO), where the quantity of parts in the mixed-part batches is capped to limit the process make-span, prioritising faster delivery for the incoming orders (Chergui, Hadj-Hamou and Vignat, 2018).

With reference to the EOS Formiga P100 machine used in this simulation study, the operations approaches lead to the following build capacity constraints:

1. IB-MtS and CM-MtO – quantity of parts in each build allowed to occupy the full build height of 330mm;

2. LTM-MtO – quantity of parts capped such that the build height does not exceed 100mm. According to the build time model, equations (3.3) – (3.4), this build height is the limit for manufacturing up to 500cm^3 of parts within 24 hours (including machine warm up and cool down time).

This simulation study also examines the effect of changing two externally-influenced process planning factors, the lead time and variation amongst the parts, on the OEE within the make-to-order operations approaches. The chosen factors are considered among the distinguishing advantages of AM (Attaran, 2017). The IB-MtS operations approach is not included, as make-to-stock operations would be unaffected by day-to-day changes in product demand.

3.4.2.1 Conceptual Model

The conceptual model outlines the inputs, model flow and outputs for this particular simulation study.

The first input, the operations approach, describes the AM workflow conditions for converting incoming orders into build jobs, as explained in the previous section. The orders themselves are the second input into the workflow simulation, and are also controlled by the external factors, lead time and product variety. The arrival rate of orders is one-per-day; and each order contains a random quantity of test parts A and B (Figure 3.8).

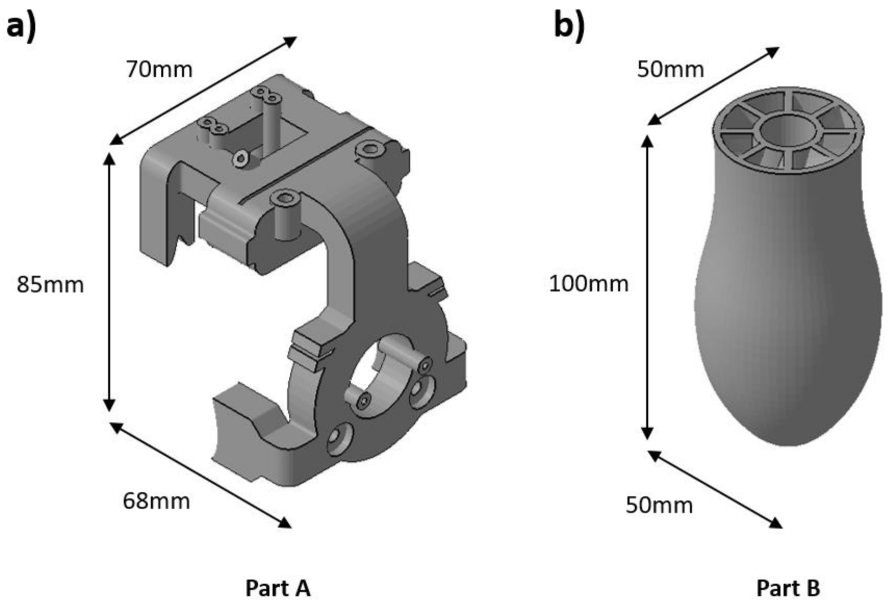


Figure 3.8: Subset of test parts used for operations approach simulation study

In make-to-order AM, orders enter a backlog (order book) and waits, as constrained by the lead time, before entering production (Hedenstierna, Disney and Holmström, 2016). For a snapshot of the order book at any given moment, the lead time governs the number of orders that are "available" for production. This defines the set of orders for each simulation experiment; Table 3.3 gives an example for a 72 hour lead time. Product variety introduces variants of the test parts to affect the order contents, as explained in Section 3.4.2.4 (on experiment design). Beyond this, identical sets of orders are used for each operations approach, avoiding unwanted process inflow or outflow effects on the OEE (De Ron and Rooda, 2006).

Table 3.3: Example of a set of orders for a lead time of 72 hours

Part	**Quantity (units)**			
	Day 1	**Day 2**	**Day 3**	**Total**
A	2	3	4	9
B	7	5	4	16

The model flow for order fulfilment is summarised in Figure 3.9: pack parts from the set of orders into build jobs, execute build jobs, and complete any required rework triggered (by machine or part MTBF) during the workflow.

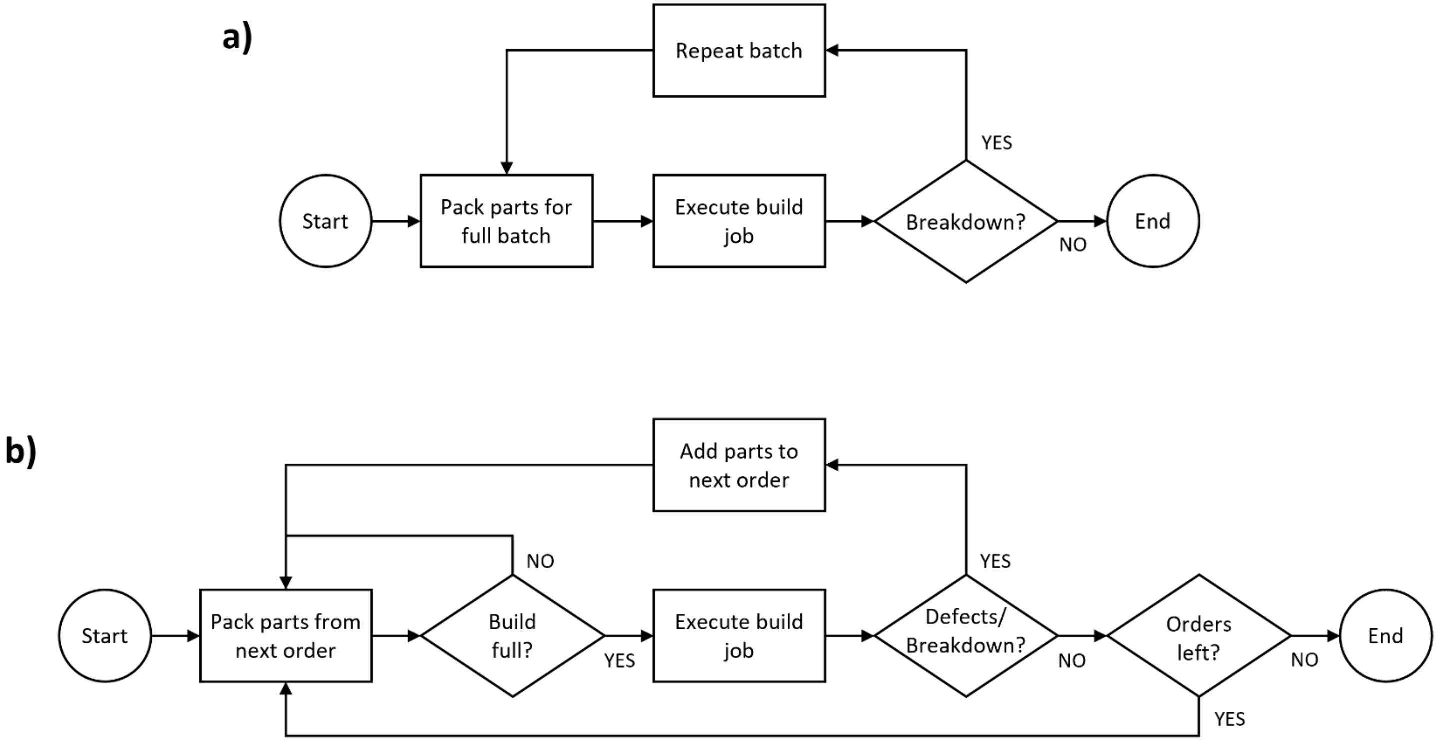


Figure 3.9: Order fulfilment process for each set of orders via a) Identical Batch Make-to-Stock AM, and b) Capacity Maximising and Lead Time Minimising Make-to-Order AM operations approaches

Rework arises for outright build failure and non-correctable part rejection. With build failure, the entire build job is repeated. Similarly, defective parts are re-made in make-to-order fulfilment; however, for IB-MtS, defects are absorbed by the inventory stock and so no replacements are required.

Having completed the order fulfilment, the outputs for each build job in the simulation study are the time taken for each step at the AM machine, along with the volume of defect-free and defective output. These data allow the OEE and its constituent metrics to be calculated over each simulation experiment. In addition, key build metrics, such as the build height, capacity utilisation, and quantity of parts per build are recorded to help establish the underlying mechanisms of production losses in the AM workflow.

3.4.2.2 Assumptions and Simplifications

The assumptions and simplifications in the model are summarised in Table 3.4. Further details of assumptions for the calculation of the production losses are given in the next sub-section.

Table 3.4: Assumptions and simplifications in the operations approaches model

	Description	Justification
Assumptions	Single AM machine in the workflow	Production losses at AM machine explored in isolated context.
	Maximum order volume is 500cm^3/day	Maximum output possible in 24 hours for on-time delivery in LTM-MtO operations approach.
	Maximum full build capacity utilisation is 10%	Match realistic levels of machine usage (Baumers and Holweg, 2019)
	Defective parts chosen at random from original size versions of parts A and B	Ensure the rework volume is consistent across the simulation experiments.
Simplifications	Incoming order stream simplified to one-time allocation and packing from a static order book	Speed up simulation by avoiding incremental time progression at order packing stage. Periodic allocation and packing from a static order book is a realistic representation of operator-led workflows in AM service bureaus.
	Part variety represented by different sized parts, rather than different geometries.	Control the consistency of volume of parts deposited in each build (via the quantity), so that only the change in the packing of more varied parts affects the OEE.

3.4.2.2.1 Assumptions for Production Loss Calculations

The production losses are calculated in a systematic manner. For outright build failure, the build time for machine heat-up, part production up to the failed layer, and machine cool-down are converted into breakdown time. The remaining production losses are averaged from prior empirical data, giving fixed mean times for the setup and idle losses arising from machine preparation, heat-up and cool-down. The theoretical volumetric process rate is an estimate of the maximum hourly output volume during the productive phase of the build. Using the theoretical maximum build rate of 20mm/hour (Loughborough University Additive Manufacturing Research Group, 2021) and assuming 10% full build volume utilisation up to the full build height, the value for the EOS Formiga P100 machine is 109.2cm^3/hour. These parameters are summarised in Table 3.5. The start-up yield losses are not measured as this would require modelling the thermal conditions within the AM build chamber, which is outside the scope of this research.

Table 3.5: Summary of parameters for calculating production losses

<table>
<tr><th>Production Loss</th><th>Value</th><th>Source</th></tr>
<tr><td>Breakdown</td><td>Mean time between failure (build failure): 6244 layers</td><td>(Baumers and Holweg, 2019)</td></tr>
<tr><td rowspan="2">Set-up & Adjustment</td><td>Fixed pre-process time: 0.25 hours</td><td rowspan="4">Prior empirical data, used in (Baumers and Holweg, 2019)</td></tr>
<tr><td>Fixed post-process time: 0.23 hours</td></tr>
<tr><td rowspan="3">Idling & Minor Stops</td><td>Fixed warm up time: 3.51 hours</td></tr>
<tr><td>Fixed cool down time: 12 hours</td></tr>
<tr><td>Theoretical volumetric processing rate: 109.2 cm^3/hour</td><td rowspan="2">Calculation based on data from (Loughborough University Additive Manufacturing Research Group, 2021)</td></tr>
<tr><td>Reduced Speed</td><td>Theoretical volumetric processing rate: 109.2 cm^3/hour</td></tr>
<tr><td>Defects & Rework</td><td>Mean time between failure (non-correctable part rejection): 40 units</td><td>(Baumers and Holweg, 2019)</td></tr>
<tr><td>Start-up Yield</td><td>Ignored in this study</td><td>Simplification: thermal conditions in build volume are not modelled</td></tr>
</table>

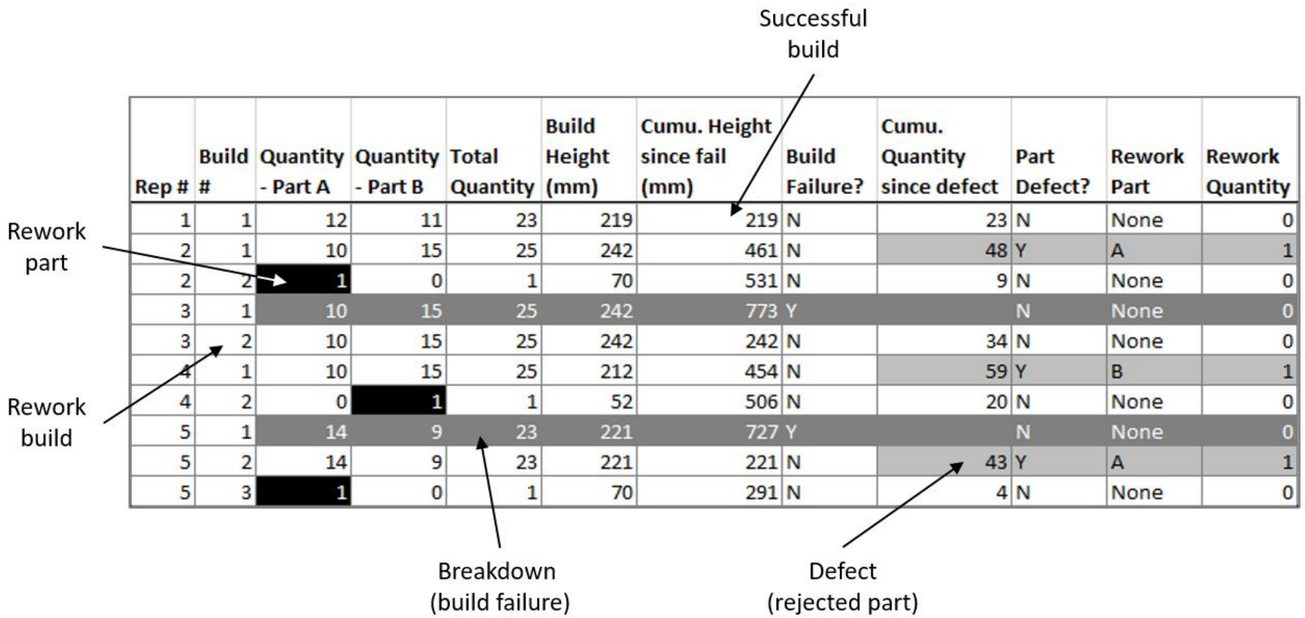
3.4.2.3 Model and Simulation Implementation

This simulation study can be described as a manual implementation of a discrete event simulation (DES) approach. DES simulations are appropriate for the operational level of decision making involved in production planning and resource utilisation studies (Jahangirian *et al.*, 2010).

The order fulfilment simulation mimics the nature of prior empirical build experiments conducted on the EOS Formiga P100 machine (Baumers and Holweg, 2016, 2019). This is done by packing the parts for each build job using 3DPackRAT, and then recording the build properties in Microsoft™ (MS) Excel.

For each build job, breakdowns and defects are simulated by comparing the cumulative build height and quantity of parts since the previous rework occurrence against the corresponding MTBF (see Table 3.5). Upon exceeding the MTBF, either the entire build terminates and is repeated, or a random part is deemed defective and then remade via re-entering the order book ahead of subsequent orders. The cumulative build height or quantity of parts since the last failure is then reset. This process is illustrated in Figure 3.10.

After the order fulfilment simulation, the time for each build job is estimated via the build time model using equations (3.3) – (3.4). Combined with the simulated breakdowns and defects, and the data in Table 3.5, it is then possible to calculate the production losses and OEE for each set of orders using equations (3.5) – (3.7). Each simulation and OEE estimate spans one day's operations, equivalent to fulfilling one set of orders, and is repeated for five sets of orders, or one working week. This aligns with industry-recommended daily OEE measurement frequency, alongside weekly summaries (Muchiri and Pintelon, 2008).



Rep #	Build #	Quantity - Part A	Quantity - Part B	Total Quantity	Build Height (mm)	Cumu. Height since fail (mm)	Build Failure?	Cumu. Quantity since defect	Part Defect?	Rework Part	Rework Quantity
1	1	12	11	23	219	219	N	23	N	None	0
2	1	10	15	25	242	461	N	48	Y	A	1
2	2	1	0	1	70	531	N	9	N	None	0
3	1	10	15	25	242	773	Y		N	None	0
3	2	10	15	25	242	242	N	34	N	None	0
4	1	10	15	25	212	454	N	59	Y	B	1
4	2	0	1	1	52	506	N	20	N	None	0
5	1	14	9	23	221	727	Y		N	None	0
5	2	14	9	23	221	221	N	43	Y	A	1
5	3	1	0	1	70	291	N	4	N	None	0

Figure 3.10: Snapshot of manual implementation of simulation in MS Excel, showing successful builds, breakdowns, defects, and rework

3.4.2.4 Experiment Design and Analysis

The simulation experiments are split into two stages. First, the influence of each operations approach on the OEE and constituent metrics are examined. A default lead time of 72 hours is used for each order. This is seen as the upper limit of responsive make-to-order AM production (Deradjat and Minshall, 2017; Chergui, Hadj-Hamou and Vignat, 2018). The post-experiment analysis probes the time expended in each build to quantify and explain the production loss drivers for polymer laser sintering. This contributes to establishing best-practices for consistent and efficient process planning.

Second, a Design of Experiments (DoE) approach is used to investigate how the OEE varies with the operations approach, lead time, and part size variety. The Central Composite Design Face-Centred design is chosen to fully examine the influence of each independent variable (factor), and interactions therein, using fewer experiments than a full factorial approach (Mason, Gunst and Hess, 2003; Myers, Montgomery and Anderson-Cook, 2016). This experiment design complements the factorial design (corner points) with a cubic centre point and face-centred points in the factorial design space, as shown in Figure 3.11.

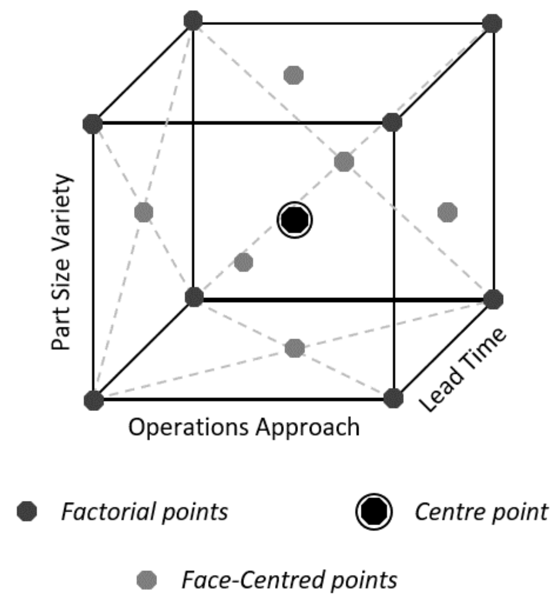


Figure 3.11: Schematic of the Central Composite Design Face-Centred factorial design space for the three experimental factors

The DoE is implemented with three levels for each factor: the extreme values match the design space edges and the middle value gives the face-centred and centre points. Table 3.6 outlines the values taken at each level for the factors.

Table 3.6: Summary of experimental factor values

Level	**Factor**		
	Allowable Build Height (mm)	**Lead Time (hours)**	**Part Size Variety (%)**
1	100 (LTM-MtO)	48	0
2	215	72	50 (50%, 100% volume parts)
3	330 (CM-MtO)	96	100 (50%, 100%, 150% volume parts)

Allowable Build Height (ABH), is a continuous proxy variable for the categorical variable, the operations approach; it references the maximum allowed build height for each operations approach. This proxy variable is used to divide the factor into three levels (required to examine the interaction terms) without adding a redundant operations approach. Lead Time (LT), controls the size of the order book snapshot through the number of orders available to fulfil. Finally, Part Size Variety (PSV), represents product variety among the incoming orders via smaller and larger versions of the test parts (Figure 3.12).

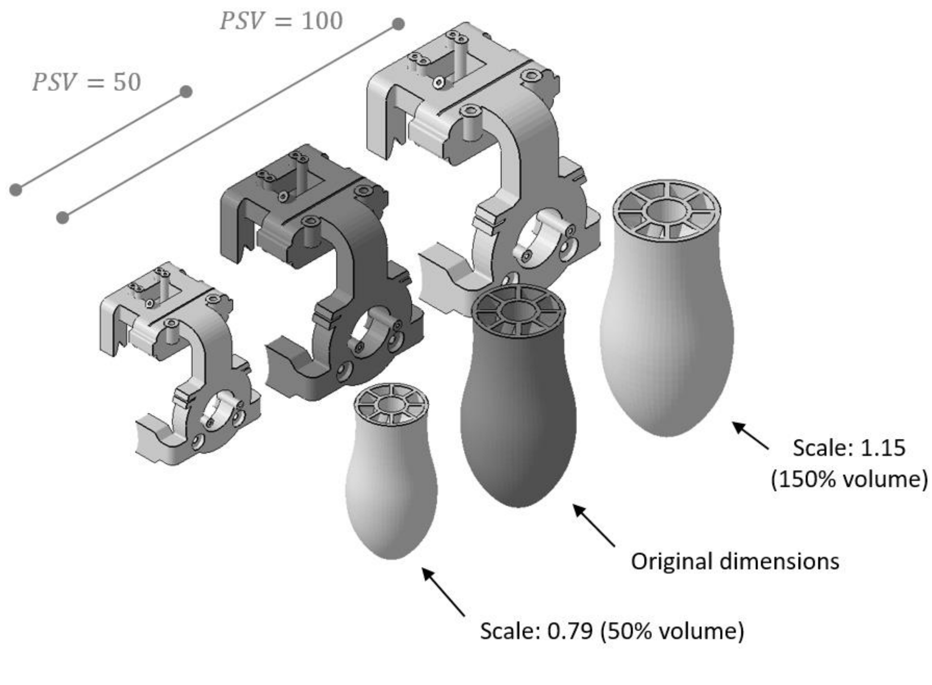


Figure 3.12: Product variety represented by scaled versions of test parts, with corresponding Part Size Variety (PSV) factor values

The range in size across the order, relative to the original test part volume, gives the PSV value (see Table 3.6). In experiments at $PSV = 50$ and $PSV = 100$, the order quantities are adjusted to maintain a constant cubic volume of output. To illustrate, Table 3.7 shows a set of orders for $PSV = 50$ and $LT = 96$, which can be compared to the baseline of $PSV = 0$ and $LT = 72$ (see Table 3.3).

Table 3.7: Example of a set of orders for a lead time of 96 hours and PSV of 50

Part	Volume	Quantity				
		Day 1	Day 2	Day 3	Day 4	Total
A	100%	1	1	1	1	4
	50%	4	6	8	2	20
B	100%	1	1	1	1	4
	50%	8	6	2	10	26

Post-experiment, the impacts of lead time and part size variety are examined separately via graphical methods and Analysis of Variance (ANOVA). ANOVA estimates the contribution of each factor and interaction to the variance in the OEE. The contribution is found by dividing the estimate of variance for each variable, given by the sum of the squared deviations from the mean, through the sum of the estimates for all variables (Lindman, 1992). Therefore, it is possible to estimate which process planning factors can be leveraged to the greatest effect in order to improve process efficiency in laser sintering.

3.5 Integrated Optimisation of the AM Workflow

The economic feasibility of a given production process depends on the balance between costs and value generation. To this end, a total cost model provides a full understanding of the various cost contributors across the AM process steps. This cost model is then used to evaluate the effect of workflow optimisation on the cost-effectiveness of the subsequent process steps. This contributes to the second research objective by identifying relationships between process planning and AM systems-level costs.

3.5.1 Development of a Total Cost Model

The cost model structure follows the activity based costing method (Alexander, Allen and Dutta, 1998), and is split according to the three key stages in the AM workflow: before (pre-process), during (process), and after (post-process) the automatic steps in Figure 3.3. These give rise to well-structured costs covering the direct resource consumption for the production process, indirect overheads for production, and labour input into manual steps. In addition, ill-structured costs related to the risk of build failure and non-adherence to delivery requirements are captured using the cost model at the end of AM workflow. This is summarised in Figure 3.13. The remainder of this section outlines the assumptions and equations for each part of the total cost model.

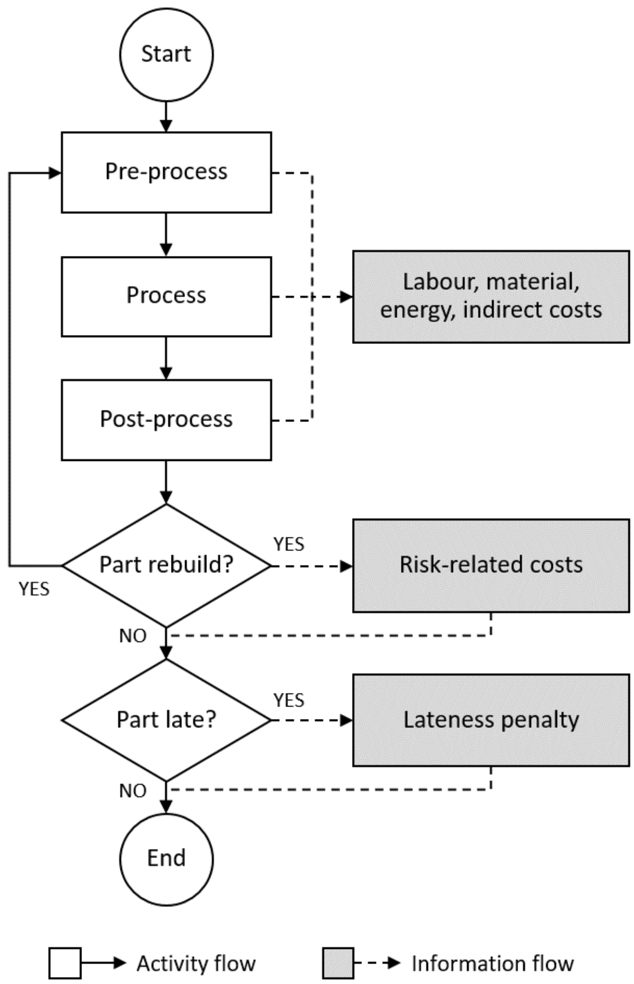


Figure 3.13: AM process stages for polymer laser sintering and associated cost model elements

3.5.1.1 Pre-Process Costs

The pre-process costs cover the manual steps to prepare the build file and AM machine ahead of each build job. These are the first four steps in the workflow (see Figure 3.3). Only the labour input is costed, as the fixed cost of the multi-purpose computer workstation is neglected. Therefore, the pre-process cost in GBP, $C_{preprocess}$, for each build is given by:

$$C_{preprocess} = \dot{C}_{labour} T_{setup} \tag{3.8}$$

where:

$\dot{C}_{labour}$ – operator's labour rate (GBP/hour)
T_{setup} – machine setup time (hours)

3.5.1.2 Process Costs

The process costs cover the warm up, deposition, and cool down steps at the AM machine. Operators periodically monitor the machine alongside other unrelated tasks, and so the labour input is neglected. The cost model covers direct costs from material use and energy consumption, and the indirect costs.

The first source of material consumption is waste material. In polymer laser sintering, exposure to thermal cycles in the build chamber negatively affects the physical properties of reused unsintered powder, resulting in "orange peel" quality defects (Bourell *et al.*, 2014; Goodridge and Ziegelmeier, 2017). To avoid this, virgin powder is mixed with the recycled powder in a material-specific ratio, known as the refresh rate (Goodridge, Tuck and Hague, 2012); and this volume is equal to the fraction of the unsintered material permanently used up in each build (Ruffo, Tuck and Hague, 2006a). Thus, the volume of unsintered material consumed during each build in mm^3, $V_{unsintered}$, is given by:

$$V_{unsintered} = r\left(V_{height} - V_{build}\right) \tag{3.9}$$

where:

r – refresh rate (%)
V_{height} – volume enclosed in the Z-height of the build (mm^3)
V_{build} – volume of parts in the build (mm^3)

Combined with the consumption of sintered material (equal to the volume of parts), the total cost of material in GBP, $C_{material}$, for each build is given by:

$$C_{material} = C_{feedstock}(\rho_{sintered}V_{build} + \rho_{unsintered}V_{unsintered}) \qquad (3.10)$$

where:

$C_{feedstock}$ – price of fresh material (GBP/kg)
$\rho_{sintered}$ – density of sintered material (kg/mm^3)
V_{build} – volume of parts in the build (mm^3)
$\rho_{unsintered}$ – density of unsintered material (kg/mm^3)
$V_{unsintered}$ – volume of unsintered material consumed (mm^3)

Next, energy consumption is calculated based on the build contents (Baumers, Tuck, Bourell, *et al.*, 2011). This method of finding the time-, geometric volume- and build height-dependent components of energy use is deemed "more accurate" than Ruffo, Tuck and Hague's (2006a) fixed overhead cost method (Costabile *et al.*, 2017). Of these elements, time-dependent consumption dominates at 75% of the total energy use (Baumers, Tuck, Bourell, *et al.*, 2011); while the remaining elements are driven by the amortisation of fixed energy use during the warm-up and cool-down steps (Baumers, Tuck, Wildman, *et al.*, 2011). Thus, to simplify the calculation, this cost model adopts a time-centric energy consumption estimate, with terms for the energy expended at different rates during warm-up, part production, and cool-down (Baumers, Tuck, Bourell, *et al.*, 2011; Baumers, Tuck and Hague, 2015). To summarise, the cost of energy consumption in GBP, C_{energy}, for each build is given by:

$$C_{energy} = C_{MJ}\big(\dot{E}_{heatup}T_{heatup} + \dot{E}_{production}T_{production} + \dot{E}_{cooldown}T_{cooldown}\big) \qquad (3.11)$$

where:

C_{MJ} – unit price of energy (GBP/MJ)
$\dot{E}_{heatup}$ – energy rate for machine heat-up (MJ/hour)
T_{heatup} – machine heat-up time (hours)
$\dot{E}_{production}$ – energy rate for part production (MJ/hour)
$T_{production}$ – part production time (hours)
$\dot{E}_{cooldown}$ – energy rate for machine cool-down (MJ/hour)
$T_{cooldown}$ – machine cool-down time (hours)

There are also varied fixed costs, such as machine depreciation, maintenance, production overheads and administrative overheads to include. These costs can be grouped into a "machine cost", which is a function of a constant cost rate and the machine use time (Son, 1991), i.e. the AM build time. This is referred to as the indirect cost, in line with prior AM cost studies (Ruffo, Tuck and Hague, 2006a; Baumers and Holweg, 2016, 2019), and is distinct from the physical resource costs. The indirect cost in GBP, $C_{indirect}$, for each build is given by:

$$C_{indirect} = \dot{C}_{fixed} T_{build} \tag{3.12}$$

where:

$\dot{C}_{fixed}$ – fixed indirect cost rate (GBP/hour)
T_{build} – machine time: sum of heat-up, production, cool-down time (hours)

Summing the three parts in equations (3.10) – (3.12), the total process cost in GBP, $C_{process}$, is given by:

$$C_{process} = C_{material} + C_{energy} + C_{indirect} \tag{3.13}$$

where:

$C_{material}$ – cost of material consumption (GBP)
C_{energy} – cost of energy consumption (GBP)
$C_{indirect}$ – indirect cost of production (GBP)

3.5.1.3 Post-Process Costs

The post-process costs cover the final four manual steps after the completion of the build job (see Figure 3.3). Steps are completed for each build job, such as unloading the build volume and cleaning the machine, or for each part, such as de-powdering and blasting. Thus, the labour time is calculated from separate per-build and per-part time contributions, as per Baumers and Holweg (2016).

The per-part post-processing time is taken to be uniform across the test parts. Whilst internal cavities and small features are more difficult to clean than plain surfaces due to powder entrapment (Gibson, Rosen and Stucker, 2015), these are present in each test part, and so variation in the time is neglected.

Therefore, the post-process cost in GBP, $C_{postprocess}$, for each build is given by:

$$C_{postprocess} = \dot{C}_{labour}\left(T_{postbuild} + nT_{postpart}\right) \tag{3.14}$$

where:

$\dot{C}_{labour}$ – operator's labour rate (GBP/hour)
$T_{postbuild}$ – build-level post-process time (hours)
$T_{postpart}$ – part-level post-process time (hours)
n – total quantity of parts in the build

3.5.1.4 Well-Structured Costs

The direct and indirect costs together cover the inputs required to manufacture the parts, forming the well-structured production costs (Son, 1991). These are captured in the pre-process, process, and post-process costs; and so the total well-structured cost in GBP, C_{build}, for the build is given by:

$$C_{build} = C_{preprocess} + C_{process} + C_{postprocess} \tag{3.15}$$

where:

$C_{preprocess}$ – cost of pre-process stage (GBP)
$C_{process}$ – cost of process stage (GBP)
$C_{postprocess}$ – cost of post-process stage (GBP)

To facilitate the onward calculation of ill-structured costs, it is necessary to switch from the per-build cost calculation to the per-part cost calculation. Given the mixed-part builds, the build cost cannot simply be divided by the quantity of parts to obtain the cost of one unit (i.e. one instance of a part geometry). Suitable alternative approaches use the volume of each part relative to the total volume of parts (Baumers *et al.*, 2012), or the relative cost of producing each part in separate high-volume identical part batches (Ruffo and Hague, 2007). While the batch cost method is more equitable than the volume method where parts are vastly dissimilar in volume (Ruffo and Hague, 2007), the test parts' volumes are of the same order of magnitude and so the simpler volume-based calculation can be used. Therefore, for the i^{th} different part in the build, the well-structured unit cost in GBP, $C_{unitWSC}$, is given by:

$$C_{unitWSC}(i) = \frac{C_{build} V_i}{V_{build}} \tag{3.16}$$

where:

C_{build} – total well-structured cost of build (GBP)
V_i – volume of one unit of i^{th} part in the build (mm^3)
V_{build} – volume of parts in the build (mm^3)

3.5.1.5 Ill-Structured Costs

This cost model incorporates aspects of both quality and flexibility costs, covering both categories identified by Son (1991). The cost of defective output that leads to scrap or rework is estimated, because scheduling and capacity management decisions affect the likelihood of failures that lead to defective output (Cai, Wu and Zhou, 2009; Baumers and Holweg, 2016). Given that in-situ process interventions are outside the scope of this research, prevention costs are not included. With respect to flexibility, the ability to respond to variations in customer demand is considered important for make-to-order fulfilment – and there is a direct link between workflow optimisation and makespan at the build-level, and monetary penalties for due-date non-adherence at the customer- or order-level (Khajavi *et al.*, 2018). Therefore, the costs of due-date adherence and likelihood of failure estimated, as follows.

3.5.1.5.1 Risk of Failure

The cost model uses the likelihood of failure to estimate the cost of rework, based on two independent failure modes (see Section 3.3.2.1). The risk of outright build failure follows a layer-wise model, as in Baumers et al. (2017), and the risk of part rejection is a constant probability per-part, as in Baumers and Holweg (2019). The probability of rebuild for a part, $p_{rebuild}$, is given by:

$$p_{rebuild} = \left(1 - \left(1 - p_{layer}\right)^{l_{build}}\right) + p_{part} \tag{3.17}$$

where:

p_{layer} – constant probability of build failure per layer
l_{build} – number of layers in the build
p_{part} – constant probability of rejection per part

The probability of part rebuild is applied as a scrap fraction to the total cost model (Ashby, 2011), inflating the well-structured cost in line with the expected risk of failure, as per Baumers and Holweg (2016) and Colosimo et al. (2019). Therefore, for the i^{th} different part in the build, the expected ill-structured cost including the risk of failure in GBP, $C_{unitISC1}(i)$, is given by:

$$C_{unitISC1}(i) = \frac{C_{unitWSC}(i)}{(1 - p_{rebuild})} \tag{3.18}$$

where:

$C_{unitWSC}(i)$ – well-structured cost for unit of i^{th} part in the build (GBP)
$p_{rebuild}$ – probability of part rebuild

3.5.1.5.2 Late Delivery Penalty

The total cost model notes the adherence to due-date constraints through a cost penalty for late delivery. Such penalties are usually defined by the customer, based on factors such as the part value, number of late units and the length of the delay (Zhang *et al.*, 2019). Here, the penalty is calculated as a proportion of the part cost, representing its value. This is then further scaled by the quantity of units and number of days delayed, following Khajavi et al. (2018), and averaged over the total units of each part in the build. The late delivery penalty for the i^{th} different part in the build, $P_{late}(i)$, is given by:

$$P_{late}(i) = \frac{c_{late} t_i l_i}{n_i} \tag{3.19}$$

where:

c_{late} – baseline penalty for late delivery, as a proportion of part cost (%)
t_i – mean number of days late for units of i^{th} part in the build
l_i – quantity of late units of i^{th} part in the build
n_i – quantity of units of i^{th} part in the build

Missing the delivery due-date inflates the production cost by the magnitude of the late delivery penalty. For the i^{th} different part in the build, the ill-structured cost including the late delivery penalty in GBP, $C_{unitISC2}(i)$, is given by:

$$C_{unitISC2}(i) = C_{unitWSC}(i) \times \left(1 + P_{late}(i)\right) \quad (3.20)$$

where:

$C_{unitWSC}(i)$ – well-structured cost for unit of i^{th} part in the build (GBP)
$P_{late}(i)$ – late delivery penalty for units of i^{th} part in the build

3.5.1.6 Total Cost of Production

The ill-structured and well-structured costs are brought together to give the total cost of production. Both ill-structured costs are applied as multipliers to the baseline (i.e. well-structured) cost. Therefore, for the i^{th} different part in the build, the expected total cost of production in GBP, $C_{unit}(i)$, is given by:

$$C_{unit}(i) = C_{unitWSC}(i) \times \frac{1}{(1 - p_{rebuild})} \times \left(1 + P_{late}(i)\right) \quad (3.21)$$

where:

$C_{unitWSC}(i)$ – well-structured cost for unit of i^{th} part in the build (GBP)
$p_{rebuild}$ – probability of part rebuild
$P_{late}(i)$ – late delivery penalty for units of i^{th} part in the build

When evaluating the influence of different process planning approaches on the cost of production, it is helpful to compare the cost per volume deposited (specific cost of production) alongside the unit cost (Baumers *et al.*, 2013). While the unit cost scales with the part volume, the specific cost is agnostic to the part size and volume. For the i^{th} different part in the build, the specific expected total cost of production in GBP/cm^3, $C_{specific}(i)$, is given by:

$$C_{specific}(i) = \frac{C_{unit}(i)}{V_i} \times 10^3 \quad (3.22)$$

where:

$C_{unit}(i)$ – total cost for unit of i^{th} part in the build (GBP)
V_i – volume of one unit of i^{th} part in the build (mm^3)

3.5.2 Model and Simulation of AM Workflow Optimisation

The second exploratory simulation study aligns with the second research objective, investigating the influence of the workflow optimisation approach on the production cost. The total cost model presented in the preceding section is used to estimate the production cost.

The "workflow optimisation approach" refers to the driving optimisation objective (and associated tools used) when converting incoming orders into a sequence of build jobs, specifically while operating multiple AM machines in parallel over a number of time periods (Figure 3.14). This addresses the packing and scheduling problem for the build file preparation step in the AM workflow. Varying the optimisation approach affects the generated number and contents of the builds, which influences the cost of production (Khajavi *et al.*, 2018). Moreover, Baumers et al. (2017) argue that integrated optimisation of packing and scheduling has the potential to outperform alternative approaches. Therefore, this research examines the different workflow optimisation approaches and their connections to cost drivers in laser sintering, and onwards suitability for scaled-up AM.

Time Period	AM Machine 1	AM Machine 2	$\cdots$	AM Machine n
1	Build slot 1.1	Build slot 2.1	$\cdots$	Build slot n.1
2	Build slot 1.2	Build slot 2.2	$\cdots$	Build slot n.2
3	Build slot 1.3	Build slot 2.3	$\cdots$	Build slot n.3
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
k	Build slot 1.k	Build slot 2.k	$\cdots$	Build slot $n.k$

Figure 3.14: Packing and scheduling of parts into build slots spanning n AM machines operating over k time periods

Depending on the application, AM users may prioritise the packing aspect of build setup (Baumers *et al.*, 2016; Griffiths *et al.*, 2019), the scheduling aspect (Li *et al.*, 2019; Rohaninejad *et al.*, 2021), or a combination thereof (Freens *et al.*, 2015; Gopsill and Hicks, 2018; Khajavi *et al.*, 2018; Kapadia *et al.*, 2021). It is therefore possible to define five distinct workflow optimisation approaches for the build file preparation step, as summarised in Table 3.8.

For validation, each optimisation approach can be linked to particular value propositions for direct digital manufacturing. Approaches A and B are more appropriate where alternative priorities outweigh the scheduling constraint. Complex product quality or engineering constraints may demand manual packing as in approach A (Delfs, T̈ows and Schmid, 2016), whereas synchronising machine activity with other steps in the workflow could promote parallel packing as in approach B (Chen *et al.*, 2015). Approach C is suitable for applications with high variability in product customisation and incoming rate of orders, for example localised manufacture at the point of sale (Ben-Ner and Siemsen, 2017). In contrast, approaches D and E would be found where the incoming rate of orders is too high to justify manual process planning steps, for example in large AM service bureaus (Deradjat and Minshall, 2017).

Table 3.8: Summary of workflow optimisation approaches for packing and scheduling in AM production planning

Optimisation Approach	**Label**	**Description of Conditions**
Manual	Approach A	Operator manually packs all of the parts, disregarding the order schedule
Packing Only	Approach B	Software packs all of the parts, disregarding the order schedule
Scheduling Only	Approach C	Operator allocates parts to build jobs according to the order schedule, and manually packs them
Packing and Scheduling, Separate	Approach D	Operator allocates parts to build jobs according to the order schedule, and software packs them
Packing and Scheduling, Integrated	Approach E	Software allocates and packs all of the parts according to the order schedule

3.5.2.1 Conceptual Model

The conceptual model outlines the inputs, model flow and outputs for this particular simulation study. Some parallels can be drawn between this study and the preceding one on production losses (see Section 3.4.2.1); and so, references are made to the previous conceptual model, where applicable.

The first input is the incoming orders. Each order fulfilment simulation has an order book, with random quantities of the five test parts (Section 3.3.2.2) to be delivered over the next five days; an example is shown in Table 3.9. The order book representation of the incoming stream of orders follows the same logic as the production losses simulation (see Section 3.4.2.1). The total quantity of parts in each order book fills between 50% and 100% of the available machine capacity. This promotes efficient use of the AM machines (Baumers *et al.*, 2013), whilst avoiding the need for order non-acceptance due to overloading the manufacturing system (Kapadia *et al.*, 2021). Importantly, the on-time delivery constraint for the scheduling aspect of the process planning problem is based on this order book. If the given quantity of each part is not fulfilled on each day, a late delivery penalty applies.

Table 3.9: Example of order book for one order fulfilment simulation

Part	**Quantity Due**					
	Day 1	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Total**
A	11	23	18	10	19	81
B	13	34	34	19	26	126
C	29	21	30	20	32	132
D	6	6	3	5	5	25
E	14	12	10	6	9	51

The second input, the workflow optimisation approach, defines the process of allocating parts from incoming orders to a sequence of build jobs, and configuring the parts therein, across a network of AM machines. The constraints for each workflow optimisation approach are described below, with reference to the operation of two AM machines in parallel.

In approach A (Manual), the operator manually packs the total quantity of available parts in the order book, filling the current build job completely before moving to the next available build slot. While manual packing precludes the use of computational optimisation, the operator may still use a systematic packing method. Here, the manual packing rules follow the “deepest bottom-left-fill” algorithm (Araújo *et al.*, 2019):

1. Insert first part in bottom left corner;
2. Maintain 5mm gap between part bounding box and side walls of build volume;
3. Insert additional parts: where possible, fill space along the shorter in-plane dimension to complete a row before starting a new row;
4. Maintain 2mm gap between part bounding boxes;
5. Where possible, fill space in the current layer of parts before starting a new layer;
6. No preferred build orientation;
7. Rotate parts in increments of 90° in global Cartesian axes as needed.

In approach B (Packing Only), the operator packs the total quantity of available parts using automated computational packing optimisation software. Parts are packed across both machines in parallel, filling the available capacity for the current time period before moving to the next.

In approach C (Scheduling Only), the operator manually packs the parts from the order book, day-by-day, to satisfy the scheduling constraint. Parts for day 1 are allocated and then configured using the same packing rules as approach A; the build job is then locked, and the process repeats for the remaining days. This workflow optimisation approach is similar to the Lead Time Minimising Make-to-Order operations approach from the production losses study.

The process for approach D (Packing and Scheduling, Separate) amalgamates approaches B and C. The operator uses automated computational packing optimisation software to allocate and configure the parts from day 1 in the order book, locks these build jobs, and then repeats the process for the remaining days. This is analogous to assigning parts to build jobs in the n, k matrix of slots (see Figure 3.14) according to their due date and then, separately, packing each build job to achieve its optimal configuration.

In approach E (Packing and Scheduling, Integrated), the operator uses automated computational packing optimisation software to allocate and pack all parts from the order book across all available build slots to simultaneously achieve compact build volume packing and minimise late delivery. The key difference between approaches D and E is that it is possible to utilise the empty space across all available builds in approach E, whereas the separation of the optimisation steps in approach D prevents this.

The model flow for order fulfilment has two steps: allocate and pack parts, and execute the resulting sequence of build jobs. Following this, the outputs are captured on a per-build job basis. Data related to the build properties (such as the production time, volume deposited and build height) contribute to the calculation of the production cost for each build. The quantity of each part present in each build is then used to allocate the build cost to the respective units, such that the late delivery penalty for non-adherence to the order schedule can be applied. The model flow, including inputs and outputs, is shown in Figure 3.15.

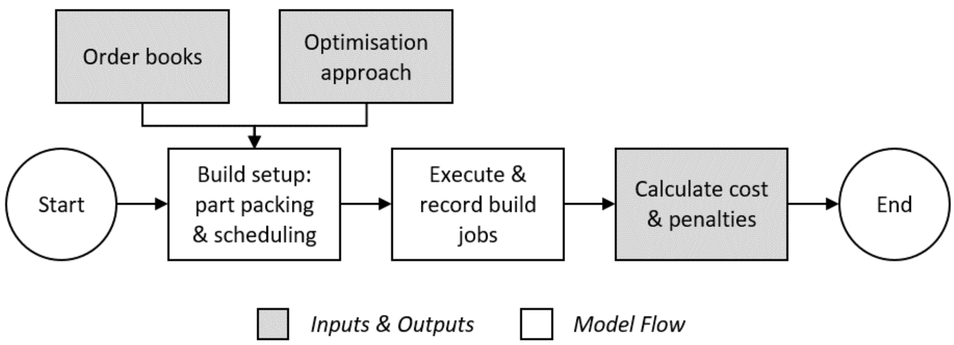


Figure 3.15: Model flow for simulation of workflow optimisation approaches

3.5.2.2 Assumptions and Simplifications

The assumptions and simplifications in the model are summarised in Table 3.10. Further details of assumptions for the total cost model calculations are given in the next sub-section.

Table 3.10: Assumptions and simplifications in the workflow optimisation model

	Description	Justification
Assumptions	Permissible lead time of up to seven days	Matches lead times offered by large (3D People UK, 2022; Protolabs, 2022) and specialist powder-bed fusion service bureaus (3DPRINTUK, 2022).
	Two AM machines in parallel operation	Parallel operation of machines is representative of scaled-up AM.
Simplifications	Time taken to prepare build file is neglected	Time affected by software speed, which is inconsistent in the research tool used.
	Rework is not triggered in the order fulfilment simulations	Cost calculations infer completion of rework via scrap fraction. Analogous to averaging failure instances over extended time horizon, as per Baumers and Holweg (2016).

3.5.2.2.1 Assumptions for Total Cost Model Constants

The total cost model expressions require several data from external sources, covering machine and material factors, and manufacturing operations costs.

The AM machine, the EOS Formiga P100, and its operating procedures match previous empirical experiments conducted by Baumers and Holweg (2016); and so the indirect and labour cost rates are adapted from the published data via inflation alone. The inflationary change is calculated using the average year-on-year Retail Prices Index between 2016 and 2019, taken from the Office for National Statistics (2020) annual data, as per the expression below:

$$C_Y = \left(1 + RPI_{average}\right)^{(Y-2016)} \times C_{2016} \tag{3.23}$$

where:

C_Y – cost rate in year of research study (GBP/hour)
Y – given year for inflated cost rate
$RPI_{average}$ – mean Retail Price Index between 2016 and 2019
C_{2016} – cost rate in 2016, year of input data (GBP/hour)

At the time of the study, conducted in 2020, the $RPI_{average}$ value was 3.2%; so the cost rates from Baumers and Holweg (2016) are inflated by 13.4%.

Similarly, the AM machine energy rates are based on prior data collected via power meters (Baumers, Tuck and Hague, 2015). The energy consumption rate for different levels of full build capacity utilisation are averaged and converted to megajoules per hour (MJ/hour), as shown in Table 3.11. The unit price of energy for the cost calculations is taken from the mean annual electricity price for 2020 (Department for Business, Energy & Industrial Strategy, 2021).

Table 3.11: Data for energy rate estimation, from Baumers, Tuck and Hague (2015)

Process Stage	**Energy Consumption (J/s)**			**Mean Energy Consumption (MJ/hour)**
	Single Part Build	**Full Build**	**Mean**	
Heat-Up	1835	1658	1747	6.3
Production	1395	1420	1408	5.1
Cool-Down	327	335	331	1.2

The AM cost and materials literature guides the values taken for the remaining constants. The material refresh rate lies between 30-50% for acceptable part quality for the EOS Formiga P100 machine (Wan Yusoff, Pham and Dotchev, 2009). A mid-value of 40% is taken, as suggested by Goodridge et al. (2012) for the standard PA2200 material. The lateness penalty is set at 100% of the part value, similar to the penalty applied by Khajavi et al. (2018) and Ransikarbum et al. (2017) for parts with similar functionality to the test parts in this research.

The probability of part rebuild is estimated from prior empirical data, taken from Baumers and Holweg (2019). The AM machine-specific probability of build failure, p_{layer}, is 0.016% per layer; and the probability of part rejection, p_{part}, is 2.5% per part. Therefore, the general expression in equation (3.17) for the probability of part rebuild, $p_{rebuild}$, becomes:

$$p_{rebuild} = 1 - \left(1 - \frac{0.016}{100}\right)^{l_{build}} + \frac{2.5}{100} = 1.025 - 0.99984^{l_{build}} \quad (3.24)$$

where:

l_{build} – number of layers in the build

For clarity, the full set of constants derived from external data are summarised in Table 3.12.

Table 3.12: Summary of total cost model constants derived from external inputs

Constant	Description	Value	Unit	Source
$\dot{C}_{labour}$	Operators' labour rate	22.24	GBP/hour	Adjusted from (Baumers and Holweg, 2016)
r	Material refresh rate	40%	-	From (Goodridge, Tuck and Hague, 2012)
$C_{feedstock}$	Price of fresh material	57.37	GBP/kg	EOS GmbH order
$\rho_{sintered}$	Density of sintered material	0.93	g/cm^3	From (EOS GmbH, 2009)
$\rho_{unsintered}$	Density of unsintered material	0.45	g/cm^3	From (EOS GmbH, 2009)
C_{MJ}	Unit price of energy	0.026	GBP/MJ	From (Department for Business, Energy & Industrial Strategy, 2021)
$\dot{E}_{heatup}$	Energy rate for machine heat-up	6.3	MJ/hour	Calculated from (Baumers, Tuck and Hague, 2015)
$\dot{E}_{production}$	Energy rate for part production	5.1	MJ/hour	Calculated from (Baumers, Tuck and Hague, 2015)
$\dot{E}_{cooldown}$	Energy rate for machine cool-down	1.2	MJ/hour	Calculated from (Baumers, Tuck and Hague, 2015)
$\dot{C}_{fixed}$	Fixed indirect cost rate	11.41	GBP/hour	Adjusted from (Baumers and Holweg, 2016)
p_{layer}	Probability of build failure per layer	0.016%	-	From (Baumers and Holweg, 2019)
$p_{rebuild}$	Probability of non-correctable part rejection per part	2.5%	-	From (Baumers and Holweg, 2019)
c_{late}	Proportion of part value applied as lateness penalty (%)	100%	-	From (Khajavi *et al.*, 2018)

3.5.2.3 Model and Simulation Implementation

This simulation study is a manual, MS Excel-based implementation of DES. The order fulfilment simulation is a computational representation of the build file preparation and production steps in the AM workflow. This follows the approach of Khajavi et al. (2018) to efficiently generate a suitable dataset for production cost analysis across a number of process planning scenarios.

For the build file preparation step, the use of two machines to fulfil a five-day order book results in a 2×5 dimension packing and scheduling problem with 10 available build slots, referencing the matrix in Figure 3.14. Table 3.13 describes the steps in the implementation of each optimisation approach.

Table 3.13: Effect of workflow optimisation approach constraints on the simulation implementation

Optimisation Approach	**Model Flow**		
	Build Slot Progression	**Scheduling Constraint**	**Packing Constraint**
Manual	1.1 then 2.1 Repeat up to 1.5 then 2.5	Pack all parts A Repeat up to all parts E	Manual: Netfabb®
Packing Only	1.1 and 2.1 together Repeat up to 1.5 and 2.5	Pack all parts A Repeat up to all parts E	Automated: 3DPackRAT
Scheduling Only	1.1 then 2.1 Repeat up to 1.5 then 2.5	Pack parts A - E for day 1 Repeat up to day 5	Manual: Netfabb®
Packing and Scheduling, Separate	1.1 and 2.1 together Repeat up to 1.5 and 2.5	Pack parts A - E for day 1 Repeat up to day 5	Automated: 3DPackRAT
Packing and Scheduling, Integrated	All build slots together	Pack parts A - E for day 1 Repeat up to day 5	Automated: 3DPackRAT

The packing and scheduling of parts is completed using Autodesk Netfabb® Premium for the workflow optimisation approaches involving manual packing, and 3DPackRAT for those involving automated computer optimised packing. MS Excel is used to record the build properties and contents, and calculate the build time to mimic the execution of the build on the EOS Formiga P100 machine. The build time model, defined in equations (3.3) and (3.4), is applied here. This process is shown in Figure 3.16.

Build contents

Build properties for time & cost calculations

Build time from model

Cost calculations

Rep #	Time Period	Mach-ine #	Part	Part Quantity / n_i	Late Quantity / l_i	Average Late-ness / t_i	Build Quantity / n	Build Z-Height (mm)	Build Volume (mm^3) / V_{build}	Production Time (hours) / $T_{production}$	Build Time (hours) / T_{build}	Waste Volume (mm^3) / $V_{unsintered}$	Cost - Build (GBP)	Part Volume Fraction / F	Cost - Unit (GBP)	Specific Cost - Unit (GBP/cm^3)
308	1	0	A	5	0	0	47	324	2438627	28.69	43.19	6100709.2	849.15	0.02	6.53	0.58
308	1	0	B	1	1	1	47	324	2438627	28.69	43.19	6100709.2	849.15	0.02	53.87	1.17
308	1	0	D	17	3	1	47	324	2438627	28.69	43.19	6100709.2	849.15	0.46	45.65	0.69
308	1	0	E	24	9	1	47	324	2438627	28.69	43.19	6100709.2	849.15	0.50	40.50	0.80
308	1	1	A	4	0	0	45	324	2361099	28.31	42.81	6131720.4	839.27	0.02	6.67	0.60
308	1	1	B	1	1	1	45	324	2361099	28.31	42.81	6131720.4	839.27	0.02	55.00	1.19
308	1	1	D	16	3	1	45	324	2361099	28.31	42.81	6131720.4	839.27	0.45	47.04	0.71
308	1	1	E	24	9	1	45	324	2361099	28.31	42.81	6131720.4	839.27	0.51	41.34	0.82
308	2	0	A	39	7	1	72	311	2020389	25.99	40.49	5984084.4	819.69	0.22	8.80	0.79
308	2	0	B	18	18	2	72	311	2020389	25.99	40.49	5984084.4	819.69	0.41	92.22	2.00
308	2	0	E	15	0	0	72	311	2020389	25.99	40.49	5984084.4	819.69	0.37	33.61	0.67
308	2	1	A	39	7	1	73	311	2062153	26.19	40.69	5967378.8	824.94	0.21	8.67	0.78
308	2	1	B	20	20	1.85	73	311	2062153	26.19	40.69	5967378.8	824.94	0.45	86.38	1.88
308	2	1	E	14	0	0	73	311	2062153	26.19	40.69	5967378.8	824.94	0.34	33.14	0.66

Figure 3.16: Snapshot of manual implementation, in MS Excel, of the simulation of workflow optimisation approaches

3.5.2.4 Experiment Design and Analysis

The simulation experiments assess the influence of each workflow optimisation approach on the production cost and constituent cost contributors. A common order book is processed via each workflow optimisation approach, resulting in output build sequences of differing length and build properties. Each simulation spans up to five days of manufacturing, depending on the sequence of builds generated, and is repeated across 10 different order books. This number of repetitions sits in the range observed across similar studies involving packing and scheduling across parallel AM machines (Chergui, Hadj-Hamou and Vignat, 2018; Zhang, Yao and Li, 2020).

The post-experiment analysis evaluates the build, unit and specific costs of production using the total cost model. This quantifies the contributors to the magnitude and spread in production cost within and between each workflow optimisation approach. Similar to the first exploratory simulation study, the build properties, such as height and capacity utilisation, are used to explain the cost drivers and any trade-offs therein. This contributes to understanding the suitability of process planning tools for cost-effective scaled-up AM production.

3.6 Facility Layout in AM

The third exploratory simulation study explores which facility layout approach, cellular or process layout, is best for process efficiency in scaled-up AM operations in terms of capacity management and scheduling.

To provide empirical grounding, the simulations are based on a case study of an AM user that employs cellular and process layouts in their AM workflows. Within the exploratory simulation research design, a descriptive case study approach is used to inform the production process and operating conditions under each facility layout approach (McCutcheon and Meredith, 1993). Choi et al. (2016) note that this combination of case study and analytical (simulation-based) methodologies is common in operations management studies, and improves the relevance and depth of insights. Here, the case study company provides data relating to the AM workflow, such as equipment characteristics and timings for each step, and the production scale, such as the frequency and size of incoming orders. The sources of process inefficiency and routes towards productive scaled-up AM are thus examined with respect to a real AM facility.

3.6.1 Case Study Company

The criteria for choosing the case study company is derived from the scope of the research, as follows:

- The company should use AM for end-part production. This requires efficient AM operations that balance customer satisfaction (high quality) and revenue generation (low cost and production losses).
- The company should operate AM in a make-to-order or manufacturing-as-a-service context. This leads to product variety in the workflow, and so the scaled-up operations must demonstrate both economies of scale and scope.
- The company should implement either cellular or process layouts in their production facility for polymer laser sintering workflows.

While the initial intention was to find two companies, one for each facility layout approach, a suitable company was found that used both layouts and satisfied the above criteria.

The case study company is a UK-based rapid manufacturing services provider to multiple industries, such as aerospace, automotive and medical. Polymer laser sintering is one of the variety of AM methods offered. The company operates large laser sintering machines, with a build volume exceeding 350mm in each dimension. These large machines enable higher economies of scale on a per-build basis (Baumers and Holweg, 2019). However, the responsiveness of manufacturing is negatively affected as operators must wait for a larger volume of orders to fill each machine and achieve cost-effective production (Costabile *et al.*, 2017). The delivery lead time offered is therefore up to 10 days. The company's laser sintering workflow is shown in Figure 3.17.

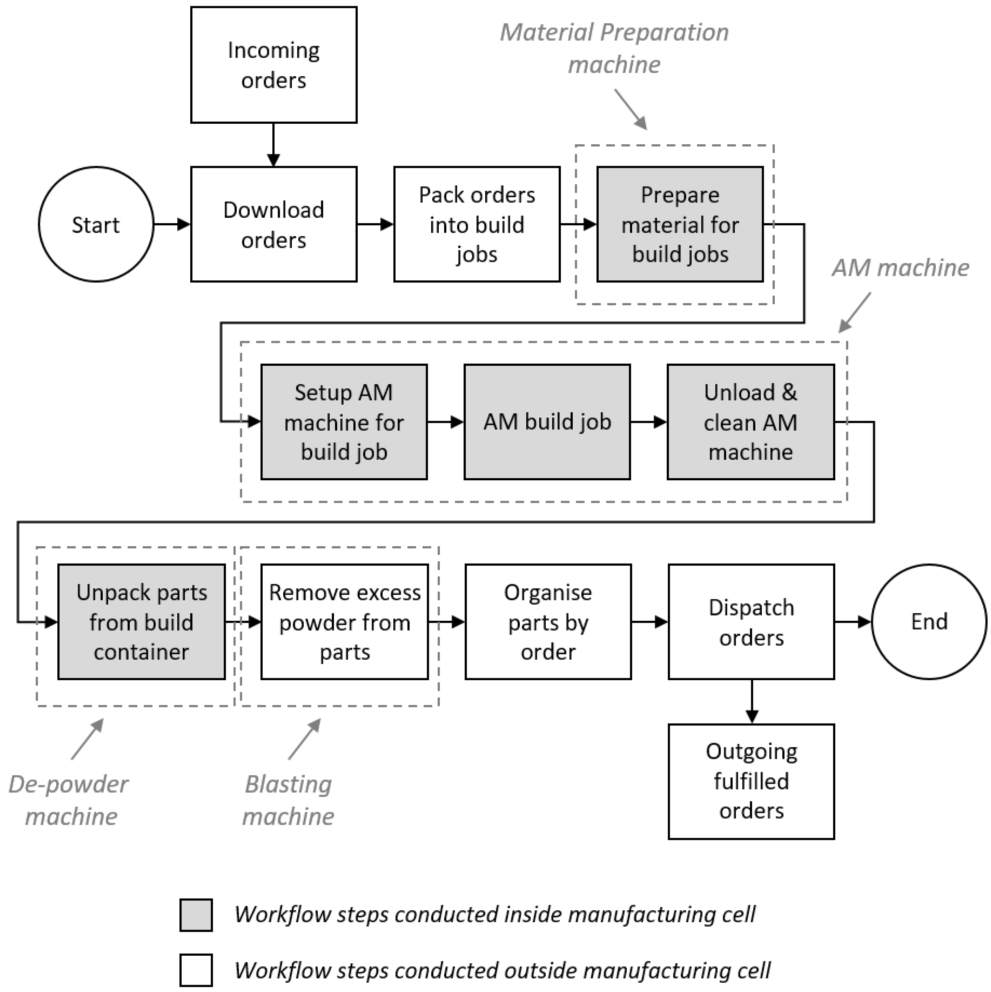


Figure 3.17: Make-to-order workflow for laser sintering at case study company

The company fulfils laser sintering orders using four machines; two set up in a cellular layout, and two in a process layout in a different part of the facility. Build jobs are routed indiscriminately to the machines, depending on their availability. At present, the customer orders are common in material, and so material changeovers are not required. Nevertheless, the company recognises the benefits of the cellular layout for material contamination control, motivating their use of production cells to manage (past) material-dependent workflows and meet industry quality control mandates. The production output for laser sintering currently exceeds 7500 parts/year. Therefore, the company's scale of production for laser sintering sits within the modal band for AM service bureaus, which is typified by 3-5 industrial AM machines and production output of 1001 to 10,000 parts (Akinsowon and Nahirna, 2019).

3.6.2 Conceptual Model

The conceptual model outlines the inputs, outputs, assumptions and simplifications in the model flow for this simulation study. Prior to this, the simulation objective is defined in two parts, each with quantifiable outputs, to help appropriately define the model scope and content. The first objective refers to the setup investment: for each facility layout approach, compare the minimum number of machines required to fulfil the incoming orders within a nine day makespan, at the given production scale. The makespan constraint ensures that the 10 day promised lead time is always met, allowing one day for delivery. The second objective refers to the operational performance (specifically cost, production losses, and non-value-adding time): for each facility layout approach, compare the operational performance when running the minimum number of machines required to meet the setup investment objective at each production scale.

3.6.2.1 Inputs

The first input is the facility layout; the constraints of which are:

1. Cellular layout – equal numbers of material preparation, AM, and de-powder machines are grouped into parallel cells that contain one of each machine, with no travel time inside each cell, and an independent number of blasting machines in a separate zone;
2. Process layout – independent numbers of material preparation, AM, de-powder, and blasting machines, operate in parallel in separate zones in the production facility, with travel time between each zone.

The second input is the scale of production, which is equivalent to the steady-state customer demand that in turn determines the required manufacturing capacity (Wang and Koren, 2012). Thus, the production scale is given by the arrival rate of orders into the workflow. The baseline is the current arrival rate of incoming orders for the case study company, and increasing this by fixed multiples simulates future scaled-up production.

The third input is the number of machines, or manufacturing capacity, required to fulfil orders at each production scale. The machines of interest are the material preparation, AM, de-powder, and blasting machines, highlighted in Figure 3.17. The number of machines of each type is independently varied for the setup investment objective to establish the minimum values for the makespan constraint. Then, this input is fixed for the subsequent simulations for the operations performance objective.

The fourth input is the orders, which are simulated here as an incoming stream with a specified arrival rate. This is feasible due to the simulation software used (see Section 3.6.3) and, as explained above, enables experimentation with the production scale. Each order contains a random quantity of test parts C, D, and E (Figure 3.18). Parts C and D are enlarged by 150% in each dimension relative to the original size (see Figure 3.4), such that the range in size across the set is more representative of the parts observed among the company's orders.

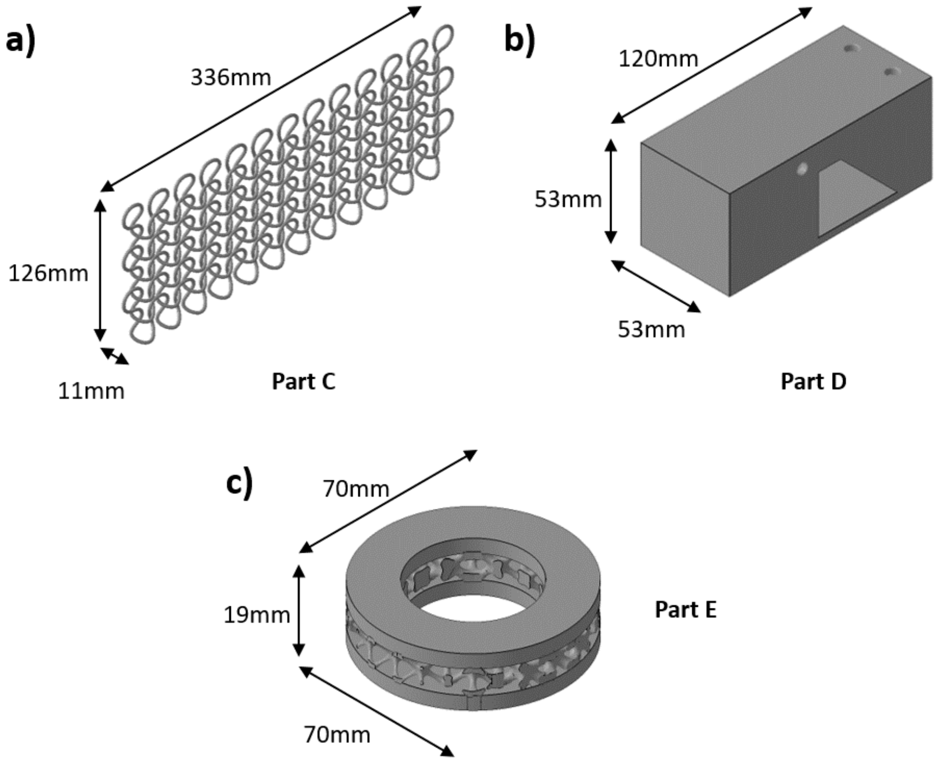


Figure 3.18: Subset of test parts used for facility layout simulation study with adjusted sizes

3.6.2.2 Outputs

A range of outputs are collected in relation to the orders, builds, resources, and overall production facility to address the simulation objectives. Table 3.14 summarises these, according to the entity over which each output is measured.

Table 3.14: Summary of outputs for facility layout simulation study

Entity	**Outputs**
Order	Makespan (and timeliness of delivery) Time spent in each step of workflow Affected by outright build failure
Build job	Time spent in each step at AM machine Time lost to breakdown (outright build failure) Volume of defect-free and defective output Time spent in travel between machines Time spent awaiting operator input
Resource	Operator: Availability on shift
	AM Machine: Time lost to unplanned maintenance
Production Facility	Number of machines required to meet the nine day makespan constraint

For the setup investment objective, the makespan (time spent in the simulated workflow) of each order is collated. Also, the minimum number of machines in the production facility required to meet the makespan constraint is recorded.

For the operational performance objective, the time spent by the orders at each workflow step is used to estimate the well-structured costs. Alongside this, the ill-structured costs are inferred from the incidence of outright build failure for the respective build job (in which the order is processed), and the timeliness of delivery (as per the makespan). For each build, the time taken for each step at the AM machine, the incidence of outright build failure, and the volumes of defect-free and defective output are collated for the production losses and OEE. In between the workflow steps, the non-value-added time for each build comprises of the travel time between machines, and the time spent awaiting the next available operator for manual tasks. Referring to resources, the on-shift operator availability and the unplanned maintenance time for each AM machine are recorded to explore their effect on non-value-adding time.

3.6.2.3 Assumptions and Simplifications

The assumptions and simplifications for the four entities (orders, builds, resources and production facility) in this model are presented in Table 3.15.

Table 3.15: Assumptions and simplifications for facility layout model

	Description	Justification
Assumptions	Volume of parts in an order less than volumetric capacity of a single build	Allows entire orders to be assigned to single build jobs. The order costs can therefore be simply calculated as a fraction of the respective build costs.
	Follow capacity-maximising make-to-order operations approach; and Packing and Scheduling, Separate workflow optimisation approach	Aligns with the process planning methods observed at the case study company. Integrated workflow optimisation is not suitable because the relevant software is not available for the AM machines used by the case study company.
	New builds and orders for rework inserted at the front of the respective workflow queues	Aligns with the process planning methods observed at the case study company, and with the assumed operations approach.
	Two sets of portable resources (material and build cartridges) for each AM machine	Material cartridges (contain feedstock material) and build cartridges (in which deposition occurs) needed. Extra set allows material for next build to be prepared while current build is ongoing.
Simplifications	Constant inter-arrival rate for orders across the year	Collected data (see Section 3.6.3.1) shows no consistent seasonal patterns, and so the average rate is used as a constant.
	Setup investment neglects cost of expanding premises	Space is available in and around the case study company's existing production facility to accommodate new equipment.
	Travel time only counted for build progressing from machine to machine	Any other sources of travel time do not explicitly contribute to the order makespan, and so are neglected.
	Only unplanned maintenance of AM machine counted	Time for planned maintenance (one hour per six months) and unplanned maintenance in other machines (less than once per year) is negligible.

For reference, in the cellular layout, builds are routed to the cell with the next available material preparation machine, and remain within the same cell for the AM build and de-powder steps. In the process layout, builds are routed to any available machine in the facility. Operators are not similarly constrained and move freely between cells and machines in both facility layout approaches.

3.6.3 Data Collection and Analysis

Data for the various inputs and model content are required to implement the conceptual model. Therefore, relevant elements of the case study company's production facility and workflow are characterised in this section.

First, data collection involves both setting the data requirements to satisfy the conceptual model, and obtaining the identified data; and this is often an iterative process, as shown in Figure 3.19, with the level of detail increasing from contextual, qualitative information to detailed, quantitative data (Robinson, 2004, pp. 95–96). In this study, three iterations were conducted.

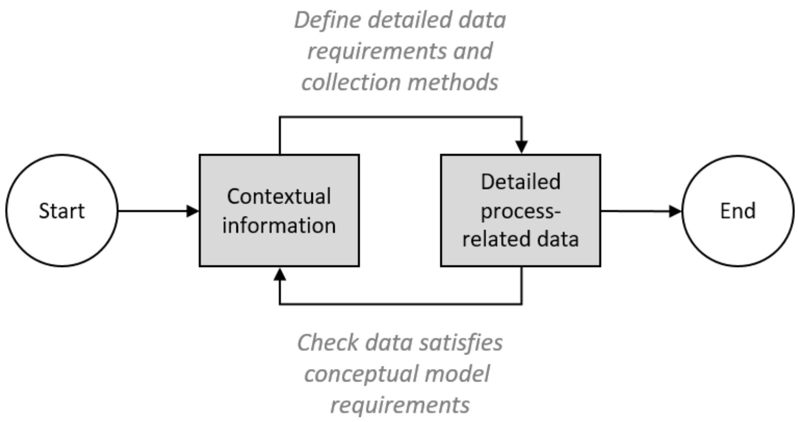


Figure 3.19: Iterative data collection process for simulation models

The first visit to the case study company was used to assess the suitability of their processes and facility layouts for investigation. This allowed the structure of the model implementation and required data to be planned. A second visit involved working with the production team to learn about the workflow, operating procedures, and any issues therein. It was then possible to fully define the quantitative data plan, and verify that these were either available or collectable, avoiding issues of unobtainable data (Robinson, 2004, p. 97). In the third visit, primary (collectable) and secondary (available) data were obtained.

Once collected, the data must be transformed into a format that is useful for the model. This is commonly a parameterised probability distribution (Skoogh and Johansson, 2008), as used in this study. The only exception is the AM build time, for which a linear regression model is generated, similar to the EOS Formiga P100 machine build time model (see Section 3.3.4). The data collected and analysis thereof are summarised in the following subsections.

3.6.3.1 Order-related Data

Order-related data are collated from the company's records. Data samples are taken using a common time frame, the financial year 2021-22 ("FY 21-22"), for consistency; this is the only annual period for which full datasets are available, and is long enough to expose any seasonal patterns. This data contribute to three elements in the model: the inter-arrival rate of orders, the number of unique parts per order, and the total quantity of parts per order.

For the inter-arrival rate, Figure 3.20 shows that the exponential distribution is a suitable fit for the collated data. The mean inter-arrival rate is 21.5 hours, which becomes the baseline production scale in the model. The order data is also checked for seasonal patterns. Figure 3.21 shows that, while the number of orders is not uniform across the year, there is no consistent seasonal pattern; and so the assumption in the conceptual model is sufficiently verified.

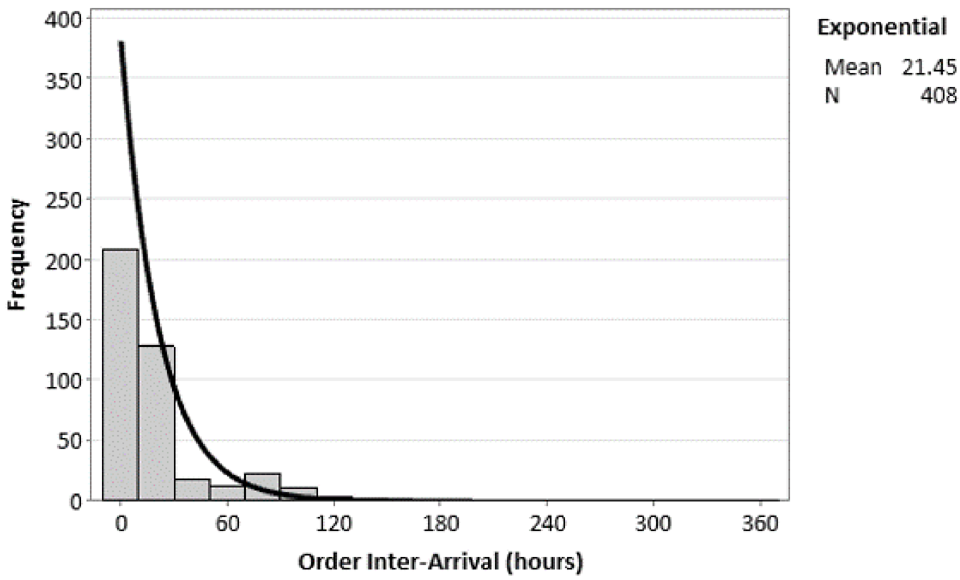


Figure 3.20: Histogram of order inter-arrival time, with fitted exponential distribution curve

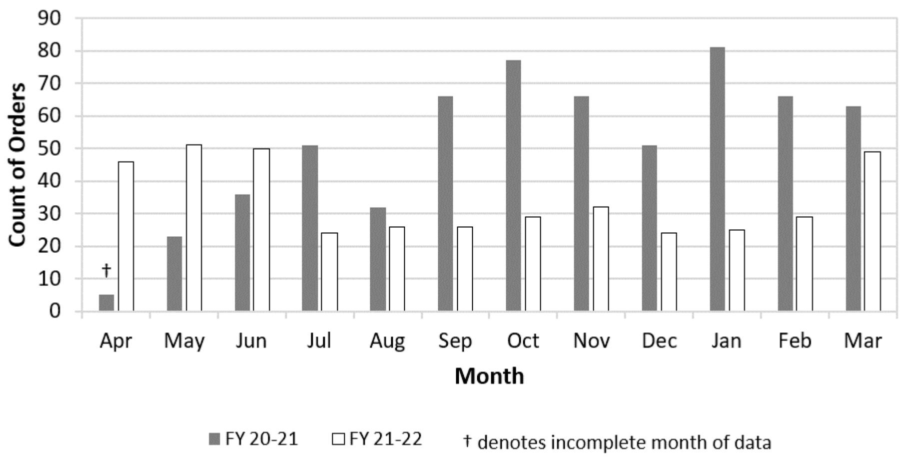


Figure 3.21: Number of orders per month, over previous two financial years

Next, the number and quantity of unique parts determines the size of each order. The box-whisker plots in Figure 3.22 show that the majority (96.4%) of orders contain fewer than 10 unique parts. The mean value, marked with a cross, is 3.1 unique parts per order, which corresponds to the use of three test parts in this study. Alongside this, Figure 3.23 shows the histogram for the quantity of each unique part across the orders in FY 21-22. The quantity range spans one to 350, but the histogram x axis is curtailed at 50 (excluding 46 of 1292 data points) to allow the frequency density pattern to be visualised. This distribution is positively skewed such that the majority of orders (86.1%) of the orders contain five or fewer instances of unique parts. Therefore, the quantity of each unique part in each order is, at most, five.

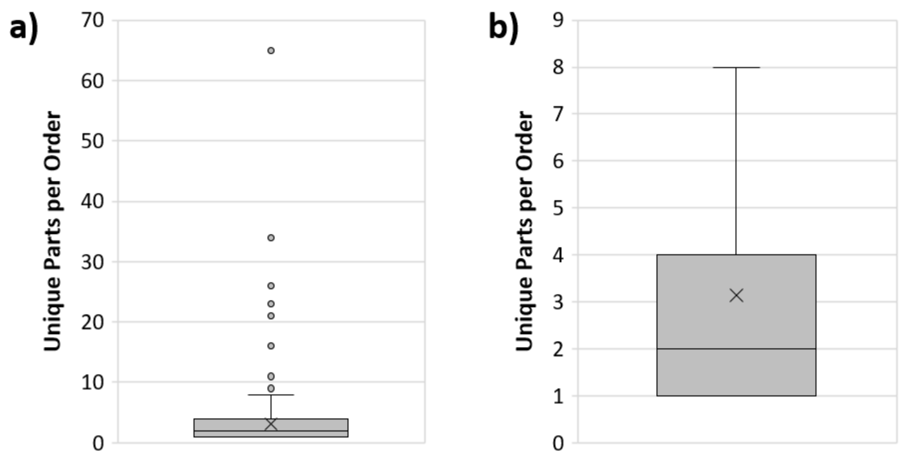


Figure 3.22: Box-whisker plots for number of unique parts per order, a) with outliers, and b) without outliers

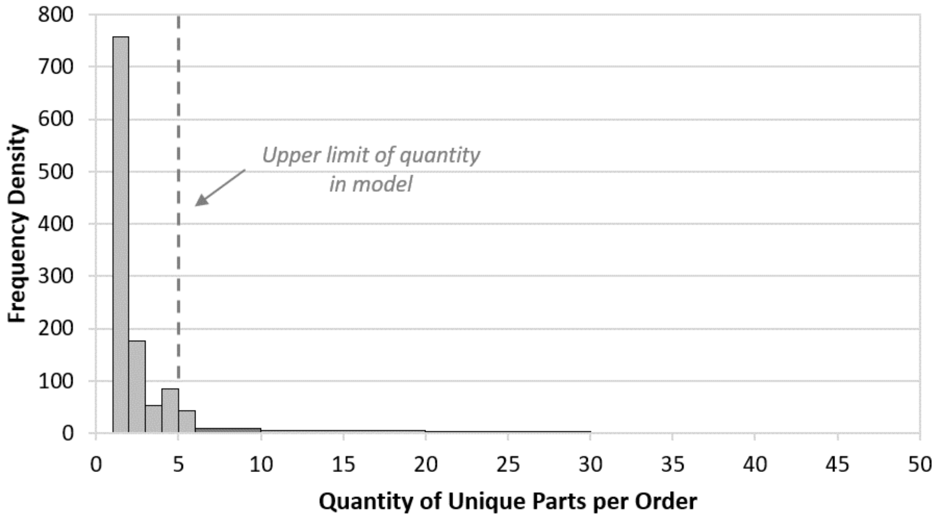


Figure 3.23: Histogram of unique parts quantity per order, up to 50 parts per order

3.6.3.2 Build-related Data

As above, the build-related data is taken from the subset of available records for FY 21-22. This data contributes to four elements in the model: the machine build time model, the build failure rate, the part defect rate, and the threshold full build capacity utilisation for converting the order stream into build jobs.

The records from 81 successful builds on the two most used AM machines show that the full build capacity utilisation distribution (Figure 3.24) is skewed towards sparse builds. With 55.5% of builds below 3% full build capacity utilisation, the assumption of capacity-maximising make-to-order operations appears to not hold. However, observations of the company's workflow confirm that the operators do indeed fill each build to the maximum possible, subject to two constraints: the large size of parts in the same order limits the ability to tightly pack each build, and orders cannot be held up at the batching stage so long that delivery is then late. As production scales up, it could be helpful to consider more sophisticated, integrated optimisation type tools, to mitigate the effects of these constraints. For now, the simulation model adopts a 6.0% target for the full build capacity utilisation, corresponding to a full-height build containing the test parts, and encompassing 88.9% of the observed data.

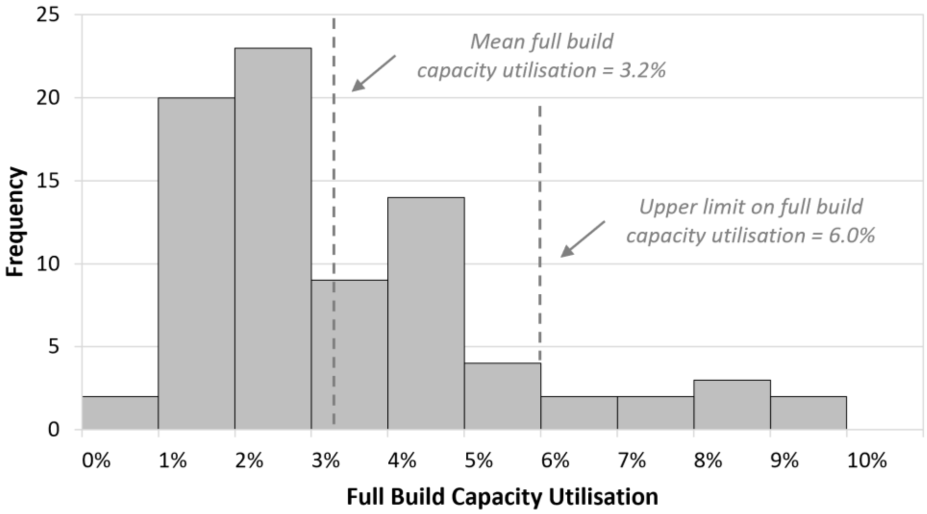


Figure 3.24: Histogram of full build capacity utilisation per build

Records from 175 builds across all available AM machines are used to estimate the prevalence of part defects. On average, 3.5% of parts are defective; however, given that the ordered parts vary significantly in size and geometry, it is not possible to set a constant probability of part rejection, as per Baumers and Holweg (2016, 2019). Instead, the proportion of the build quantity that is defective is estimated from the distribution shown in Figure 3.25. The majority of builds, 80.6%, contain no defects; and of the remainder, 38.2% of builds lose up to one-tenth of the parts. Thus, the range used in the model is 0 – 10.0% of parts rejected. As production scales up, increased use of data-driven part packing and process control may further reduce the defect rates.

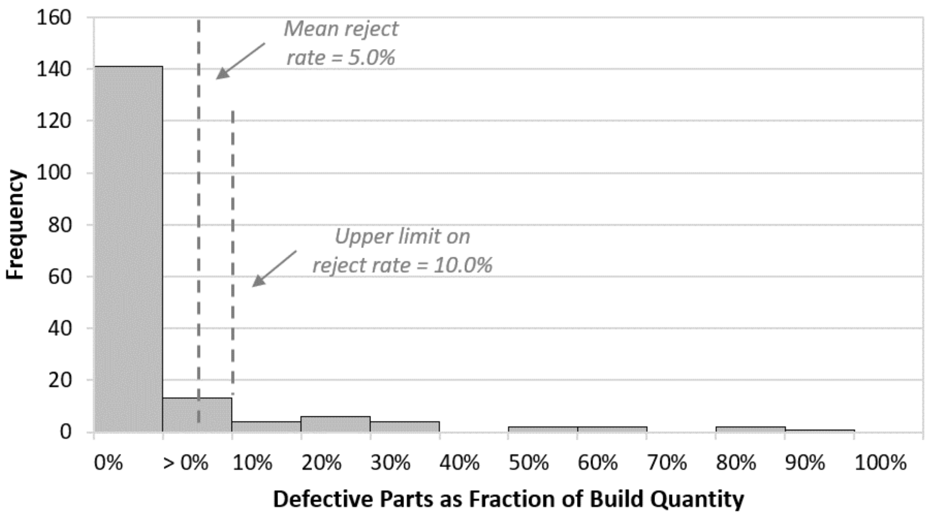


Figure 3.25: Histogram of defect part quantity as a fraction of the build quantity

The MTBF for build failures is estimated from 23 build failures across 118 records in the machine logs for the two most used AM machines. Figure 3.26 shows the distribution of the build failure inter-arrival times, which is the time between the end of one failure and the start of the next. Time (rather than number of layers) between failures is used, as the empirical distributions for time are more consistent across the machines. As the AM machines are all identical, the model MTBF takes the mean value of 250 hours for simplicity.

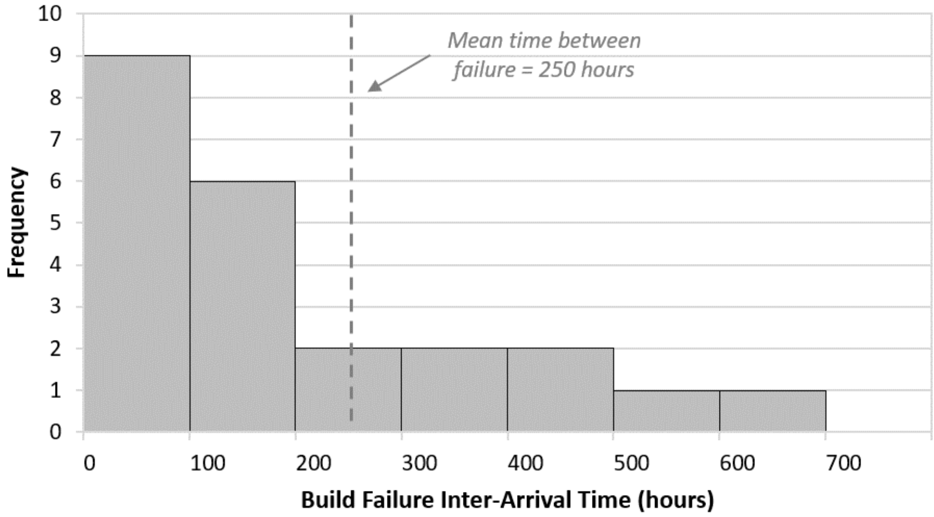


Figure 3.26: Histogram of build failure inter-arrival time

3.6.3.2.1 Build Time Model

Similar to the build time model for the EOS Formiga P100 machine (see Section 3.3.4), a multivariate linear regression model is used to predict the build time on the case study company's AM machine. The FY 21-22 build records and machine logs for error-free builds on the two most used machines provide the input and test data of 47 and 34 builds, respectively, for this build time model.

The heat-up time is consistent across both the input and verification datasets, at one hour. As per the previous model in equation (3.4), the production time is split into layer-wise and volume-wise elements. Indeed, both build volume and build height are statistically significant in this model, at the 1% confidence interval. However, unlike the EOS Formiga P100 machine, the cool-down time is not uniform on the case study company's machines. To investigate further, the cool-down time is also regressed against the build contents, wherein the build height is statistically significant (1% confidence interval) but the volume is not. The heat-up, production and cool-down times, T_{heatup}, $T_{production}$, $T_{cooldown}$, in hours are therefore given by:

$$T_{heatup} = 1 \tag{3.25}$$

$$T_{production} = -2.0 + 0.099H_{build} + (7.7 \times 10^{-7})V_{build} \tag{3.26}$$

$$T_{cooldown} = 15.0 - 0.0099H_{build} \tag{3.27}$$

where:

H_{build} – height of the build (mm)
V_{build} – volume of parts in the build (mm^3)

Notably, the cool-down time is negatively correlated with the build height. This is presumably because the build temperature sensor, used during the cool-down stage, is near the bottom of the build cartridge and registers a cooler temperature in taller builds as the build has progressed further.

The goodness of fit for the production and cool-down time models are 0.90 and 0.91, respectively. Further, to verify that the linear regression models match with the empirical data, the model-fitted data are compared to the test dataset. Figure 3.27 shows that the two datasets are closely matched for both the part production and machine cool-down times, and so the build time model is used in the simulations, ensuring that build heights are within the modelled range.

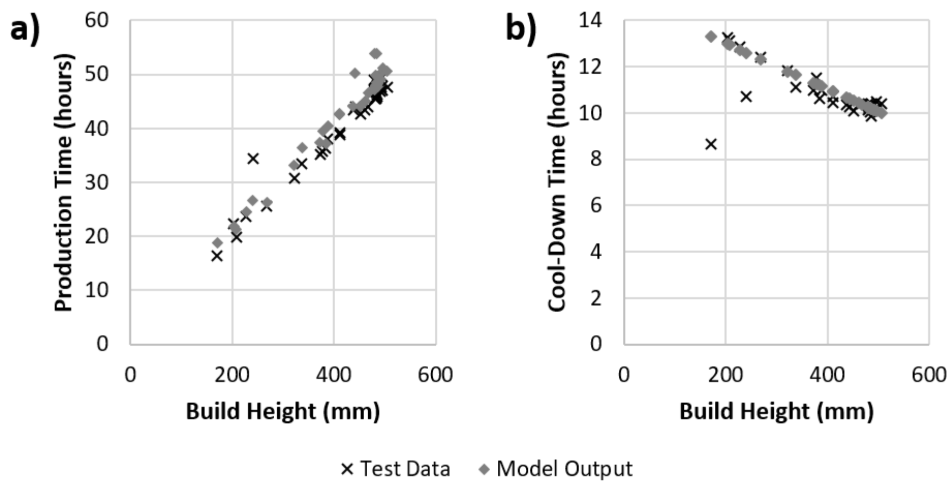


Figure 3.27: Test dataset and corresponding model output plotted against build height for a) production time, and b) cool-down time

3.6.3.3 Unplanned Maintenance Data

The unplanned maintenance data for the AM machine is derived from records of maintenance requests and repair jobs completed in FY 21-22. Unplanned maintenance is the reactive repair of faults uncovered in between build jobs, and only the highest priority level faults are included here, as these prohibit use until the repair is completed. The AM machine with the highest number of such maintenance requests, 15 in total, is used to estimate the MTBF and the mean time to repair (MTTR). The box-whisker plots, excluding outliers, in Figure 3.28 show that both parameters are positively skewed: unplanned maintenance events are relatively frequent, but the time to repair is also short. Nonetheless, given the spread in times across the few observed data points, a triangular distribution that corresponds to the middle quartiles is chosen to represent the data in a straightforward manner, as shown in Table 3.16.

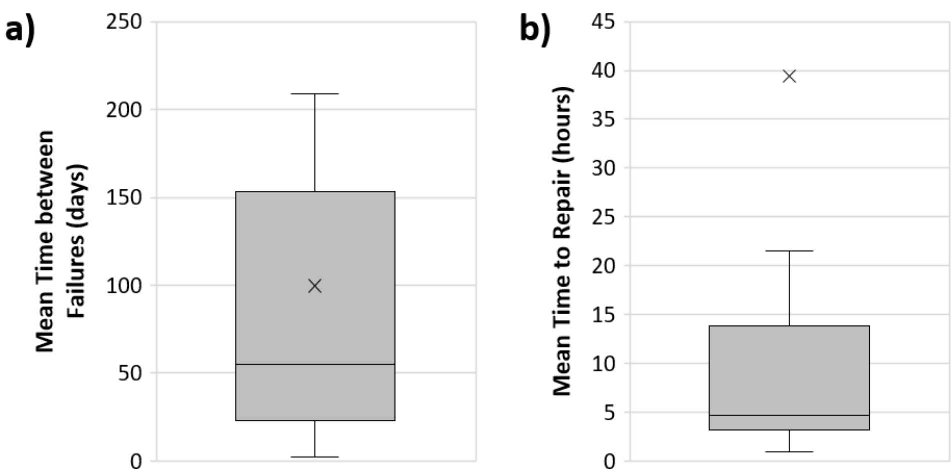


Figure 3.28: Box-whisker plots of a) mean time between failure, and b) mean time to repair for unplanned maintenance events

Table 3.16: Summary of triangular distribution parameters for unplanned maintenance events

Unplanned Maintenance Parameter	**Triangular Distribution Parameter**		
	Lower Limit	**Mode**	**Upper Limit**
Mean Time between Failures (days)	23.1	54.9	153.1
Mean Time to Repair (hours)	3.2	4.6	13.9

3.6.3.4 Workflow Process Step Times

Among the data kindly made available by the case study company, the time taken to complete each step and travel between machines in the workflow did not exist. Therefore, this data is collected via a simplified manufacturing time study to capture the value-adding and non-value-adding tasks at each step (Pattanaik and Sharma, 2009). Referring to the workflow in Figure 3.17, all steps are studied apart from the AM build step (covered by the build time model).

In this time study, voice notes were used (rather than a stopwatch) to describe and capture the timestamps of different, asynchronous tasks. These were later transcribed into a spreadsheet. Post-analysis, the process step and travel times are represented using a triangular distribution, as below.

Table 3.17: Process step times in the workflow for laser sintering

Process Step	**Triangular Distribution Parameter (minutes)**		
	Lower Limit	**Mode**	**Upper Limit**
Download orders	1.8	3.2	4.6
Pack orders	6.5	19.4	32.3
Material prep. (setup machine)	0.9	1.9	2.8
Material prep. (machine time)	15.0	15.0	15.0
Material prep. (unload machine)	2.0	3.3	4.5
AM machine (setup machine)	7.8	13.2	18.5
AM machine (unload machine)	12.9	14.4	15.8
Unpack and de-powder parts	37.1	41.2	45.3
Blasting (setup machine)	0.2	0.2	0.2
Blasting (machine time)	13.5	15.0	16.5
Blasting (unload machine)	0.8	0.9	1.0

Table 3.18: Travel times in the workflow for laser sintering

Travel between…	**Triangular Distribution Parameter (minutes)**		
	Lower Limit	**Mode**	**Upper Limit**
Workstation & Material Prep.	0.3	0.3	0.4
*Material Prep. & AM Machine**	3.8	4.5	5.3
*AM Machine & De-Powder**	1.6	1.8	1.9
De-Powder & Blasting	0.8	0.9	1.0

Note: * denotes elements that apply to the process layout only

3.6.4 Model and Simulation Implementation

The DES simulation of the case study company's make-to-order workflow is implemented using specialist software, Anylogic (Personal Learning Edition, version 8.8.1), that is suitable for simulating the AM workflow and effects of capacity management in an efficient manner (Avventuroso *et al.*, 2017). The software employs an customisable object-oriented architecture and process-specific libraries to allow powerful and flexible simulation of production operations (Anylogic, 2023a). A simplified version of the model logic is shown in Figure 3.29, and its implementation in Anylogic is shown in Figure 3.30.

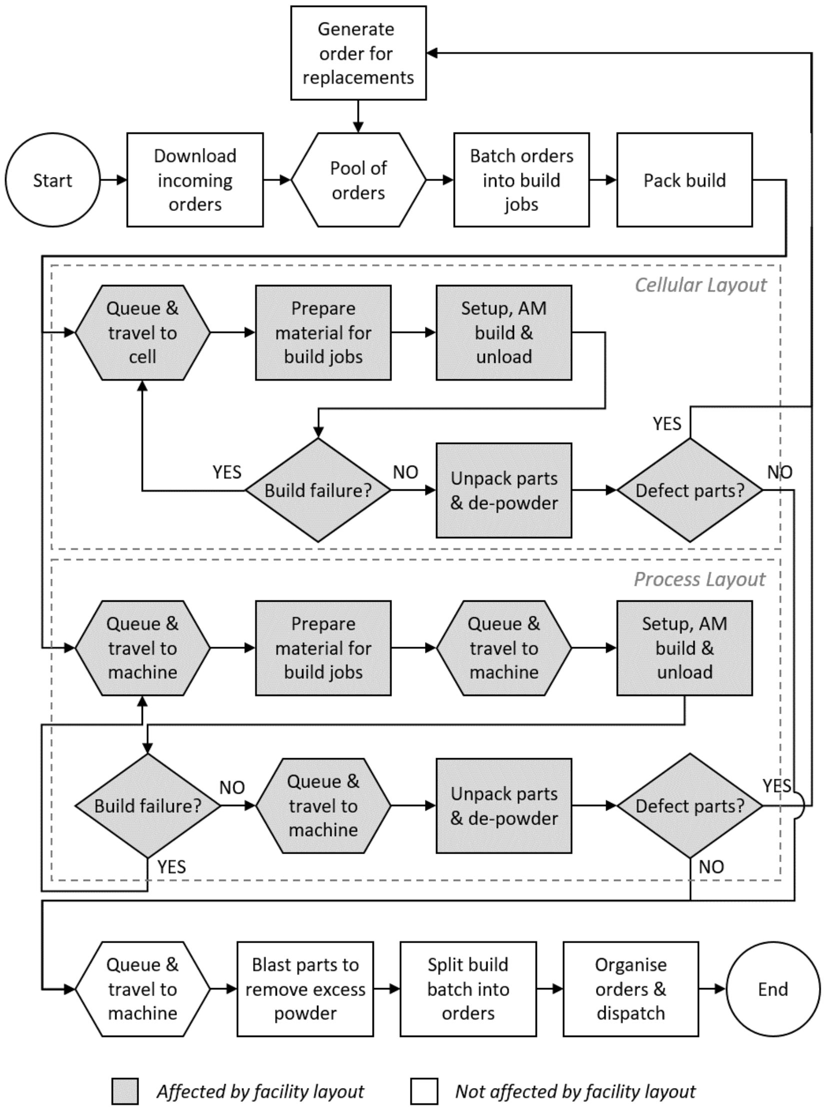


Figure 3.29: Logic for facility layout simulation model with parallel branches for cellular and process layout

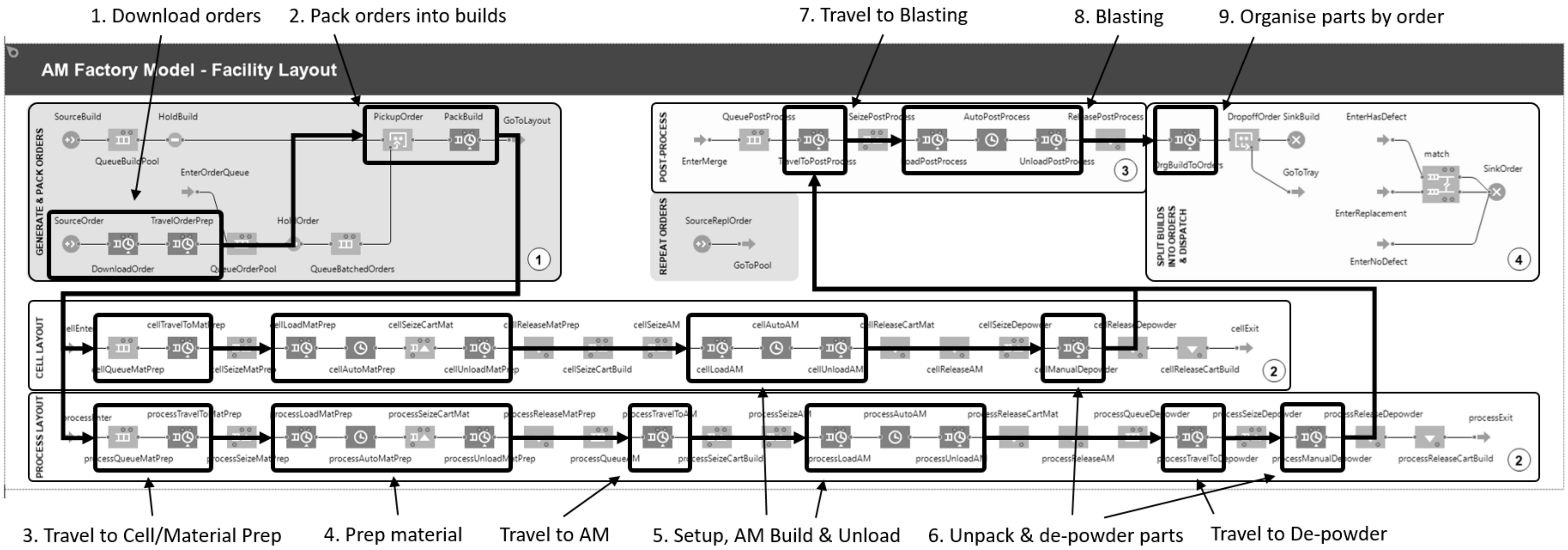


Figure 3.30: Annotated snapshot of facility layout simulation implementation in Anylogic

Given that the facility layout affects only part of the AM workflow (see Figure 3.17), a single simulation model is developed with two parallel branches for the cellular and process layouts. Builds are routed through the appropriate branch for the experiment settings. This model structure is more compact than the alternative of two separate models. More importantly, Anylogic can achieve reproducible simulation runs (Anylogic, 2023b), avoiding spurious effects from randomly generated inputs (e.g. the incoming order stream); and this can only be applied within a single model. All elements of the workflow are executed within the Anylogic software, except the packing of parts in the build volume. While the time taken for this step falls within the capability of the software, it is not possible to complete the actual orientation and positioning of parts. This is completed using Autodesk Netfabb® Premium, and the resulting build properties are encoded into the simulation.

3.6.5 Experiment Design

The influence of two facility layout approaches on the setup investment and operational performance of make-to-order fulfilment is examined at four scales of production. As a result, eight workflow scenarios are generated (Figure 3.31).

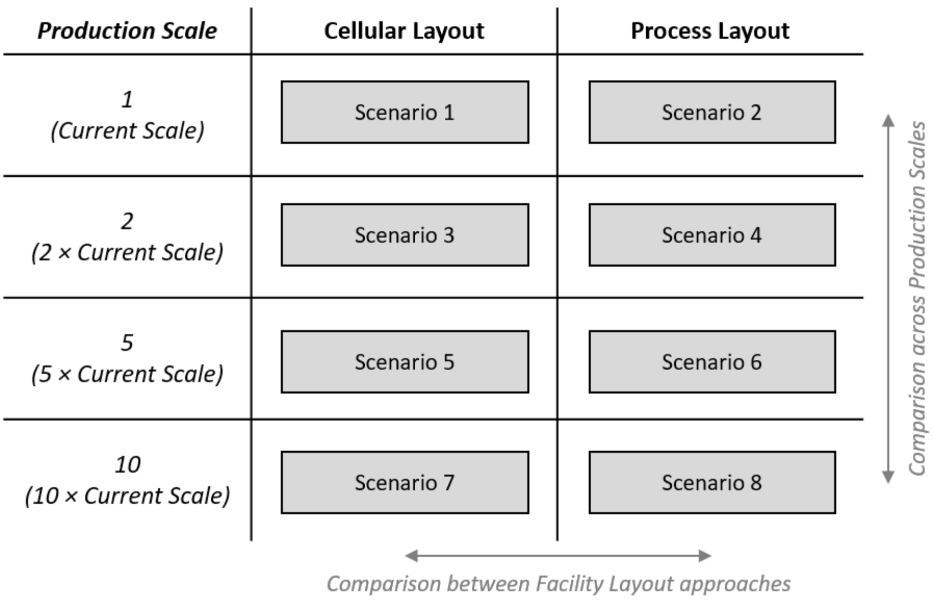


Figure 3.31: Workflow scenarios arising from facility layout and production scale inputs to the simulation study

For each workflow scenario, a sensitivity analysis is conducted by altering the number of machines available and observing the effects on the makespan and operational performance. This follows the approach of Avventuroso et al. (2017) in studying a simple AM-based production facility. Moreover, sensitivity analysis is useful for highlighting which elements of capacity management have a greater or lesser impact on process efficiency (Robinson, 2004, pp. 194–195).

Each experiment fulfils a randomly-generated order stream, with the arrival rate set by the production scale, for 14 months. To ensure that the output data is free from initiation bias (Robinson, 2004, pp. 141–142) and represents steady-state operations, the first and last month of data from each run is discarded, leaving a dataset spanning 12 repetitions of one month's operations.

In line with the two parts of the simulation objective, the post-experiment analysis of the output data is split into two parts. First, for the setup investment, the number of material preparation, AM, de-powder machines are varied within the range shown in Table 3.19, and the time taken for each order to progress through the workflow is assessed. This establishes the minimum number of machines for each facility layout for each production scale. It should be noted that, during trial runs to set the input ranges, a single blasting machine was found to be sufficient for the workflow. Second, the operational performance is assessed in each minimum-capacity setup. For this, the time spent in each part of the workflow is probed, and cost and productivity-related metrics (see the following section) are calculated. Thus, the balance of value-adding and non-value-adding time in each facility layout, and the impact on the cost- and time-effectiveness of production is evaluated.

Table 3.19: Input range for available capacity for facility layout simulation

Production Scale	**Input range for no. of machines**			
	Material Preparation	**AM**	**De-Powder**	**Blasting**
1	1 – 3	1 – 3	1 – 3	1
2	1 – 3	1 – 3	1 – 3	1
5	1 – 4	1 – 4	1 – 4	1
10	1 – 7	1 – 7	1 – 7	1

3.6.6 Calculation of Metrics

3.6.6.1 Setup Investment

The setup investment is evaluated via the minimum number of machines that provide sufficient capacity to meet the nine day makespan target. Therefore, for each productivity scale, i, the objective function to minimise, F_1, is given by:

$$F_1(i) = MP_i + AM_i + DP_i \tag{3.28}$$

where:

MP_i, AM_i, DP_i – number of material preparation, AM, and de-powder machines, respectively

3.6.6.2 Operations Performance

The operations performance is assessed from two perspectives, production losses and production cost. For the production losses, the OEE (see Section 3.4.1) measures the impact of the facility layout on the productive use of the AM machine capacity. In addition, the facility layout is expected to affect the value-adding and non-value-adding time across the entire workflow, and so the time spent by each order or build in each workflow step is recorded and probed further. The value-adding and non-value-adding time elements in the total workflow time in hours, $T_{workflow}$, can therefore be split as follows:

$$T_{workflow} = T_{auto} + T_{manual} + T_{travel} + T_{waiting} \tag{3.29}$$

where:

T_{auto} – time spent in automatic, machine steps (hours)
T_{manual} – time spent in operator-dependent steps (hours)
T_{travel} – time spent in travel between machines (hours)
$T_{waiting}$ – time spent awaiting operators or resources (hours)

For the production cost, a simplified version of the total cost model (see Section 3.5.1) covers two time-related well-structured cost contributors: the indirect cost of time spent in the automatic steps, and the labour cost of time spent in the operator-dependent steps and travel in between. Given commercial sensitivity, the cost rates from the case study company's AM workflow are not disclosed, and so the cost-incurring time per part is used as a proxy for the unit cost. The relationship between the time-dependent well-structured unit cost, C_{T-WS}, and cost-incurring time per part, T_{costed}, can therefore be given by:

$$C_{T-WS} = \dot{C}_{indirect}T_{auto} + \dot{C}_{labour}(T_{manual} + T_{travel}) \tag{3.30}$$

$$T_{costed} = T_{auto} + (T_{manual} + T_{travel}) \tag{3.31}$$

Similarly, for the ill-structured costs, the time domain replaces the cost penalties arising from the failure mode scrap fractions and late delivery. This relies on detailed analysis of the time spent by each order and build in the different stages of the simulated workflow. The extra time consumed in processing extra builds (for build failure) and replacement orders (for part defects) is compared. Alongside this, the makespan constraint of nine days is used to assess the extent to which orders are processed in a timely manner in each workflow scenario. The time-domain outputs of the simulation experiments are therefore deployed in multiple ways to provide insights into the effect of facility layout on both the time- and cost-effectiveness of production.

4 Results on Production Losses in AM

4.1 Overview

This chapter presents the results of research towards the first research objective, to evaluate the effect of process planning on the machine-level production losses.

The approach for addressing this research objective is a combination of a theoretical framework and experimentation via exploratory simulation. The framework explains sources of production losses in the AM process, and how the characteristics of AM operations affect the prevalence of production losses. This is the first step to inform process planning decisions towards minimising production losses at the AM machine. The exploratory simulation study then investigates the effect of different process planning approaches (referred to as "operations approaches") on the production losses. The OEE metric developed in this research (Section 3.4.1) is used to quantify the relative merit of each operations approach with respect to operational efficiency at the machine-level. The development of the framework and exploratory simulation models are explained in Section 3.4.

The remainder of this chapter is organised as follows. First, Section 4.2 provides the theoretical framework for production losses in the AM workflow. Section 4.3 then presents the results for the first exploratory simulation on the effect of the operations approach on the production losses and OEE. The sensitivity of the OEE to externally-controlled factors within the AM operations is then investigated in the second exploratory simulation, as reported in Section 4.4.

4.2 Framework of Production Losses in AM

The theoretical framework for production losses in AM adapts the existing understanding of production losses in conventional manufacturing to the process and operations characteristics of AM. This builds upon and complements the methodological work to "translate" the OEE metric so that it is suited for AM (Section 3.4.1). Therefore, the results in this section provide a systematic interpretation of the contributors to machine-level waste for polymer laser sintering AM. More generally, this framework provides a better understanding of the drivers of AM efficiency and, importantly, improves the clarity of the process efficiency implications of pursuing responsive direct digital manufacturing using AM.

4.2.1 Inherent and Non-Inherent Production Losses in the AM Machine

Production losses in the manufacturing workflow are underpinned by the notion of value-adding steps as a fraction of the total planned production time (see Figure 2.10 for schematic representation). As explained in Section 2.2.1 of the literature review, a value-adding step is that which directly contributes towards creating features and functionality that the customer desires. In the AM machine, therefore, the only value-adding step is the deposition (or automated build) step. With reference to the process workflow for polymer laser sintering (Figure 3.7), this is the fifth of eight steps at the AM machine. Ancillary steps that lead up to the build step and thereafter ensure that the parts are successfully retrieved for post-processing are considered necessary-but-non-value-adding steps (see Figure 2.9 for graph of taxonomy). As emphasised by Gibson et al. (2015) and Gardan's (2016) explanation of the full AM workflow (see Figure 2.1), without these steps, the AM process would not function correctly. However, from a productivity and revenue-generation perspective, the AM machine is not generating value outside of the build step. Rather the time spent on the ancillary steps reduces the process' capacity to produce more good quality parts, and costs the manufacturer in overheads, labour and equipment depreciation.

The non-value-adding and necessary-but-non-value-adding steps in the AM process can be further categorised into inherent and non-inherent production losses (Figure 4.1). Inherent production losses are those which arise as a result of the batch process nature of AM and the layer-by-layer deposition during the build. The associated steps and time lost occur for each build, e.g. machine setup, or for each layer added to the build, e.g. waiting to heat the new powder layer. In contrast, non-inherent production losses arise from a variety of other sources, for example sporadic disturbances in the process or unsuitable standard operating procedures. The distinguishing feature of inherent production losses in AM is that they would be present even if all of the process steps were completed correctly and efficiently, and no random defects occurred.

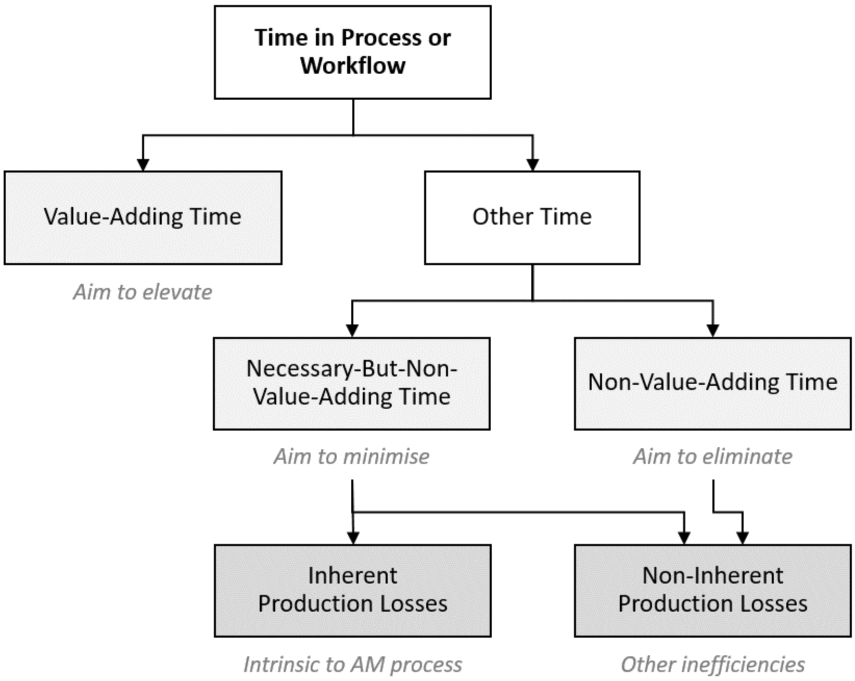


Figure 4.1: Taxonomy of inherent and non-inherent losses, extending the theory of value-adding and non-value-adding time

The difference between inherent and non-inherent production losses can be further explained using examples in the polymer laser sintering process workflow. Figure 4.2 provides examples of production losses in polymer laser sintering, where inherent losses are marked with an asterisk.

Inherent production losses are more prevalent in three of the six production loss categories: setup and adjustment, idling and minor stops, and start-up yield. The batch nature of the AM process necessitates ancillary steps to prepare the machine for the build process. In the setup and adjustment category, these include setting up machine hardware and software, replacing the build volume container, and cleaning the build chamber between each build. The machine then sits idle as the build volume and chamber heat up (and cool down, after the build). Once the build step has started, blank layers must be deposited in the build volume to form a thermal barrier at the base, constituting lost output capacity at the start of each build. On a layer-by-layer basis, minor stops occur between completing the sintering for one layer, applying the next layer of powder, and starting the next sintering cycle; the primary source of time lost is the pause to heat up the new powder layer.

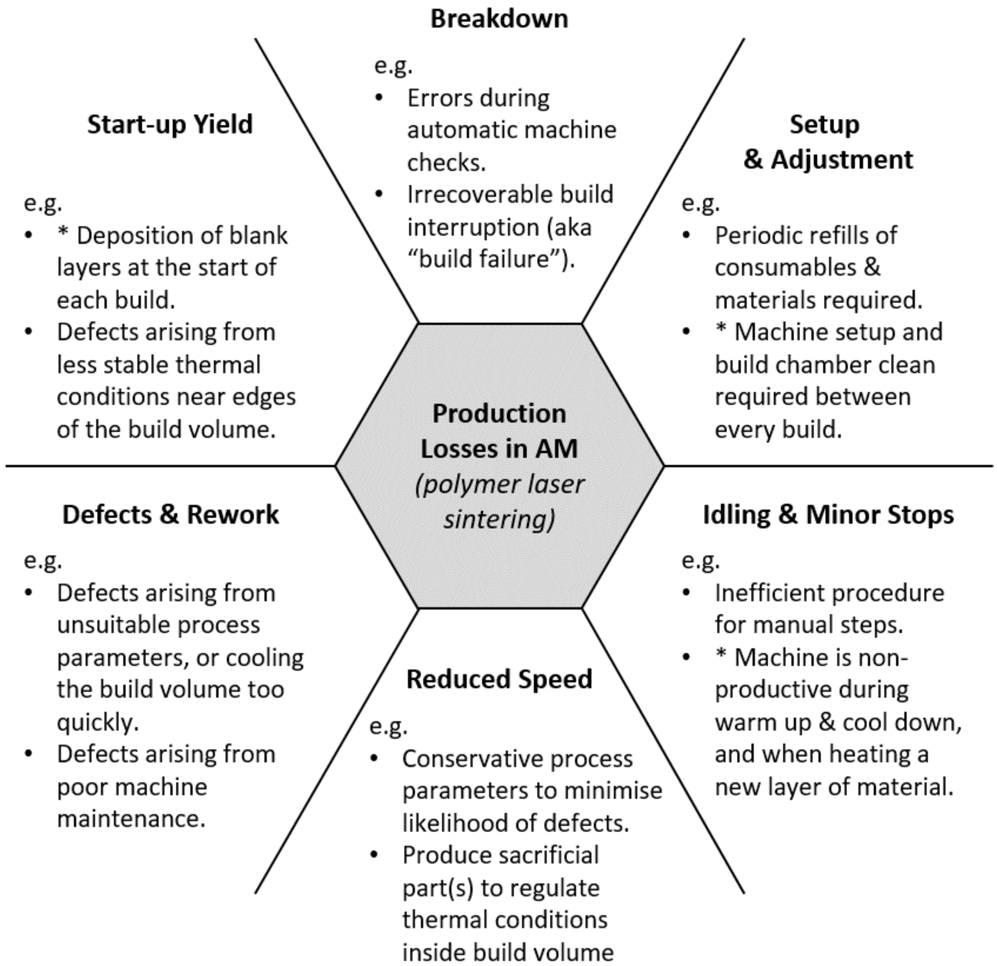


Figure 4.2: Examples of production losses in polymer laser sintering workflow

On the other hand, non-inherent production losses can be found in all six production loss categories. The sources of these losses include machine and process instability (breakdown, defects), reducing machine capacity in an attempt to regulate thermal conditions (reduced speed, start-up yield), and poor management of manual steps (idle and minor stops).

Both inherent and non-inherent production losses can be addressed by a combination of AM operations management, and innovations and improvements in the AM technology. Such innovations include process monitoring and control systems for thermal regulation and reducing pauses during the build process; however, these fall outside the scope of this thesis. In the following section, the focus shifts to the operations characteristics of the AM process, which can then inform operations management approaches to tackle production losses in AM machines.

4.2.2 Effect of AM Operations Characteristics on Production Losses

The differences between AM and conventional manufacturing operations can be distilled into five AM operations characteristics, as found by Baumers and Holweg (2019):

1. Product variety can be produced at close to zero marginal cost;
2. Each build is a vertical batch process with a maximum batch size determined by the build volume capacity;
3. Volume-driven static economies of scale apply up to full build volume utilization, but not beyond;
4. Learning curve effects apply to both pre- and post-processing steps; and
5. The risk of build failure increases with the number of layers produced.

These characteristics describe how the technological and human factors influence the operations constraints and opportunities in AM. Therefore, it is pertinent to explore how controlling the AM operations can influence the production losses. In this part of the framework, the operations characteristics are mapped against the six production losses to show the sources of operational efficiency and inefficiency in the AM process. By codifying the relationship between production losses and AM operations in Table 4.1 and

Table 4.2, these results indicate where AM operations managers can focus their attention to maximise the output from machine capacity.

The mapping identifies three key relationships between the operations characteristics and the production losses. First, each new build is accompanied by non-value-adding time in setup, pre-process and post-process idle time, and lost output on process start-up. Therefore, minimising the number of builds reduces these production losses. This corresponds to physically filling the machine capacity.

Second, the risk of build failure increases with the machine capacity utilisation, and so the production losses for breakdown and rework is negatively impacted. Moreover, the above penalties for a new build would be incurred for the new build, which is required to fulfil rework.

Third, sources of variation in the production content and operator-dependent manual steps affect the ability to standardise the process, which affects production losses across the AM machine workflow. No link is found in the mapping between these operations characteristics and causes of part defects or machine breakdowns, which depend on the equipment reliability.

The sources of operational efficiency and inefficiency can also be related back to the inherent losses from the previous section. The batch-related inherent losses are highlighted in this mapping, particularly via the operations characteristic that defines the batch process nature of AM. An additional connection is made between process instability and inherent losses, through extra builds for rework. The mapping also links together the batch- and layer-related inherent losses through build volume utilisation. Increasing the build volume utilisation amortises batch-related losses across the output, minimises losses due to new batches, and improves the productivity of each layer in the build. These operational cues are further tested through exploratory simulation experiments in the following sections of this chapter.

Table 4.1: Mapping the production losses to the AM operations characteristics (for first three production losses)

AM Operational Characteristics	**Production Loss**		
	Breakdown	**Setup & Adjustment**	**Idling & Minor Stops**
Product variety at minimal marginal cost		Process parameters in control system may change, depending on the parts in each build, requiring checks each time (–) (Proff and Staffen, 2019) Feedstock material variety incurs time penalty for material changeover in the machine (–) (Proff and Staffen, 2019)	
Each build is a vertical batch process, limited by build volume capacity	Build failure can lead to loss of entire batch of parts, as an interrupted build cannot be restarted (–) (Baumers and Holweg, 2016)	Each build incurs a time penalty for pre- and post-process steps (–) (Fera *et al.*, 2017) Periodic time penalty for feedstock material refresh (–) (Fera *et al.*, 2017)	Each build incurs a time penalty for warm up and cool down of build volume (–) (Ruffo, Tuck and Hague, 2006a)
Static economies of scale up to full build volume utilisation in each build			Higher utilisation of space in each layer increases the proportion of productive time to layer-wise idle time (+) (Ruffo, Tuck and Hague, 2006a; Dirks and Schleifenbaum, 2020)
Learning curve in pre-process and post-process steps		Operator skill/experience affects time to set up machine (+) (Baumers and Holweg, 2019)	Efficient standard operating procedures for manual steps minimise errors and minor stops (+) (Reid, 2019)
Risk of build failure increases with number of layers	Likelihood of breakdown increases with the number of layers deposited (–) (Baumers and Holweg, 2016)	Extra builds required to accommodate reworked parts incur a time penalty for pre- and post-process steps (–) (Baumers and Holweg, 2016)	Extra builds required to accommodate reworked parts incur a time penalty for warm up and cool down of build volume (–) (Baumers and Holweg, 2016)

Table 4.2: Mapping the production losses to the AM operations characteristics (for the second three production losses)

AM Operational Characteristics	**Production Loss**		
	Reduced Speed	**Defects & Rework**	**Start-up Yield**
Product variety at minimal marginal cost	Sacrificial parts may be required to regulate thermal conditions across dissimilar product geometries (–) (Pavan *et al.*, 2017)		Non-productive blank layers phase may be more conservative to account for dissimilar thermal conditions across product geometries (–)
Each build is a vertical batch process, limited by build volume capacity		Extra build required to accommodate reworked parts (–) (Baumers and Holweg, 2016)	Defects may arise in parts near the bottom of the build volume due to less stable thermal conditions (–) (Wegner and Witt, 2015) Each build requires deposition of blank layers prior to productive phase (–) (Baumers and Holweg, 2016)
Static economies of scale up to full build volume utilisation in each build	Space-efficient part positioning reduces time taken for laser spot to traverse between sintered regions (+) (Pham and Wang, 2000)		Higher utilization of space in each build increases the proportion of productive phase to non-productive blank layers (+)
Learning curve in pre-process and post-process steps			
Risk of build failure increases with number of layers	Equipment may be operated using conservative process parameters to reduce likelihood of breakdown (–)	Likelihood of rework increases with number of layers occupied by parts (–) (Baumers and Holweg, 2016)	

(+) or (–) indicate positive or negative effect on production losses and OEE, respectively, in Tables 4.1 and 4.2

4.3 Effect of Operations Approach on OEE

This section presents the results for the first exploratory simulation, which investigates the effect of the AM operations approach on the OEE of the AM machine for polymer laser sintering.

4.3.1 Effect of Operations Approach on AM Build Properties

Opening with the descriptive statistics, Table 4.3 shows the mean and standard deviation of the build properties and their output across five repetitions for each operations approach. It should be noted that the results for the Identical Batch Make-to-Stock (IB-MtS) operations approach are aggregated across two sets of simulation experiments, corresponding to the two test parts. Each statistic shown in Table 4.3 is calculated separately for the IB-MtS experiments involving part A and part B; and then the mean and standard deviation is evaluated across the total of 10 repetitions. This ensures that the results for the IB-MtS experiments reflect the variation in build properties when fulfilling different but internally identical batches, and that the descriptive statistics are comparable across the different operations approaches.

Table 4.3: Descriptive statistics for operations approach simulation experiments

Statistic	**Operations Approach**					
	Identical Batch Make-to-Stock		**Capacity Maximising Make-to-Order**		**Lead Time Minimising Make-to-Order**	
	Mean	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
No. of Builds	1.4	0.5	2.0	0.7	3.6	0.9
No. of Breakdowns	0.4	0.5	0.4	0.6	0.4	0.6
No. of Parts Produced	31.0	4.2	24.8	1.3	24.8	1.3
No. of Defective Parts	0.7	0.5	0.6	0.6	0.6	0.6
Build Height (mm)	273.0	7.4	178.9	48.6	87.0	4.0
Full Build Capacity Utilisation	9.9%	0.1%	5.5%	0.3%	2.5%	0.3%
Occupied Cuboid Capacity Utilisation	11.9%	0.2%	8.4%	1.1%	9.5%	1.1%

The effect of the operations approach on the AM workflow and resulting build properties is explored first, referring to Table 4.3. The IB-MtS operations approach results in the fewest number of builds at 1.4 builds per experiment, followed by Capacity Maximising Make-to-Order (CM-MtO) at 2.0 builds per experiment, and lastly Lead Time Minimising Make-to-Order (LTM-MtO) at 3.6 builds per experiment. The standardised batches in IB-MtS also result in higher output than the make-to-order operations approaches, at 31.0 parts per experiment for IB-MtS compared to 24.8 for CM-MtO and LTM-MtO. This is because the make-to-stock approach is agnostic to the incoming demand, and the batch size is set according to the upper limit of the practical build volume capacity, which is 10% full build capacity utilisation. The number of breakdowns and defective parts is consistent across the operations approaches. This is because both are modelled as fixed rates of occurrence: breakdown every 6244 layers and defects every 40 parts, following Baumers and Holweg (2019).

The final three statistics in Table 4.3 characterise the extent to which the available build space is used and how densely parts are packed therein. To aid with visualisation, Figure 4.3 shows the typical configuration of parts in each operations approach: standardised arrangement of parts A and B in IB-MtS, and order-dependent fulfilment in CM-MtO and LTM-MtO. On average, IB-MtS has the tallest builds (build height) with the greatest volume of parts filling the machine capacity (full build capacity utilisation) that are packed most densely (occupied cuboid capacity utilisation). In descending order for each of the three statistics, IB-MtS is followed by CM-MtO and lastly LTM-MtO.

However, given its priority to maximise use of machine space, the full build capacity utilisation in the CM-MtO experiments of 5.5% is lower than expected, especially when compared to the value of 9.9% in IB-MtS. The relatively low mean value arises due to sparse, single-part builds containing rework, i.e. replacements for defective parts, which occur in experiments 1, 4, and 5. Without these extra builds in each experiment, the full build volume utilisation for CM-MtO would be higher on average (7.8%) and more consistent (standard deviation of 0.2%), as seen in Figure 4.4a.

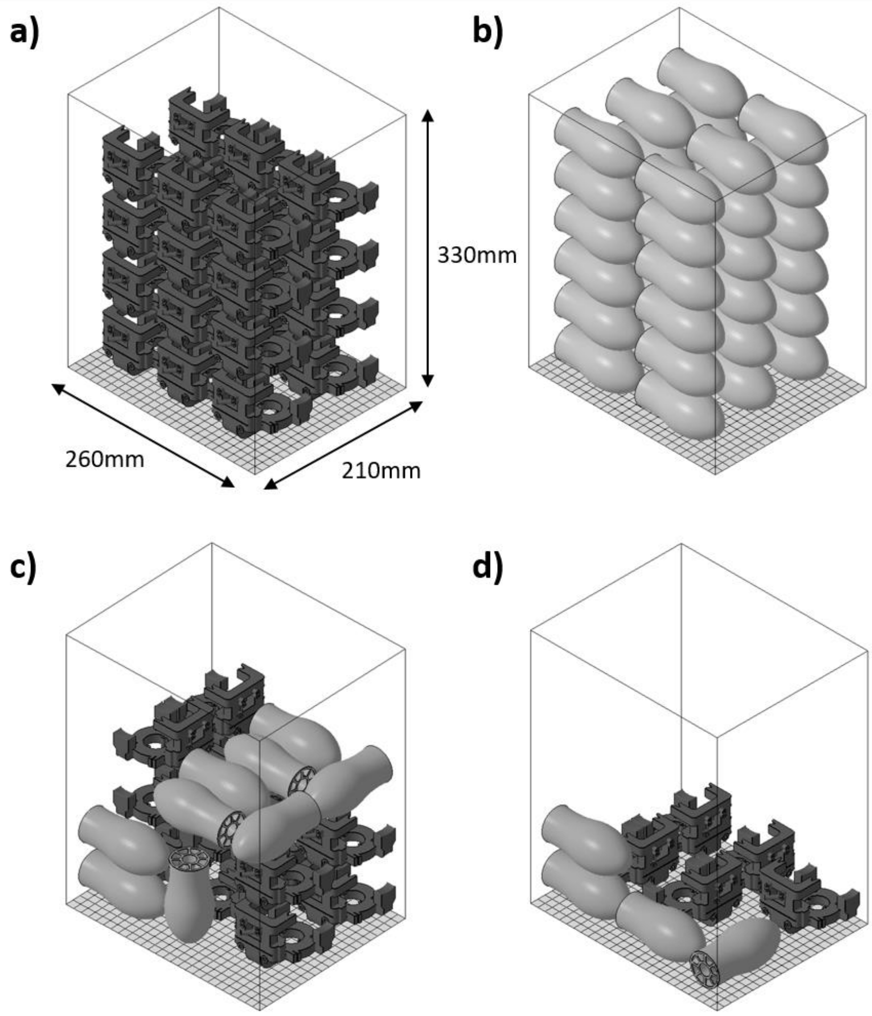


Figure 4.3: Typical packing of parts in builds for a) IB-MtS part A batches, b) IB-MtS part B batches, c) CM-MtO, and d) LTM-MtO operations approaches

The extra builds also affect the occupied cuboid capacity utilisation and build height in the CM-MtO operations approach in a similar manner. Figure 4.4a shows that the typical CM-MtO build, i.e. the mean excluding builds for single-part rework, is 227.2mm tall and packs parts to 11.3% occupied cuboid capacity utilisation. These values are, respectively, 27.0% and 40.6% higher than the average of all builds in the CM-MtO operations approach. Therefore, the gap between the typical CM-MtO build and IB-MtS build closes to 45.8mm in mean build height and 2.1% in mean occupied cuboid capacity utilisation.

In contrast, the other make-to-order operations approach, LTM-MtO, is only marginally affected by the single-part extra builds for rework. Figure 4.4b demonstrates a small increase in the average build height (0.8mm), full build capacity utilisation (0.1%), and occupied cuboid capacity utilisation (0.4%) when these extra builds are excluded. However, the spread in the results as indicated by the standard deviation, falls by up to two-thirds. Figure 4.4 emphasises the difference between the response of the CM-MtO and LTM-MtO operations approaches to the single-part extra builds. This is because the single-part builds are much sparser relative to the typical CM-MtO build than the typical LTM-MtO build, and so there is a greater negative influence on the mean values for the former operations approach.

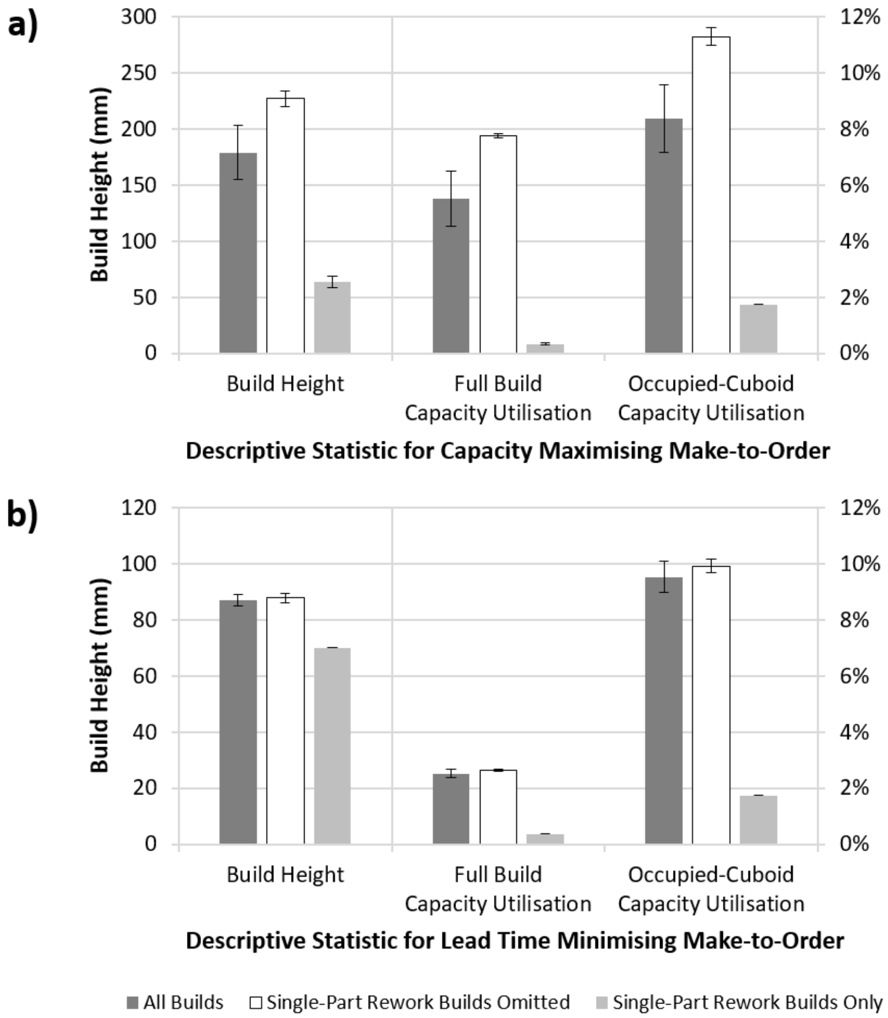


Figure 4.4: Influence of extra single-part builds for rework on build properties for a) CM-MtO and b) LTM-MtO operations approaches

4.3.2 Effect of Operations Approach on Production Losses & OEE

Having explained the influence of the operations approaches on the AM build properties, this section focuses on the consequences for production losses and OEE.

Figure 4.5 illustrates the OEE and constituent metrics (availability, performance, and quality) for the three operations approaches. The IB-MtS operations approach has the highest OEE at 35.1%, followed by the CM-MtO operations approach at 24.5%, and lastly the LTM-MtO operations approach at 16.4%. Therefore, of the three operations approaches investigated, IB-MtS incurs the least production losses. This is equivalent to the most value-adding time as a proportion of the planned production time, as illustrated in Figure 4.6.

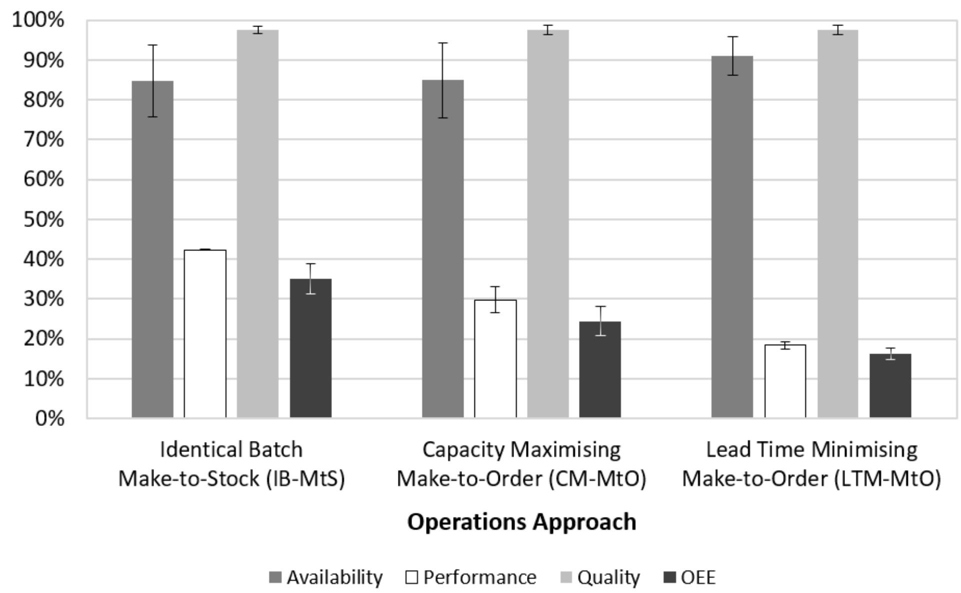


Figure 4.5: Influence of operations approach on OEE and constituent metrics

Nevertheless, these OEE values fall far short of the ideal target of 85% (Nakajima, 1988), and both make-to-order operations approaches result in an OEE below the commonly-accepted range in conventional manufacturing of 30 – 80% (Dal, Tugwell and Greatbanks, 2000). Therefore, the constituent metrics, alongside the itemisation of planned production time in the simulation experiments in Figure 4.6, can be used to probe the contributors to production losses in the AM workflow for each operations approach.

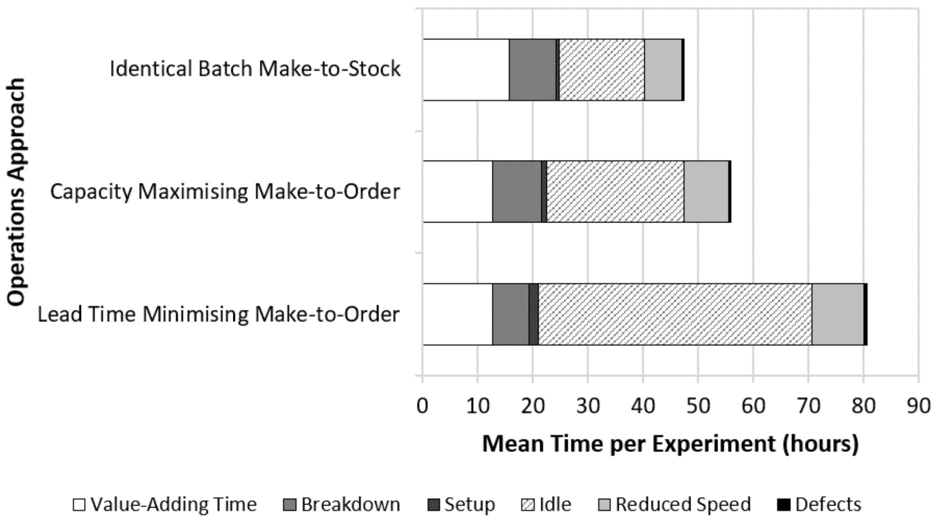


Figure 4.6: Itemisation of planned production time for each operations approach

Contrary to expectations, Figure 4.5 shows that the availability of machines is highest for the LTM-MtO operations approach, at 91.0% compared to 84.9% for CM-MtO and 84.7% for IB-MtS. The setup losses arise as a fixed time per build and so are highest in LTM-MtO, corresponding to the larger number of builds required to fulfil production. However, Figure 4.6 shows that breakdown is a far more significant availability loss: almost four times more time is lost to breakdown than setup in the LTM-MtO operations approach, and this increases to a 12-fold difference for IB-MtS.

Even though the equipment breakdown rate is constant, the operations approach influences the magnitude of the breakdown losses. More time is lost to breakdown in the CM-MtO and IB-MtS operations approaches than in LTM-MtO (9.0, 8.4, and 6.6 hours, respectively). The reason for this is build height. Given that the build time up to the failed layer (along with the fixed time taken to setup the failed build and clean the machine afterwards) becomes waste, a taller failed build incurs a larger breakdown loss. The mean height of failed builds is 78.0mm for IB-MtS and 105.5mm in CM-MtO, compared to 8.5mm tall in LTM-MtO. Comparing the two make-to-order operations approaches, the 93mm difference in mean build-height-at-failure translates to a 36.2% increase in time lost to breakdown.

Bringing these together, Figure 4.7 illustrates the trade-off between the breakdown and setup losses, depending on the build height and number of builds across the operations approaches. Given that the breakdown losses for taller builds far outweigh the setup losses for each new build, the results suggest that a larger number of shorter builds should be favoured over fewer, taller builds to maximise the availability metric. LTM-MtO is therefore the best operations approaches option for machine uptime and availability.

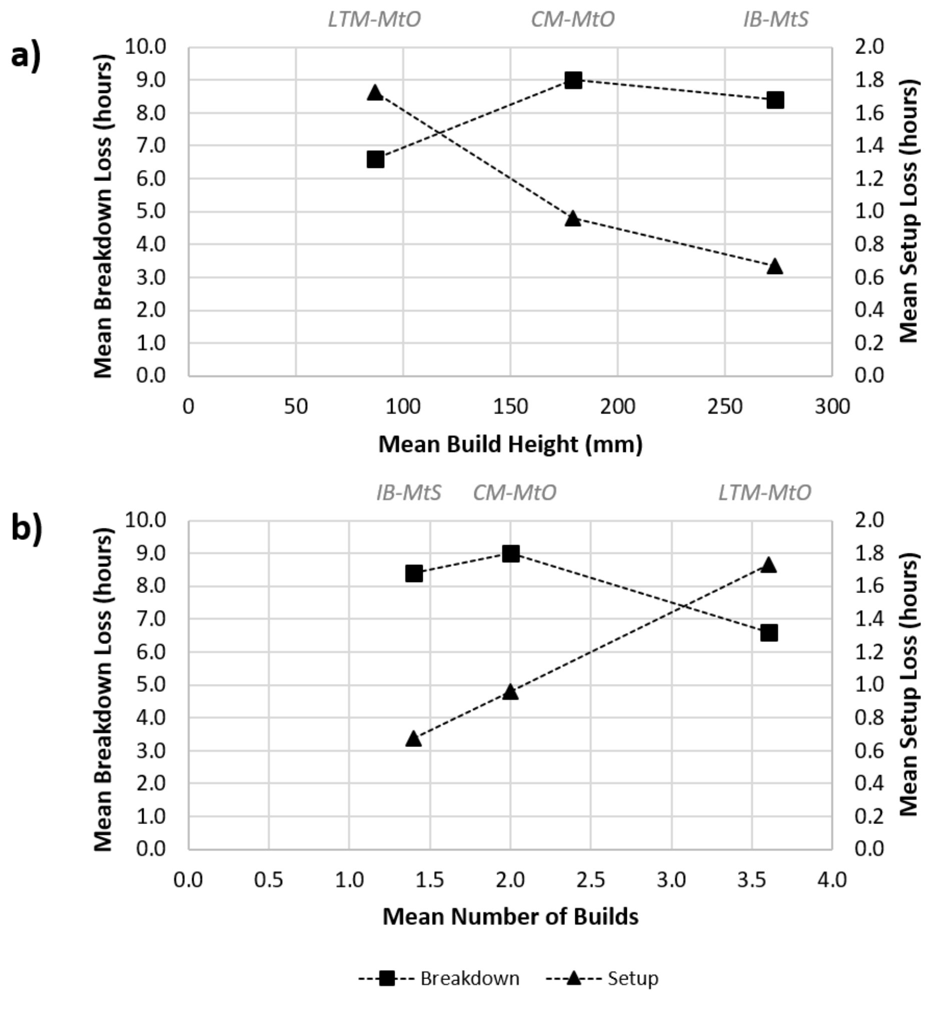


Figure 4.7: Trade-off in availability losses across operations approaches, according to a) build height and b) number of builds, per repetition

Shifting to the next metric, Figure 4.5 shows that the performance of machines is highest for the IB-MtS operations approach at 42.4%, followed by CM-MtO at 29.8% and LTM-MtO at 18.4%. Furthermore, Figure 4.6 shows that idle time is the largest production loss of all five investigated for all three operations approaches. This loss occupies 33% of the total planned production time for IB-MtS, and this fraction rises to 44% for CM-MtO and 62% for LTM-MtO. The idle losses also outweigh the reduced speed losses in terms of impact on the performance metric. The magnitude of this difference is largest for the LTM-MtO operations approach, at just over five-fold. Therefore, the performance losses are driven by machine idle time.

The source of idle losses is the fixed time for automated machine checks, build chamber warm up and build container cool down that accompany each build in the polymer laser sintering machine. For each build, there is 3.5 hours of automatic machine checks and warm up, and 12 hours of cool down. Therefore, the operations approach influences the idle time through the number of builds required to fulfil production. As noted in Table 4.3, the IB-MtS has the fewest number of builds per experiment and, correspondingly, the lowest idle losses.

The balance between idle time and productive time in each build is important for the performance metric, and this is affected by how full each build is. The linear trend line in Figure 4.8 demonstrates a clear link between the full build capacity utilisation of each build and the idle loss incurred as a fraction of the actual production time therein. As the full build capacity utilisation increases, the fixed per-build idle time is amortised over a larger volume of output in the build. Of the operations approaches, the CM-MtO and IB-MtS builds (denoted by diagonal crosses and diamond markers, respectively, in Figure 4.8) have the highest full build capacity utilisation. Therefore, the AM machine is running for a larger fraction of the actual production time in these experiments, and the rate of output is closer to the theoretical processing rate, which improves the performance metric. It is worth noting that the single-part extra builds for rework, found in CM-MtO and LTM-MtO operations approaches, have the highest fraction of idle time at 78-82% of the actual production time; and so the AM machine is operating most inefficiently from a performance perspective here.

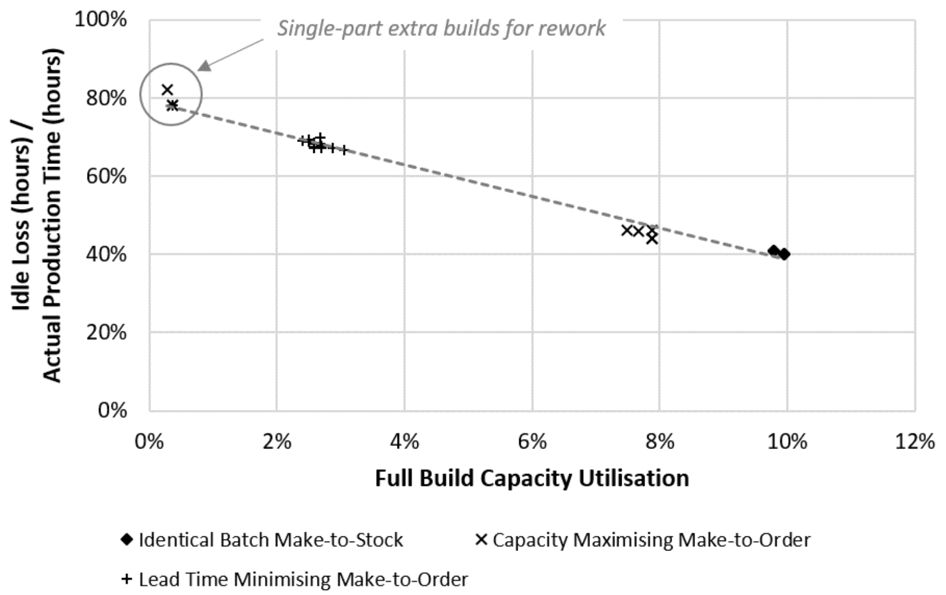


Figure 4.8: Influence of filling the build capacity on the idle time as a fraction of the actual production time for each build

The second contributor to the performance metric is the reduced speed losses. The time lost here is calculated as the difference between the experimental build time and the minimum build time if the equipment were operating at the theoretical volumetric build rate. Figure 4.9 shows that the reduced speed losses in each build are influenced by the packing of parts therein. In Figure 4.9a, there is a positive correlation between the build height and the reduced speed loss within each operations approach. This suggests that layer-wise losses accumulate as the build is packed with more parts and becomes taller. However, when the reduced speed loss per cubic volume of output is considered, the negative effect of the taller, fuller builds is reversed. Figure 4.9b shows an amortisation effect across all builds that is similar to the idle losses, but weaker in correlation. Lastly, Figure 4.9c depicts a negative correlation between the occupied cuboid capacity utilisation and reduced speed losses within each operations approach. This indicates that the denser the packing, the higher the processing rate relative to the theoretical ideal.

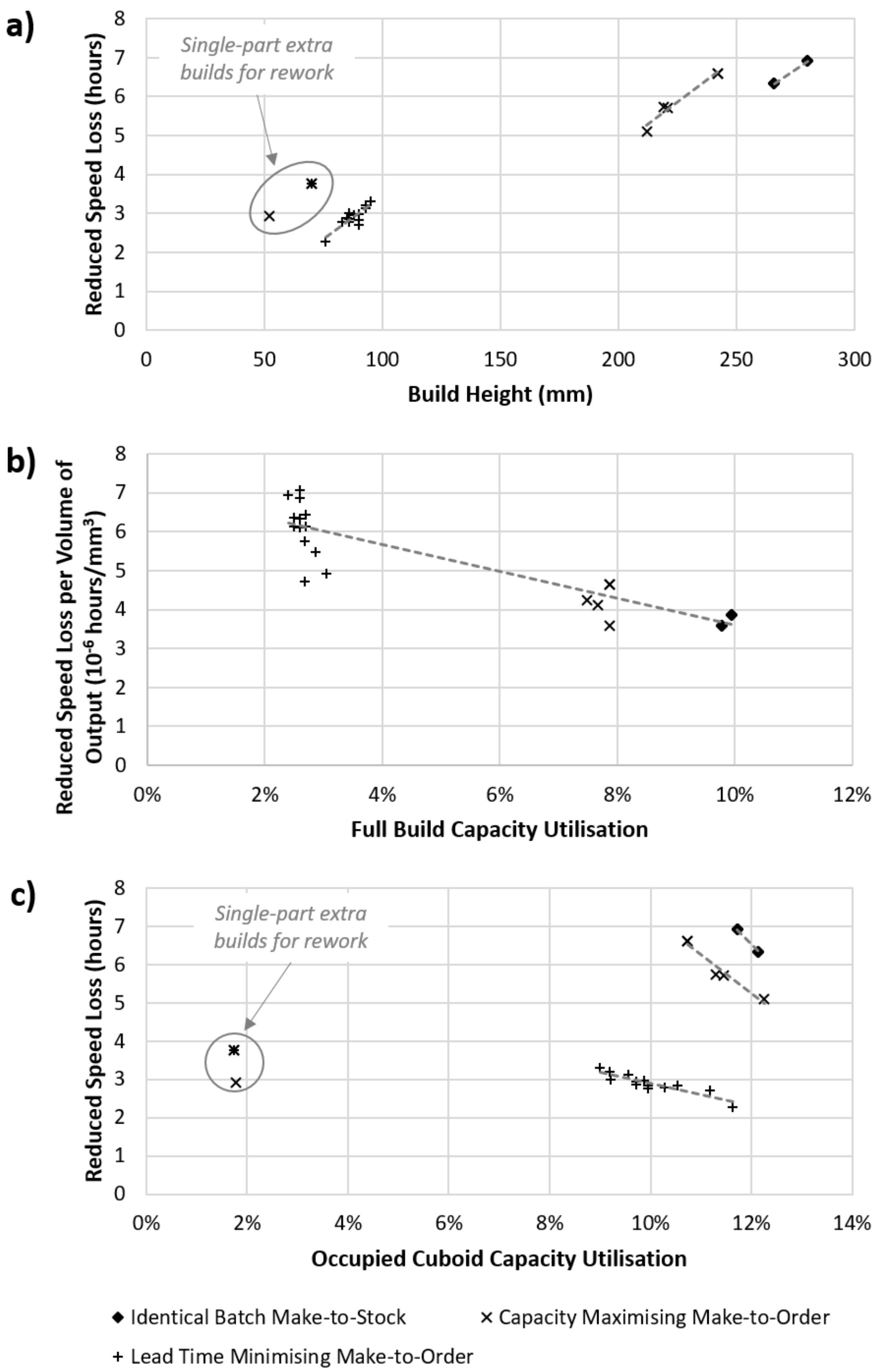


Figure 4.9: Relationship between reduced speed losses and a) build height, b) full build capacity utilisation, and c) occupied cuboid capacity utilisation

The operations approaches influence the reduced speed losses through the build properties achieved. Figure 4.9a and Figure 4.9c demonstrate that IB-MtS and CM-MtO result in higher reduced speed losses per build than LTM-MtO. On the other hand, as the output per build is correspondingly higher, the losses per unit of output are up to 49% lower in both IB-MtS and CM-MtO relative to LTM-MtO, as seen in Figure 4.9b. Therefore, the taller and fuller builds in IB-MtS and CM-MtO are beneficial for reduced speed losses.

Overall, performance losses can be reduced by packing a larger volume of parts in fewer builds in a space-efficient manner, such that the full build capacity utilisation and occupied cuboid capacity utilisation are both maximised. Figure 4.10 shows that the IB-MtS operations approach achieves this most effectively, and so is the best option for minimising idle and reduced speed losses per unit volume of output. This corresponds to the highest performance metric (see Figure 4.5).

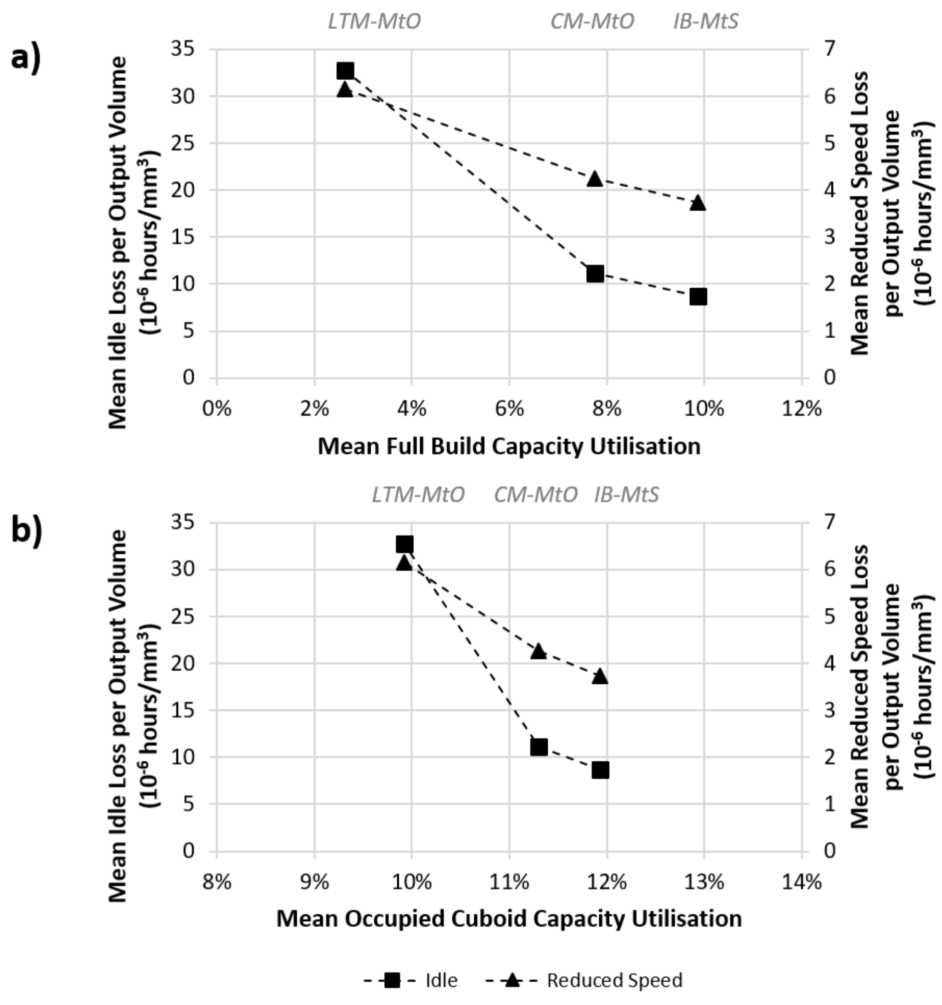


Figure 4.10: Performance losses across operations approaches, according to a) full build and b) occupied cuboid capacity utilisation, per repetition

The third metric to consider is quality. In this study, only the losses due to defects are considered, as the thermal conditions that lead to start-up yield losses are not modelled. Figure 4.5 shows that the quality metric is near identical across the operations approaches, at 97.7% for IB-MtS and 97.5% for both CM-MtO and LTM-MtO. Defective parts appear at a constant rate of one every 40 parts, and so identical values for quality would be expected across the operations approaches. However, the slight discrepancy between IB-MtS and the make-to-order operations approaches arises because of the total quantity of parts produced. Given that 15 parts are produced since the last defect in IB-MtS, versus 4 parts in both CM-MtO and LTM-MtO, the proportion of good output to defective output is slightly higher in IB-MtS. Nevertheless, relatively little time is lost to defects, as seen in Figure 4.6. On average, a loss of 0.5 hours per experiment is incurred, which is just 1% of the total production losses. Therefore, while the defect rate in this study is equivalent to 3.5 sigma, the availability and performance losses far outweigh the quality losses.

Two final observations are noted to close this section, which relate the spread in the OEE metrics. The error bars in Figure 4.5 show the standard deviation for the availability, performance, quality, and overall OEE. In particular, the availability metric has a high standard deviation across the operations approaches, from 5.3% of the mean in LTM-MtO up to 11.0% of the mean in CM-MtO. This arises from the effect of breakdown losses on the total downtime. Across all operations approaches, the mean downtime in experiments where there are no build failures is 0.8 hours (over 12 experiments); whereas the occurrence of build failures increases the downtime by 27-fold to 21.6 hours (over 8 experiments). This difference rises to 38-fold for IB-MtS and CM-MtO, because both the breakdown losses are higher and setup losses lower in these operations approaches. Therefore, the consistency in equipment uptime is poorer for the IB-MtS and CM-MtO operations approaches, relative to the LTM-MtO operations approach.

Similarly, the standard deviation of the performance metric is relatively high for the make-to-order operations, at 11.1% of the mean for CM-MtO and 5.4% for

LTM-MtO, compared to 0.2% of the mean in IB-MtS. Figure 4.11 demonstrates that the single-part extra builds for rework, mentioned in the previous section, are the reason behind the large spread in the make-to-order performance. The addition of a build to the workflow incurs a fixed idle time loss during the machine checks, warm up and cool down. Also, Figure 4.9a and Figure 4.9c illustrate that the single-part build incurs 22.0% higher reduced speed loss to the typical LTM-MtO build despite containing one eighth of the output, thanks to sparse packing relative to the build height. Therefore performance-related losses are higher in the repetitions with single-part extra builds for rework, which reduces the mean and increases the spread in the performance metric.

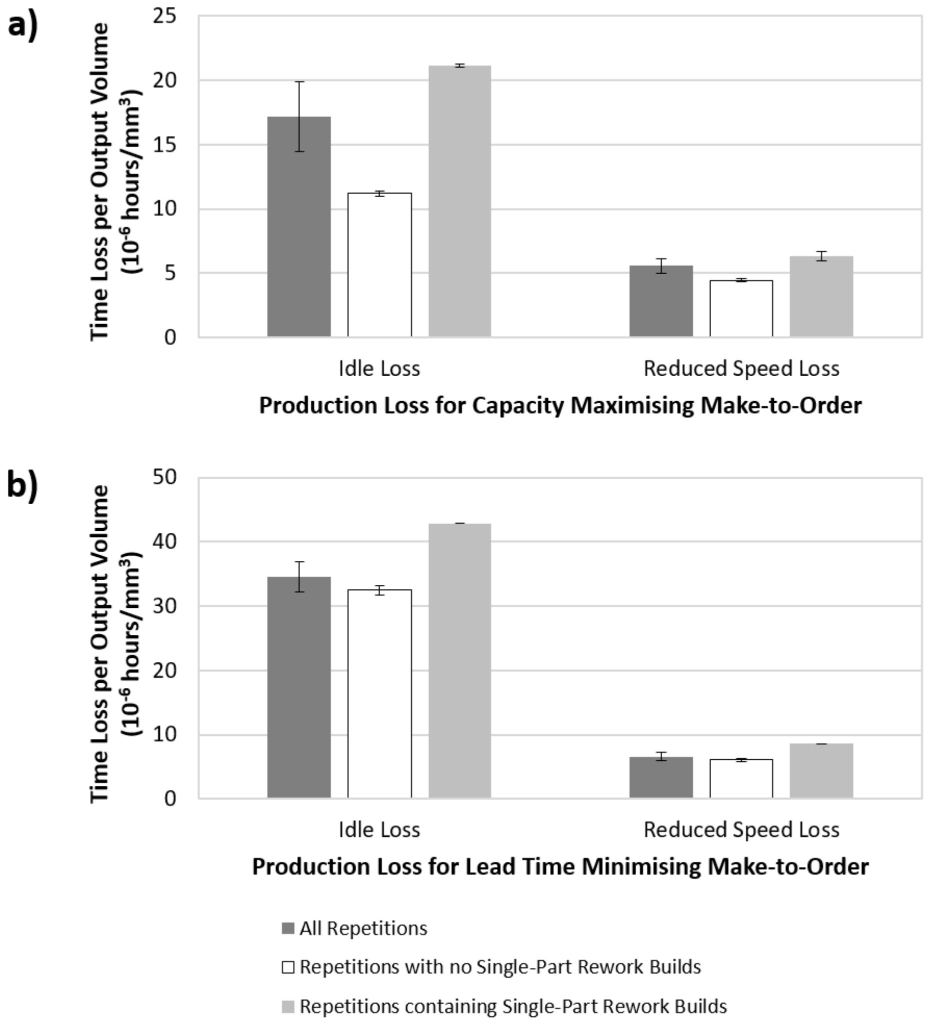


Figure 4.11: Influence of extra single-part builds for rework on performance-related losses for a) CM-MtO and b) LTM-MtO operations approaches

4.4 Sensitivity of OEE to External Factors

This section presents the results for the second exploratory simulation, which investigates the effect of two external factors on the OEE of the AM machine for polymer laser sintering. The two external factors are delivery lead time and variety in the size of parts being packed. The third variable in these experiments is the Allowable Build Height (ABH), which represents the two make-to-order operations approaches, LTM-MtO (ABH = 100mm) and CM-MtO (ABH = 330mm).

The three variables and their interactions are covered by 16 experiments in a face-centred central composite design DOE configuration, as explained in Section 3.4.2.4. Table 4.4 and Table 4.5 show the experiment factor levels, alongside the mean and standard deviation of the build properties and output across five repetitions for each experiment. Alongside this, Figure 4.12 shows the availability, performance, and quality metrics for each experiment. Together, this overview of the experiment outputs confirm that the properties such as build height, full build capacity utilisation and occupied cuboid capacity utilisation vary (in both average and spread) with changes in the operations approaches and the external factors, influencing the operational efficiency of the AM machine.

To explore these relationships systematically, the linear and quadratic main effects of each variable on the OEE and their two-way interactions are modelled at the 10% statistical significance level, as shown in Figure 4.13. The main effects and interactions, respectively, identify the independent and combined influence of each variable on the OEE. The linear main effect terms for ABH and Lead Time (LT) are both statistically significant, alongside the quadratic main effect terms for ABH and Part Size Variety (PSV). The only statistically significant interaction is between ABH (representing the operations approach) and LT. Model hierarchy is also observed. Consequently, the linear term for PSV is kept, even though only the quadratic term is statistically significant.

Table 4.4: Descriptive statistics for external factors simulation experiments (for experiments 1-8)

Factor / *Statistic*	**Experiment**															
	1		**2**		**3**		**4**		**5**		**6**		**7**		**8**	
	Mean	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
Allowable Build Height (mm)	215	-	215	-	100	-	330	-	100	-	330	-	100	-	330	-
Lead Time (hours)	72	-	72	-	48	-	48	-	96	-	96	-	48	-	48	-
Part Size Variety	50	-	50	-	0	-	0	-	0	-	0	-	100	-	100	-
No. of Builds	2.8	0.8	2.8	0.8	2.6	0.5	1.6	0.5	4.8	0.8	2.2	0.8	2.4	0.5	1.6	0.5
No. of Breakdowns	0.4	0.5	0.4	0.5	0.2	0.4	0.2	0.4	0.6	0.5	0.4	0.5	0.2	0.4	0.2	0.4
No. of Parts Produced	43.4	2.2	43.4	2.2	16.6	0.5	16.6	0.5	33.0	1.2	33.0	1.2	16.6	0.5	16.6	0.5
No. of Defective Parts	1.0	0	1.0	0	0.4	0.5	0.4	0.5	0.8	0.4	0.8	0.4	0.4	0.5	0.4	0.5
Build Height (mm)	123.9	16.5	124.7	14.4	83.3	7.5	134.3	24.6	86.4	5.4	188.1	61.7	86.2	4.3	142.7	29.4
Full Build Capacity Utilisation	3.5%	0.7%	3.5%	0.8%	2.3%	0.4%	4.2%	1.4%	2.5%	0.2%	6.2%	2.0%	2.5%	0.4%	4.3%	1.4%
Occupied Cuboid Capacity Utilisation	8.3%	1.6%	8.5%	1.6%	8.8%	1.4%	9.4%	2.8%	9.6%	0.6%	9.1%	1.1%	9.5%	1.4%	8.8%	2.5%

Table 4.5: Descriptive statistics for external factors simulation experiments (for experiments 9-16)

Factor / *Statistic*	**Experiment**															
	9		**10**		**11**		**12**		**13**		**14**		**15**		**16**	
	Mean	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
Allowable Build Height (mm)	100	-	330	-	100	-	330	-	215	-	215	-	215	-	215	-
Lead Time (hours)	96	-	96	-	72	-	72	-	48	-	96	-	72	-	72	-
Part Size Variety	100	-	100	-	50	-	50	-	50	-	50	-	0	-	100	-
No. of Builds	4.6	0.5	2.4	0.9	4.0	0.7	2.4	0.5	1.8	0.4	3.0	0.7	2.4	1.1	2.0	0.7
No. of Breakdowns	0.4	0.5	0.6	0.5	0.4	0.5	0.4	0.5	0.2	0.4	0.6	0.5	0.4	0.5	0.4	0.5
No. of Parts Produced	33.0	1.2	33.0	1.2	43.4	2.2	42.6	3.6	29.0	1.6	57.8	1.9	24.8	1.3	24.8	1.3
No. of Defective Parts	0.8	0.4	0.8	0.4	1.0	0	1.0	0	0.6	0.5	1.4	0.5	0.6	0.5	0.6	0.5
Build Height (mm)	84.4	3.0	199.2	51.7	84.9	7.7	142.2	7.5	131.7	24.9	150.1	15.1	148.9	38.8	167.6	41.7
Full Build Capacity Utilisation	2.5%	0.2%	6.3%	2.0%	2.3%	0.4%	3.9%	0.3%	3.7%	1.3%	4.6%	0.9%	4.5%	1.8%	5.5%	2.0%
Occupied Cuboid Capacity Utilisation	9.9%	0.9%	8.5%	1.6%	8.5%	1.0%	6.3%	0.5%	8.1%	2.5%	9.3%	1.7%	8.7%	2.1%	10.1%	2.1%

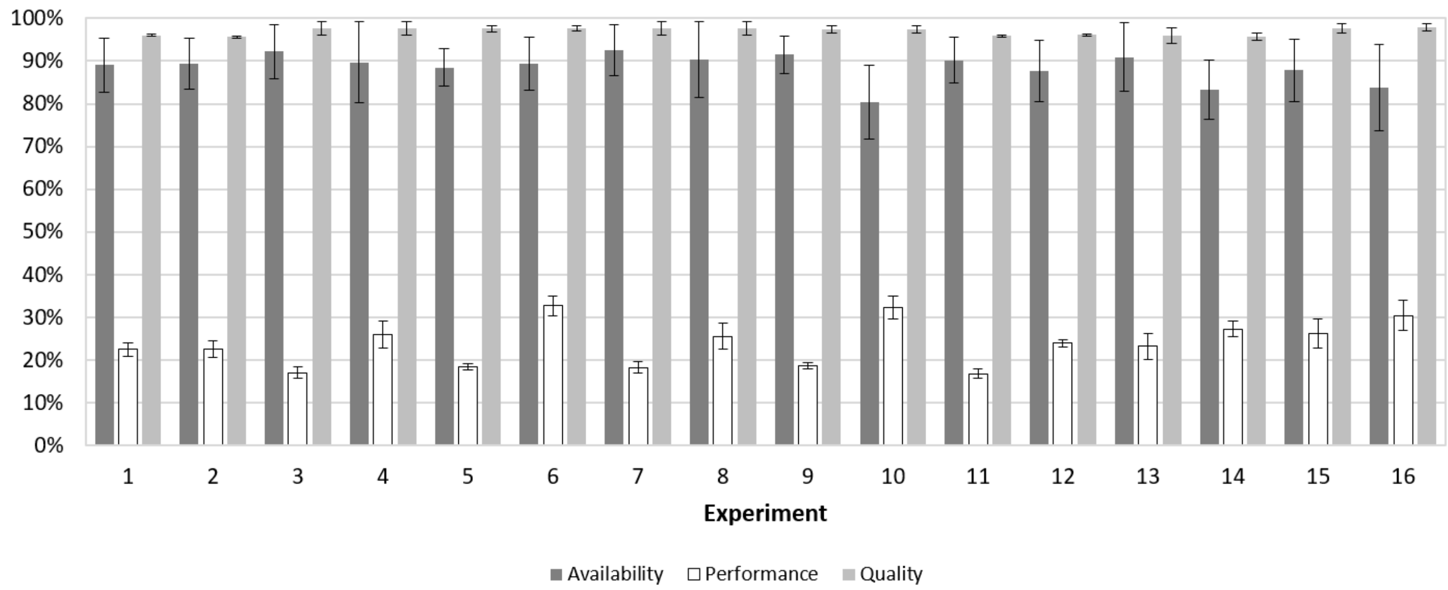
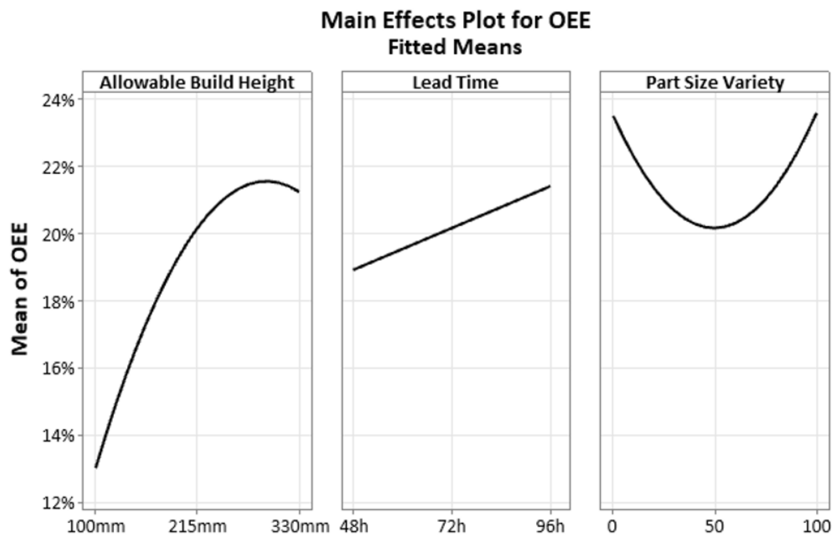


Figure 4.12: Availability, performance and quality metrics for external factors simulation experiments

a)



b)

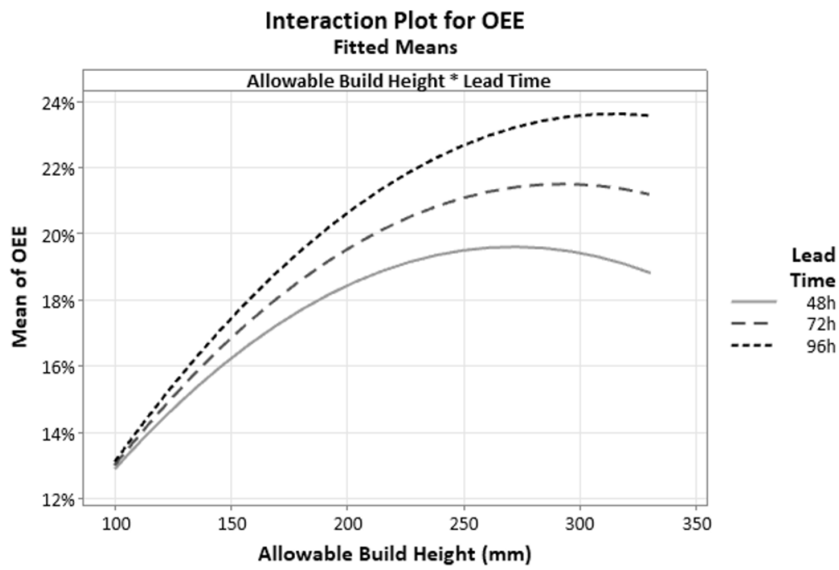


Figure 4.13: Sensitivity of OEE to a) allowable build height and external factors, and b) statistically significant two-way interactions

Analysing each variable in turn, the left panel in Figure 4.13a shows that increasing the ABH improves the OEE by allowing more parts to be packed within each build. The curve spans 8.2 percentage points, which is nearly equal to the difference between the OEE achieved by the CM-MtO and LTM-MtO operations approaches in the previous section (at 8.1 percentage points). Therefore, the main effect of the two make-to-order operations approaches on the OEE is consistent between both sets of exploratory simulations. Additionally, a maximum point can be seen in the main effects curve, at approximately ABH = 295mm in the model. This reflects the trade-off between availability and performance losses as the build height and full build capacity utilisation increase between LTM-MtO and CM-MtO, as explained in Section 4.3.2.

The middle panel in Figure 4.13a shows that the OEE improves linearly by 2.5 percentage points upon increasing the lead time from 48 hours to 96 hours. This change is driven by the amortisation of performance losses over the output, a phenomenon that was also seen in Section 4.3.2. One practical implication of extending the order lead time, and expanding the capacity of the buffer order book, is that the volume of parts available to pack in each build of the simulation experiments also increases. As a result, the volume of parts deposited per build increases in line with the lead time, by 16.3% on average for every 24 hours.

However, it should be noted that the volume of parts deposited per build can only increase up to the limit of the build capacity utilisation. In the experiments where ABH = 100mm (equivalent to LTM-MtO), the builds can only accommodate 24 hours' worth of orders. Therefore, the mean volume of parts available in the order book increases at a similar rate to the number of builds required to fulfil them. For example, averaging experiments at LT = 48 hours and LT = 96 hours, 82.6% more builds deliver 97.5% more output in volume; this equates to 7.9% more volume deposited per build. In contrast, experiments at ABH = 330mm see 53.4% more volume deposited per build for the corresponding increase in the lead time (28.6% more builds are required for 97.5% more output volume). This interaction between the ABH and LT in influencing the OEE is succinctly captured in Figure 4.13b. The non-parallel curves show that the positive effect of the lead time on the OEE increases as the ABH increases. The OEE curves for lead time converge at ABH = 100mm, whereas doubling the lead time at ABH = 330mm improves the OEE by 4.6 percentage points. Therefore, it is important to control the operations approach and lead time in tandem to improve use of the available machine capacity.

The right panel in Figure 4.13a illustrates a quadratic relationship between the PSV and OEE. Switching from no size variety (PSV = 0) to a mix of 50% volume and 100% volume parts (PSV = 50) leads to a fall of 3.2 percentage points in the OEE. Upon introducing larger, 150% volume parts to the mix (PSV = 100), the OEE recovers to the same value as for PSV = 0. This change in the OEE is driven by the density of part packing that is achievable with the different sized parts. In experiments at PSV = 0 and PSV = 100, the occupied cuboid capacity utilisation is 8.7% and 8.9% on average, respectively. However, for PSV = 50, this value falls to 7.9%. As a result, reduced speed losses are 8.4% higher when PSV= 50, versus PSV = 0; and so the performance metric is negatively affected. Contrary to expectations, the part dimensions are such that the packing density improves upon introducing more size variety in the experiments at PSV = 100, as shown in Figure 4.14. While it is not known what the mathematical nature of the relationship between PSV and OEE would be outside the range in part size variety investigated, the underlying drivers for performance losses and OEE still apply. Therefore, the performance and OEE are sensitive to the variety in part size due to its impact on the occupied cuboid capacity utilisation.

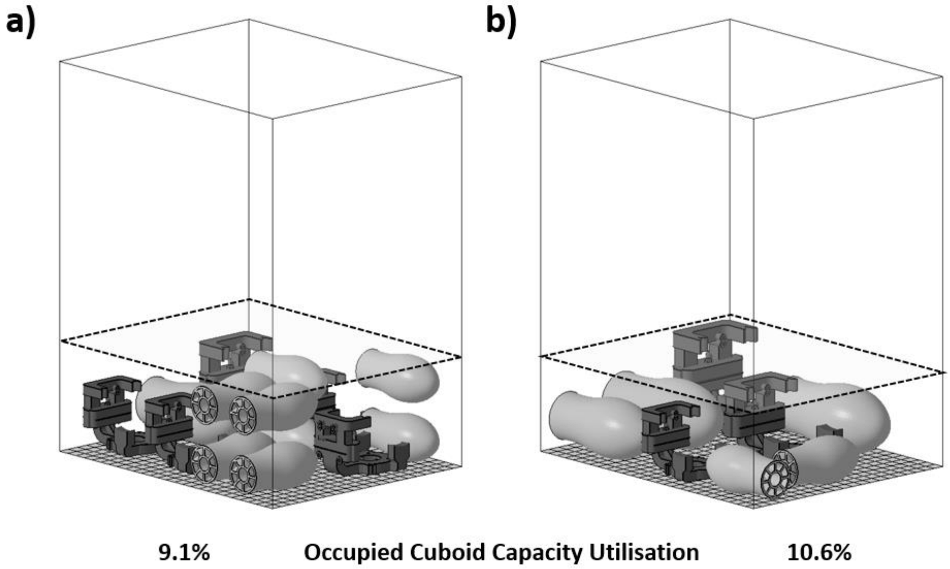


Figure 4.14: Demonstration of part packing for experiments at a) PSV = 50 and b) PSV = 100, with respective values for occupied cuboid capacity utilisation

In addition to the main effects and interactions, ANOVA is used to compare the influence of the operations approach and external factors on the OEE. Table 4.6 shows the model degrees of freedom (DF), adjusted sum of squares (Adj. SS), adjusted mean squares (Adj. MS), F-value, P-value and percentage contribution of the repetition order (blocks), model terms that are statistically significant or otherwise kept for model hierarchy, and the residual error. The percentage contribution is calculated by dividing the adjusted sum of squares for each term by the total sum of squares; this summary metric therefore indicates the relative contribution of each term to the variance in the OEE.

Taking the linear and quadratic main effects together, the lead time influences the OEE the least, as only 2% of the variance can be attributed to the LT variable. This is followed by the part size variety at 5% contribution to the variance. The blocks in the observations, i.e. the correlation between the experiment repetition number and the OEE, contribute to 25% of the variance. This occurs because breakdowns and part defects occur at a constant rate, systematically affecting repetitions 2, 4, and 5 more than repetitions 1 and 3. More importantly, Table 4.6 shows that the operations approach dominates the change in OEE. The proxy variable of allowable build height contributes 30% of the variance. Therefore, efforts to improve the OEE should be focused on the operations approach, while the lead time interaction and part size variety offer moderate extra control during process planning.

Table 4.6: ANOVA for model assessing OEE sensitivity to external factors

Model Term	**DF**	**Adj. SS**	**Adj. MS**	**F-Value**	**P-Value**	**% Contribution**
Blocks	4	0.081	0.020	10.93	0.000	25%
Allowable Build Height (ABH)	1	0.084	0.084	45.62	0.000	26%
Lead Time (LT)	1	0.008	0.008	4.18	0.045	2%
Part Size Variety (PSV)	1	0.000	0.000	0	0.944	0%
ABH × ABH	1	0.013	0.013	7.28	0.009	4%
PSV × PSV	1	0.017	0.017	9.07	0.004	5%
Interaction: ABH, LT	1	0.005	0.005	2.83	0.097	2%
Error	69	0.128	0.002	-	-	-
Total	79	0.326				

5 Results on Workflow Optimisation in AM

5.1 Overview

This chapter presents the results of research towards the second research objective, to evaluate the effect of process planning on the total cost of make-to-order fulfilment using scaled-up AM production.

Similar to the previous chapter (Sections 4.3 and 4.4), this research objective is addressed via an exploratory simulation study. Each simulation experiment follows a particular approach for optimising the packing and scheduling steps within the process planning stage (referred to as “workflow optimisation”). The total cost model developed in this research (Section 3.5.1) is used to quantify the cost-effectiveness of each workflow optimisation approach over the AM production line within a single manufacturing facility. The development of the workflow optimisation approaches and exploratory simulation models are explained in Section 3.5.2. In particular, the suggested unique advantages associated with the integrated workflow optimisation approach will be quantitatively tested in this exploratory simulation study.

The remainder of this chapter is organised as follows. First, Section 5.2 explains the influence of each workflow optimisation approach on the properties of the packed and scheduled AM builds. Section 5.3 then investigates the consequent impact on the production cost. Finally, the trade-off between the dominant cost drivers and impact of the integrated workflow optimisation approach are examined in Sections 5.4 and 5.5.

5.2 Effect of Workflow Optimisation Approach on AM Build Properties

In the exploratory simulation study, the order fulfilment experiments are repeated 10 times for each of the five workflow optimisation approaches, resulting in a total of 460 simulated builds. Summarising the output, Table 5.1 shows the mean and standard deviation of the production and build properties.

The same 10 sets of input orders are used in the repetitions for each workflow optimisation approach, and so each statistic is averaged over the same production volume of 6054 parts split across five different geometries.

The descriptive statistics for the number of builds per experiment and number of parts per build show that there are two distinct patterns for the conversion of the incoming order stream into sets of build jobs. First, the Manual and Packing Only approaches compress production into fewer builds with a higher quantity of parts per build, at eight builds containing 75-76 parts on average. In contrast, applying the scheduling constraint in the remaining three workflow optimisation approaches means that parts are spread over 10 builds with 60.5 parts each on average. However, it should be noted that the number of parts per build is relatively inconsistent in the approaches A-C (Manual, Packing Only, Scheduling Only) as shown by the standard deviation, which is approximately half of the mean value in magnitude. Given that the number of parts per build directly relates to the full build capacity utilisation, the above patterns in the average and spread of values are also seen in the latter statistic.

Shifting attention to the packing-related build properties, the mean build height shows that the average build is at least three-quarters full in the Z dimension, across the workflow optimisation approaches. The operator-controlled Manual approach has the highest mean build height, reflecting the objective to entirely fill each build volume before starting a new build job. On the other hand, in the Scheduling Only approach, the parts are allocated to build jobs strictly on the basis of the due date, resulting in shorter and sparser builds on average, and the largest spread in build height. More generally, approaches A-C generate an inconsistent mix of short and tall builds in fulfilling the production orders, indicated by the build height standard deviation which is greater than one fifth of the mean. The approaches that optimise both packing and scheduling (either separately, D, or in an integrated manner, E), result in consistent builds with moderate build height relative to the alternative approaches.

Table 5.1: Descriptive statistics for workflow optimisation simulation experiments

Statistic	**Workflow Optimisation Approach**									
	Manual (A)		**Packing Only (B)**		**Scheduling Only (C)**		**Packing and Scheduling, Separate (D)**		**Packing and Scheduling, Integrated (E)**	
	Mean	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
No. of Builds	8	0.7	8	0	10	0	10	0	10	0
No. of Parts per Build	76.0	38.5	75.6	35.7	60.5	26.9	60.5	6.9	60.5	5.7
No. of Late Parts	150.5	44.3	121.8	36.6	0	0	0	0	0	0
No. of Builds containing Late Parts	5.6	0.7	5.6	0.8	0	0	0	0	0	0
Build Height (mm)	295.3	60.4	288.7	64.7	245.4	78.8	262.6	21.8	259.3	18.6
Full Build Capacity Utilisation	15.4%	8.7%	15.3%	7.9%	12.3%	5.5%	12.3%	1.5%	12.3%	1.2%
Occupied Cuboid Capacity Utilisation	16.9%	8.9%	17.4%	7.8%	16.4%	5.6%	15.4%	1.1%	15.6%	1.1%

The occupied cuboid capacity utilisation also describes the density of parts packing within each build volume. The Packing Only approach achieves the densest part packing, followed by the operator-controlled Manual and Schedule Only approaches, and finally the two approaches optimising both Packing and Scheduling. While a high occupied cuboid capacity utilisation is expected in the software-controlled Packing Only approach, this contrasts to the lowest values for approaches D and E, which are also software-controlled. Together with difference in occupied cuboid capacity utilisation of up to one percentage point between approach C (operator-controlled) and approaches D and E (software-controlled), this suggests that the packing software used in the study cannot pack dissimilar geometries as space-efficiently as an operator.

Finally, Table 5.1 shows how each workflow optimisation approach performs with respect to schedule attainment. Only approaches A and B result in late parts, which occurs because the scheduling constraint is neglected when allocating parts to build jobs. There are 23.5% more late parts in total via the Manual approach than the Packing Only approach, while the number of builds containing late parts is equal. Therefore, there is a greater concentration of late parts in individual builds in the Manual approach, which is more detrimental from a cost penalty perspective. Nevertheless, the obvious note must be made that timely delivery is desirable, if not essential, and so approaches C-E are effective in this regard.

5.3 Effect of Workflow Optimisation Approach on Production Cost

5.3.1 Effect of Workflow Optimisation Approach on Overall Specific Cost of Production

Having examined the impact of the workflow optimisation approach on the production output, build properties and timeliness of delivery, this section focuses on the consequences for production cost. The specific cost of production, units GBP/cm^3, is used throughout the results to eliminate the influence of part size on the cost results.

Figure 5.1 shows the mean specific production cost for the five workflow optimisation approaches. The Manual approach is the most expensive at 0.97 GBP/cm^3, followed by Packing Only at 0.82 GBP/cm^3 and Scheduling Only at 0.56 GBP/cm^3. Of the approaches that optimise both packing and scheduling, approach D is slightly more expensive at 0.54 GBP/cm^3, and the cheapest option is approach E at 0.53 GBP/cm^3. The Packing and Scheduling, Integrated approach delivers a saving of 46% against the Manual approach, on average.

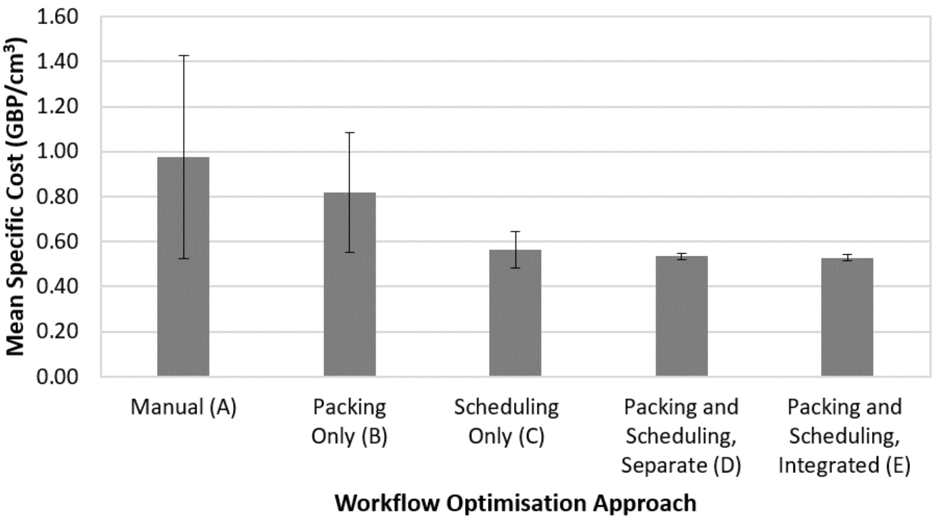


Figure 5.1: Influence of workflow optimisation approach on production cost

The workflow optimisation approach also has a notable effect on the spread in the production cost, as indicated by the error bars in Figure 5.1, which span one standard deviation. The most cost-effective workflow optimisation approaches are also the most consistent in cost. In the Packing and Scheduling, Separate and Packing and Scheduling, Integrated approaches, the magnitude of the standard deviation is less than 5% of the mean. On the other hand, this fraction increases to 32.4% for the Packing Only approach and 46.5% for the Manual approach. In these workflow optimisation approaches, the cost-effectiveness of production is unpredictable from build to build; and referring back to Table 5.1, this large spread is linked to the inconsistency in the build properties during order fulfilment. Therefore, the workflow optimisation approaches that consider both packing and scheduling constraints lead to the most consistent build setups and, concurrently, production cost.

The workflow optimisation approaches also indicate the relative impact of packing optimisation versus scheduling optimisation. Figure 5.1 shows that, relative to the constraint-free Manual approach, the mean production cost is 42.2% lower when using the Scheduling Only approach as compared to just 15.5% lower when using the Packing Only approach. Thus, adhering to scheduling requirements, albeit with operator-controlled packing, results in an almost three-fold increase in the cost saving than relying on software-controlled packing alone. This emphasises the important contribution of the scheduling constraint during process planning, enabling timely delivery and by extension more cost-effective production. However, the labour time in manually packing parts for approaches A and B versus setting up the computer-controlled packing software in approaches C, D, and E is not measured in this study. It is likely that computer-controlled packing would incur lower labour content than manual packing; this would increase the gap in production cost between approaches A and B whilst simultaneously decreasing the gap between approaches B and C.

5.3.2 Effect of Workflow Optimisation Approach on the Cost Model Components

Splitting the specific production cost results into the cost model components helps to identify and examine the key cost drivers in more detail. Figure 5.2 shows that the indirect, failure and lateness costs are the largest contributors to the production cost, albeit in different patterns across the workflow optimisation approaches. For three of the five approaches, C-E, the pattern is similar: the indirect cost is the foremost cost contributor at 0.20 – 0.22 GBP/cm^3, followed by the failure cost at 0.18 – 0.19 GBP/cm^3; there is no lateness cost in these approaches. By contrast, in approach B, the failure cost is the largest contributor at 0.23 GBP/cm^3; the indirect cost and lateness penalty follow closely at 0.22 GBP/cm^3 and 0.21 GBP/cm^3, respectively. Finally, in approach A, the lateness penalty dominates at 0.32 GBP/cm^3, and the indirect cost is second at 0.25 GBP/cm^3 followed by the failure cost at 0.24 GBP/cm^3. Across all five workflow optimisation approaches, the final three cost contributors are material (0.11 – 0.13 GBP/cm^3), labour (3.6 – 4.1 pence/cm^3) and lastly, energy (0.2 pence/cm^3).

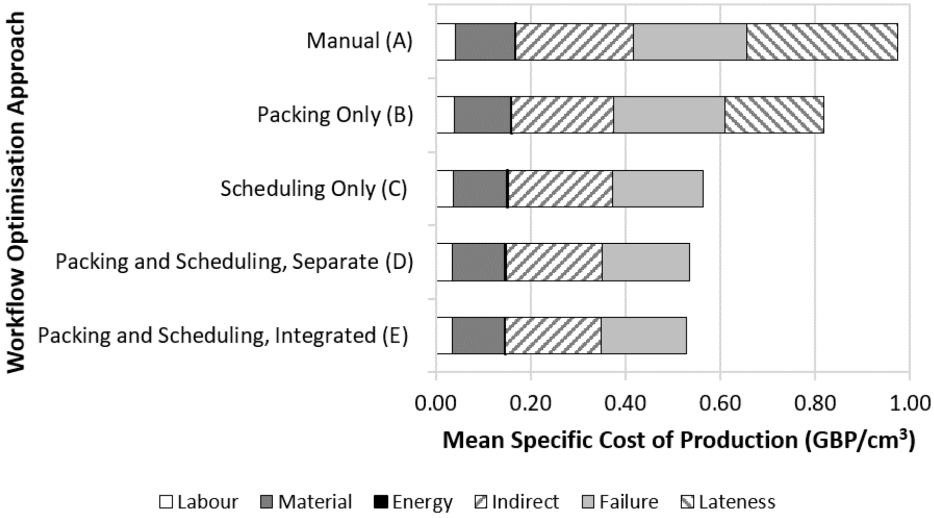


Figure 5.2: Production cost split into cost model components for each workflow optimisation approach

In addition to being the largest cost contributors, Figure 5.2 indicates that the indirect, failure and lateness costs are most strongly influenced by the workflow optimisation approach. Figure 5.3 shows the mean and spread in each of these three cost model contributors across the workflow optimisation approaches.

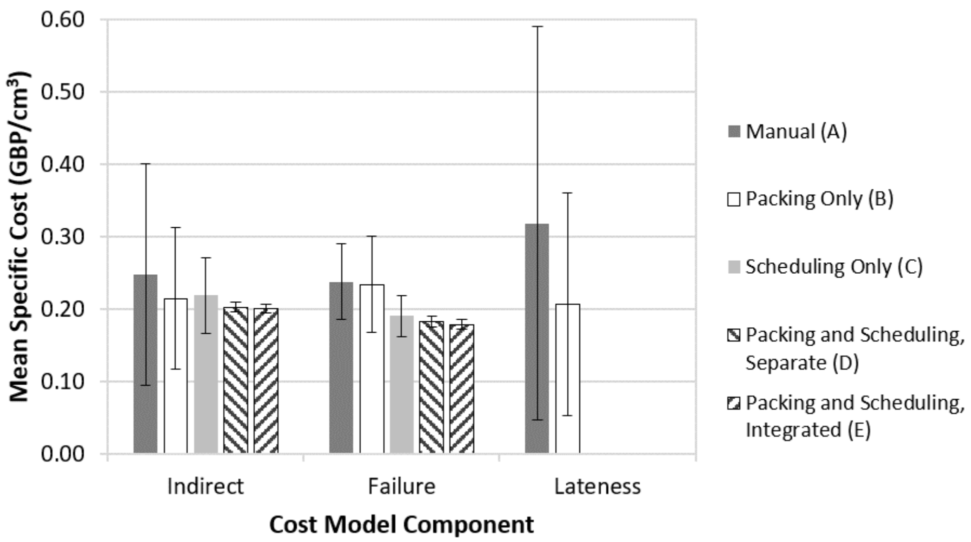


Figure 5.3: Influence of workflow optimisation approach on three largest contributors to production cost

Referring to the indirect costs first, the mean specific cost falls by 18.5% between the Manual approach and the Packing and Scheduling, Integrated approach. In a similar manner to the overall production cost in Figure 5.1, the spread in the indirect cost also decreases by 25-fold between the aforementioned workflow optimisation approaches. For the mean failure costs, the difference between the best-performing Packing and Scheduling, Integrated approach and worst-performing Manual approach is 24.8%. Here, both the Manual and Packing Only approaches have a similar mean failure cost, separated by 0.4 pence per cm^3. However, the Packing Only approach has the largest spread, which is nine times larger than the Packing and Scheduling, Integrated approach. Finally, the lateness costs are both the largest cost contributor in the Manual approach at 32.8% of the total production cost, and the source of greatest uncertainty in the cost due to the spread of 0.27 GBP/cm^3. As noted in Section 5.2, the Manual approach performs worse than Packing Only in terms of schedule attainment, and this is reflected in the higher average and spread in the lateness penalty.

Importantly, Figure 5.3 also shows that approaches D and E consistently have the lowest production cost across the three major cost contributors. The following section will explore the build properties and cost contributors in conjunction to explain the cost-effectiveness of optimising both packing and scheduling during process planning.

5.4 Trade-off between Capacity-, Failure-, and Schedule-related Costs

Expanding on the descriptive statistics from Section 5.2, Figure 5.4 and Figure 5.5 show the distribution of build height and corresponding means for the three major cost contributors (indirect, failure, and lateness) across the five workflow optimisation approaches.

The imprecise specific cost of production in the Manual (A), Packing Only (B) and Scheduling Only (C) approaches has been noted in the previous sections. Figure 5.4a and Figure 5.5a show that the cost contributors are particularly inconsistent in operator-packed builds shorter than 150mm (in approaches A and C). On the other hand, Figure 5.4b indicates that the builds between 200mm and 300mm in height are most erratic in approach B. In both cases, the workflow optimisation approach means that the builds in these height groups are found in the latter time periods of the experiments, and so the contents of these builds is difficult to predict. On average, these builds occur on days 4.2, 3.8, and 3.2 out of the five slots for approaches A, B and C respectively. The allocation of parts depends entirely on the uniformity of the incoming order stream (in approach C) or the parts left over after space-efficiently packing preceding builds (approaches A and B); and so the indirect and failure costs do not follow a consistent trend in these builds. Moreover, the lateness penalties are highest in magnitude in these corresponding builds for approaches A and B (Figure 5.4a and Figure 5.4b). Probing the experimental results further shows that 70% of the parts are late in the shorter builds (<150mm) via approach A, and 41% in the 200-300mm builds via approach B. This corresponds to the later position of these builds in the production sequence.

In contrast, Figure 5.4 and Figure 5.5a show that the three major cost contributors converge in the taller builds. Across approaches A-C, magnitude of the indirect, failure and lateness costs (where applicable) is approximately 0.20 GBP/cm^3 in builds exceeding 270mm in height, which also occur earlier in the production sequence. On average across approaches A-C, these builds occur on day 2.4 out of five, corresponding to the first half of the production sequence. The transition occurs at 270mm for approaches A and C (Figure 5.4a and Figure 5.5a), and 315mm for approach B (Figure 5.4b).

This transition also coincides with the trade-off between indirect costs and failure costs as the build height increases. Below 270mm, the indirect costs dominate across all workflow optimisation approaches (Figure 5.4 and Figure 5.5). This is because the fixed time for machine warm up and cool down, and associated time-dependent costs are divided over fewer parts in these relatively sparsely filled builds. As the number of parts increases in line with the build height, the fraction of the specific production cost that is apportioned to indirect costs reduces. On the other hand, the failure costs depend on the risk of failure, which rises with each additional layer deposited. Therefore, the upward-trending failure cost overtakes the indirect cost, at 285mm for approaches A-B and 270mm for approaches C-E.

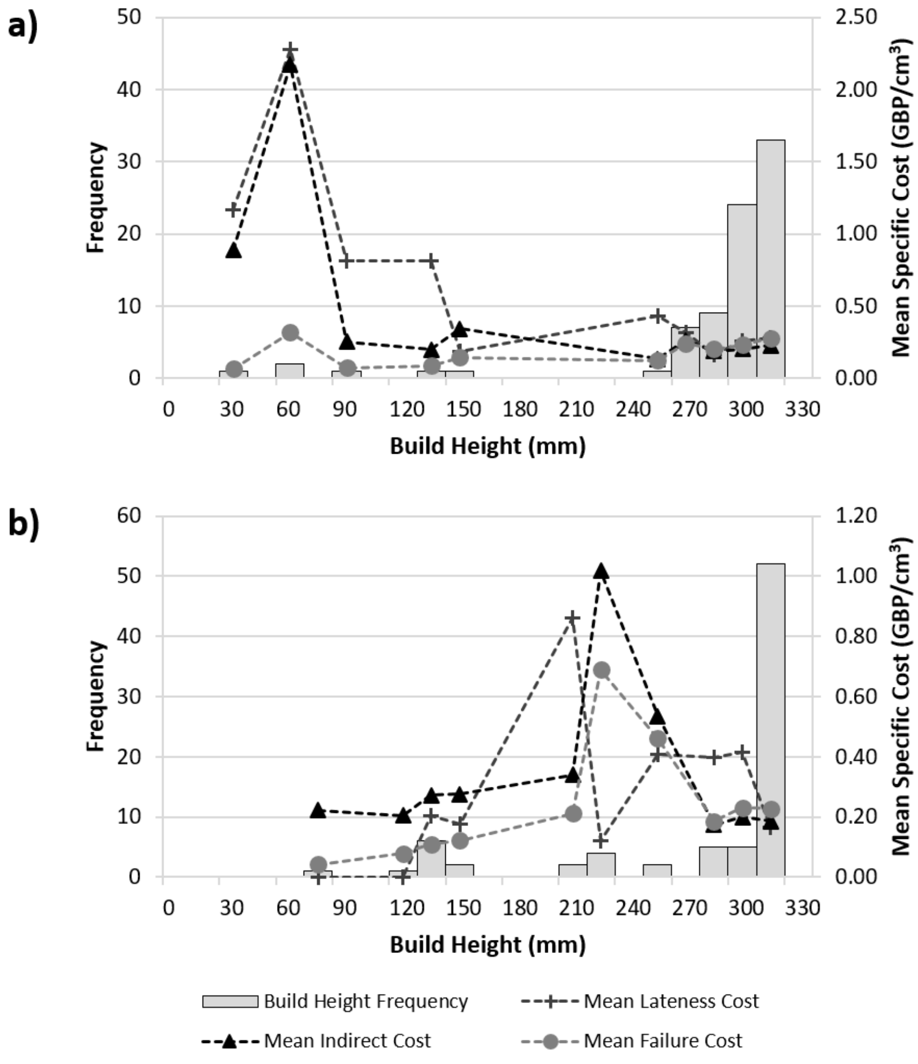


Figure 5.4: Build height distribution and influence on indirect, failure and lateness costs for a) Manual and b) Packing Only workflow optimisation approaches

The trade-off between the indirect, failure and lateness costs, and the role of the workflow optimisation approach in balancing these costs, is summarised in Figure 5.6. The grid of pie charts shows how the division of the specific production cost varies across the aforementioned short (<225mm), moderate (225-315mm), and tall builds (>315mm) for each workflow optimisation approach.

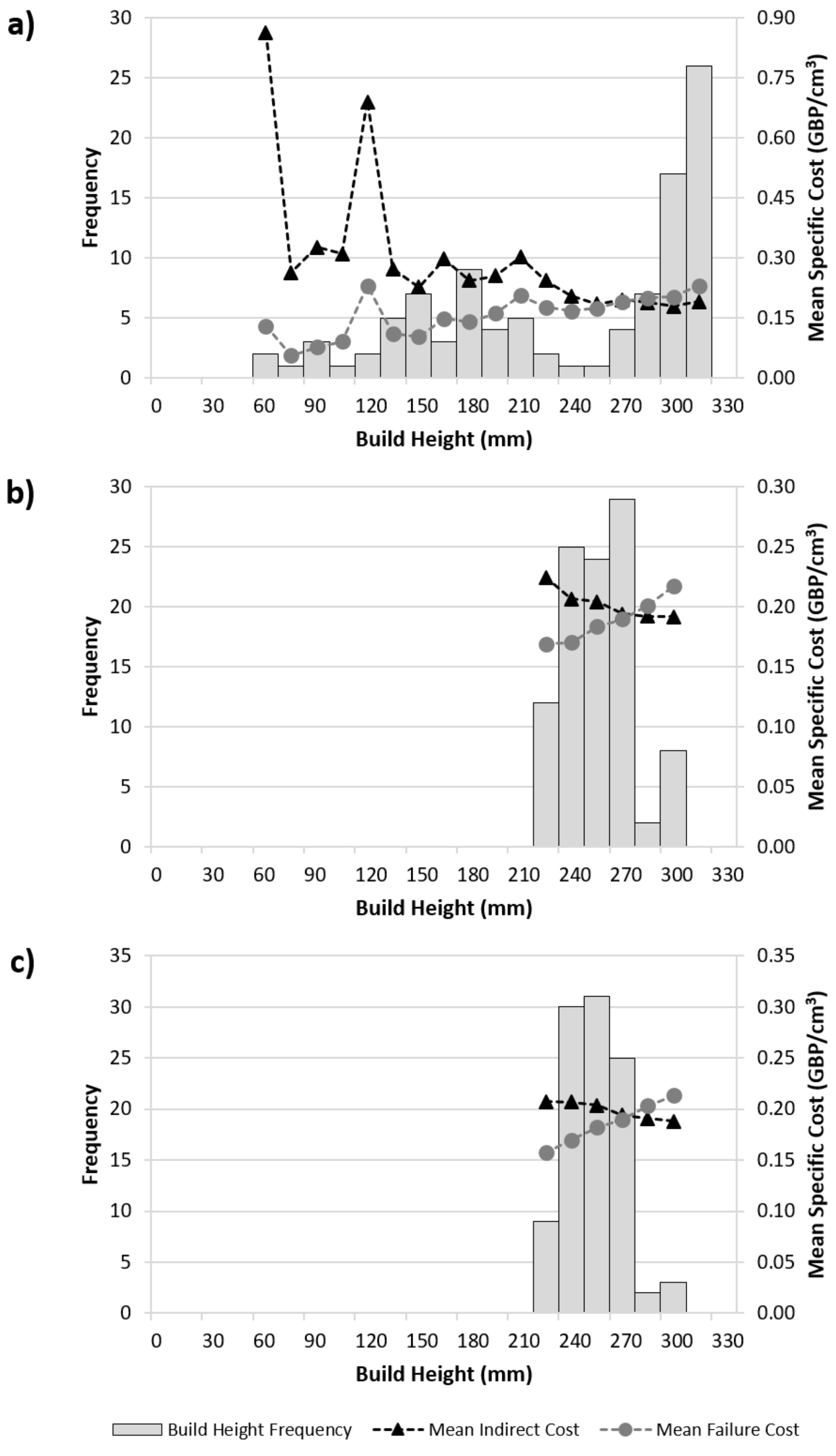


Figure 5.5: Build height distribution and influence on indirect and failure costs for a) Scheduling Only, b) Packing and Scheduling, Separate, and b) Packing and Scheduling, Integrated workflow optimisation approaches

The left column of Figure 5.6 shows that the indirect costs dominate in the short builds for the Manual, Packing Only, and Scheduling only approaches. In the first two approaches, this is also accompanied by the lateness cost. These builds benefit from reduced failure-related costs, at the expense of poor use of machine capacity and adherence to the schedule constraints. At the opposite end of the build height scale, the right column of Figure 5.6 shows that the contribution of the failure cost to the total production cost increases. Relative to the shorter builds, the failure cost fraction rises by two-fold for approaches B and C, and four-fold for approach A. Alongside this, the share apportioned to indirect and even lateness costs falls. Therefore, the taller builds exchange improved capacity utilisation and better schedule attainment across the output for increased failure-related costs.

In the middle column of Figure 5.6, the builds of moderate height between 225mm and 315mm tall occupy the most cost-effective position in this trade-off. This is confirmed by the mean specific cost of production, quoted for the respective build height group and workflow optimisation approach below each pie chart. In this height group, there is a good balance between a well-packed build that amortises indirect costs over a larger quantity of output, at 60-75 parts per build, and a shorter build height that reduces failure-related costs. The contribution of lateness costs, where applicable in approaches A and B, is also similar in proportion to the advantageous taller builds.

For reasons noted earlier in this section, the exception to this trend is the Packing Only approach, where the moderate build height group has the most expensive production cost. Nevertheless, Figure 5.5b and Figure 5.5c show that the approaches D and E consistently produce builds in the cost-effective, moderate build height range. By balancing the three-way trade-off between capacity-, failure-, and schedule-related costs, the optimisation of both packing and scheduling in approaches D and E results in cost savings of up to 81% against the most expensive build configuration (short builds in the Manual approach), and even 62% against moderately tall builds via the alternative workflow optimisation approaches.

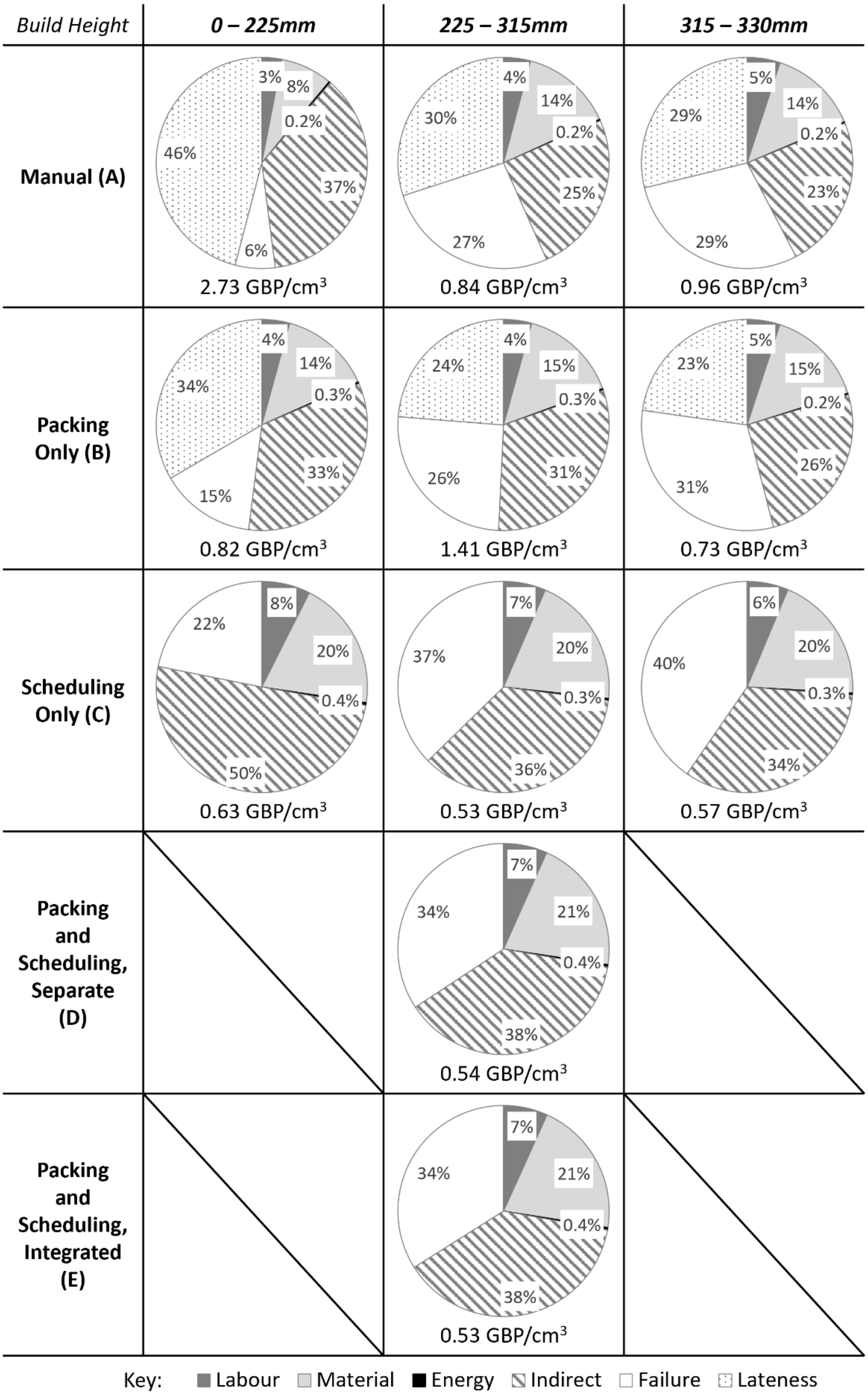


Figure 5.6: Split of mean specific production cost depending on build height for each workflow optimisation approach

5.5 Role of Integrated Workflow Optimisation

While optimising both packing and scheduling in approaches D and E result in cost-effective production, the effect of integrated workflow optimisation has yet to be examined. Figure 5.7 compares the build properties for separate and integrated optimisation of packing and scheduling, approaches D and E, to help explain the benefits of the latter approach.

Figure 5.7a shows that Approach E results in shorter builds across the experiments than approach D, with the exception of experiment 4. Builds are up to 9mm shorter, despite being presented with identical sets of orders. Consequently, the builds generated from integrated optimisation are also more densely packed across each experiment than those from separate optimisation of packing and scheduling. Figure 5.7c shows that the occupied cuboid capacity utilisation is up to 4% higher in approach E than approach D. Therefore, integrated optimisation leads to more compact builds, with parts allocated such that the software-controlled packing results in a smaller enclosed volume by height. As a result, approach E reduces the build time, risk of failure, and volume of unsintered material relative to approach D; and the indirect, failure, and material costs improve, albeit marginally, by 0.1 pence per cm^3, 0.3 pence per cm^3, and 0.1 pence per cm^3, respectively.

When using integrated optimisation, the build heights are also more uniform within each experiment, as shown by the standard deviation (error bars in Figure 5.7a). Despite a coefficient of variation of up to 40% in the quantity of parts to be delivered per day in each experiment, integrated optimisation reduces the impact on the build height to a coefficient of variation of 5.5% (compared to 7.1% for approach D), averaged across all experiments.

The full build capacity utilisation indicates how this is achieved. The error bars in Figure 5.7b show that the standard deviation in the cubic volume of parts per build (full build capacity utilisation) within each experiment is 18.5% lower in approach E than approach D. Note that the mean values for full build capacity utilisation are equal for each experiment because the order schedules are identical across the workflow optimisation approaches. Integrated optimisation spreads parts more uniformly across builds by accounting for available machine capacity in future builds during the part allocation process, not just the current day's builds as in approach D. Therefore, integrated optimisation is able to convert inconsistent demand into builds with more consistent properties than separate optimisation of packing and scheduling, resulting in lower mean specific production cost by 0.1 GBP/cm^3.

In all, integrated optimisation provides two key advantages for process planning. First, it leads to more compact builds, which result in lower capacity-related, failure-related, and material-related costs due to lower build height and higher occupied cuboid capacity utilisation. Second, integrated optimisation leads to more consistent builds in terms of the quantity of parts and, thus, build height and full build capacity utilisation. The machine capacity is filled more uniformly and predictably, despite variation in the incoming order quantity; this is beneficial for higher scale production planning and particularly for managing unpredictable demand (Deradjat and Minshall 2017).

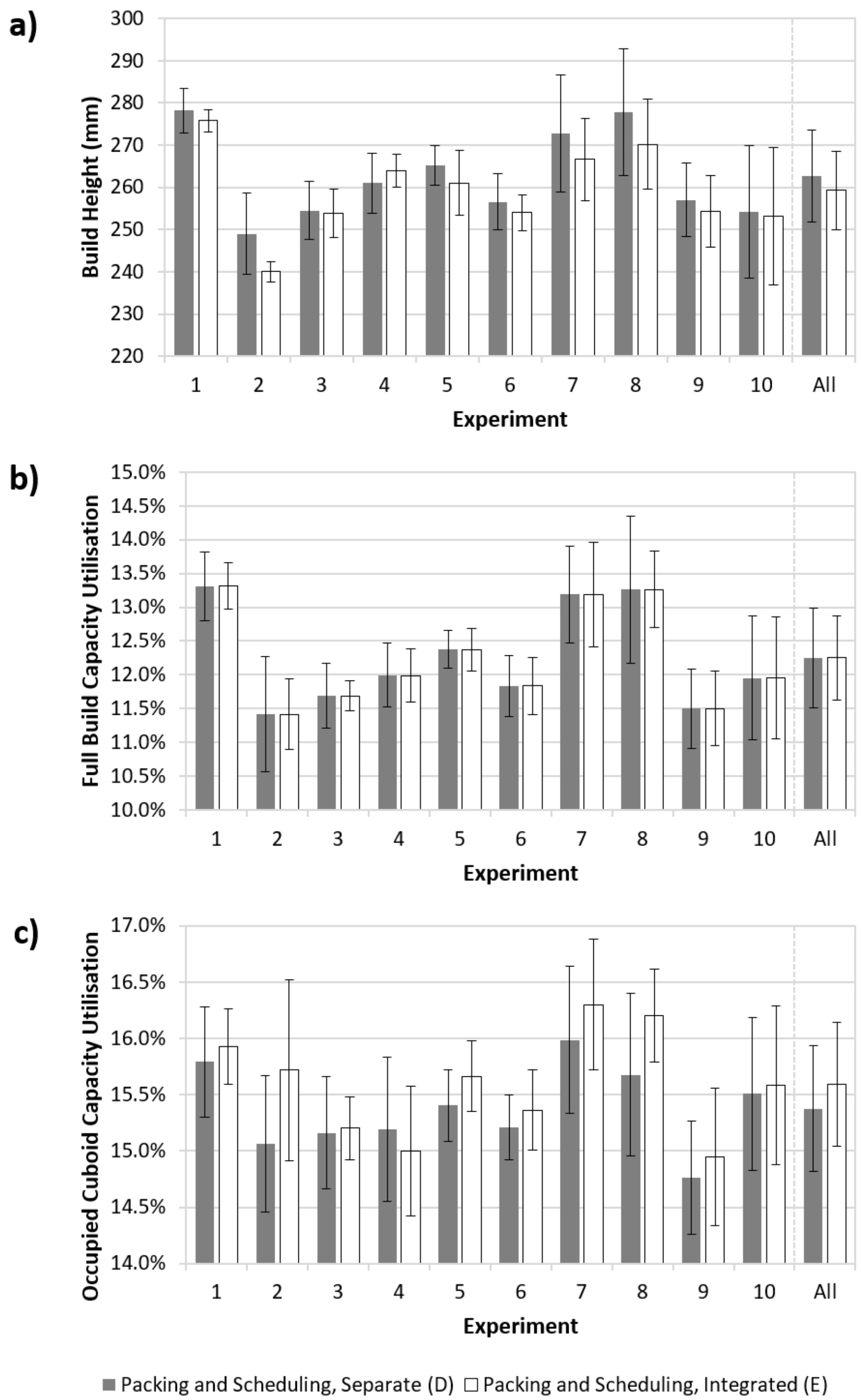


Figure 5.7: Change in a) build height, b) full build capacity utilisation, and c) occupied cuboid capacity utilisation due to integrated workflow optimisation

6 Results on Facility Layout in AM

6.1 Overview

This chapter presents the results of research towards the third research objective, to investigate the suitability and effect of different facility layouts on process efficiency for scaled-up AM production.

Like the previous chapters, an exploratory simulation study is used to address this research objective. However, this part of the research differs from the previous studies, as the model and simulation are based on a case study of an existing AM user rather than a generic AM workflow of make-to-order AM fulfilment. Nevertheless, the experiment design aims to provide structured and generalizable insights that cover process efficiency across the AM production facility from two different perspectives, production losses and cost. Importantly, these aspects are investigated at different scales of production to further inform operations management of AM at scale.

To achieve this, each simulation experiment covers order fulfilment in a single manufacturing facility where the arrangement of AM workflow equipment, and subsequent scheduling of activities, follows one of two layout approaches, cellular and process layouts. The equipment capacity required to satisfy the incoming orders at the given scale of production is evaluated, informing the setup investment and cost of capacity for each facility layout approach. Furthermore, the flow of orders through the simulated AM facility is examined from a time and throughput perspective, in order to elucidate the impact of facility layout on the scheduling of production. This is quantified via estimates of production losses, OEE and production cost contributors. The development of the simulation model and evaluating metrics are explained in Section 3.6.

The remainder of this chapter is organised as follows. First, Section 6.2 outlines the characteristics of each AM workflow in terms of the production throughput and resulting build properties. Second, the effect of facility layout on the capacity management of the AM workflow at different scales of production is examined in Section 6.3. Finally, Sections 6.4 and 6.5 investigate the effect of the facility layout on the operations performance of the AM workflow from production loss and production cost perspectives, respectively, and how this changes as the scale of production increases.

6.2 Summary of Build Properties and Production Throughput

In the exploratory simulation study, the facility operations experiments cover the fulfilment of incoming orders for one month, repeated 12 times to provide data for one full calendar year of operations. Experiments span four production scales, reflecting the baseline average of the case study AM user and set multiples thereof; and for each production scale, the AM production facilities are organised according to two layout approaches, cellular and process layout. Across the resulting eight workflow scenarios, covering each distinct layout-production scale combination, a total of 69 experiments are conducted to establish the required resources to meet the incoming demand of orders, and operations performance therein. Of these experiments, the equipment capacity was not sufficient to generate a full dataset in 14 experiments. Thus, excluding these incomplete experiments, Table 6.1 and Table 6.2 outline the descriptive statistics for production throughput and the build properties across the 12 months of order fulfilment.

Prior to exploring the effects of facility layout in the following sections, a few pertinent observations can be noted. First, as per expectations, the number of orders and parts processed rises in line with the production scale, which confirms that the available capacity in the analysed experiments is sufficient for the incoming demand, and does not unduly constrain the outputs related to the production losses and cost. It should also be noted that the incoming order stream is identical across experiments at the same production scale, controlled by a fixed seed random number generator the simulation software, so as to avoid confounding effects when comparing the facility layout performance.

Table 6.1: Descriptive statistics for facility layout experiments (for production scales 1 & 2)

Statistic	**Production Scale and Facility Layout**							
	Production Scale = 1				**Production Scale = 2**			
	Cellular Layout		**Process Layout**		**Cellular Layout**		**Process Layout**	
	Mean	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
No. of Orders Processed	405.5	21.5	407.9	13.7	794.5	9.2	793.4	10.3
No. of Parts Processed	3637.5	248.6	3652.5	129.0	7143.0	101.8	7122.8	105.8
No. of Scheduled Builds	59.5	3.1	59.9	2.8	107.0	2.8	105.4	1.9
No. of Actual Builds	63.3	4.6	65.3	2.2	120.0	2.8	115.6	2.4
No. of Parts per Build	64.3	1.0	64.4	1.2	71.0	0.9	71.3	0.6
Build Height (mm)	347.9	4.4	348.2	5.6	376.5	6.1	379.9	4.6
Full Build Capacity Utilisation	4.0%	0.1%	4.0%	0.1%	4.5%	0.1%	4.5%	0.0%
Occupied Cuboid Capacity Utilisation	5.6%	0.0%	5.6%	0.0%	5.7%	0.0%	5.6%	0.0%

Table 6.2: Descriptive statistics for facility layout experiments (for production scales 5 & 10)

Statistic	**Production Scale and Facility Layout**							
	Production Scale = 5				**Production Scale = 10**			
	Cellular Layout		**Process Layout**		**Cellular Layout**		**Process Layout**	
	Mean	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
No. of Orders Processed	2038.0	15.6	2051.0	42.4	4074.0	50.9	4061.9	62.5
No. of Parts Processed	18246.0	161.2	18445.1	411.1	36693.0	585.5	36582.0	620.0
No. of Scheduled Builds	259.5	3.5	258.8	6.4	512.5	6.4	510.8	7.5
No. of Actual Builds	283.0	4.2	284.2	6.8	556.0	7.1	553.7	8.2
No. of Parts per Build	73.9	0.7	75.0	0.2	75.2	0.1	75.1	0.3
Build Height (mm)	391.9	3.8	396.3	1.2	398.3	0.4	397.4	1.2
Full Build Capacity Utilisation	4.6%	0.0%	4.7%	0.0%	4.7%	0.0%	4.7%	0.0%
Occupied Cuboid Capacity Utilisation	5.7%	0.0%	5.7%	0.0%	5.7%	0.0%	5.7%	0.0%

Second, the number of parts per build rises in line with the production scale, from approximately 64 parts per build at the baseline production scale 1 up to 75 parts per build at the highest production scale 10. Alongside this, the full build capacity utilisation in the builds also grows by the same rate (17.1% increase) between the lowermost and uppermost production scales. This indicates that the available capacity is not maximally utilised at production scales 1 and 2 (see Table 6.1) as compared to production scales 5 and 10 (see Table 6.2). Additionally, given that both the mean build height and parts per build continue to increase between production scales 5 and 10, economies of scale are present in the AM workflow, which lead to more efficient use of the available resources as the production scale increases. This concept is revisited throughout this chapter.

Third, the number of builds taken to fulfil the incoming demand is relatively uniform between the cellular and process layouts, at less than ± 4% difference, when comparing within each production scale. Again, this is anticipated, as a common, consistent packing and scheduling approach is used across the eight different workflow scenarios; and results from Chapters 4 and 5 emphasise the influence of the packing and scheduling on the generation of consistent builds in single and multi-machine production environments. Further corroborating this, the occupied cuboid capacity utilisation is identical (5.6 – 5.7%) across all of the experiments. Therefore, the facility layout does not affect the organisation of orders into build jobs, and this allows an unbiased investigation into the influence of the facility layout on other parts of the AM workflow.

6.3 Effect of Facility Layout on Setup Investment

The first part of the exploratory simulation examines the effect of facility layout on the investment in capacity, as per the number of machines required to fulfil the incoming orders at each production scale. For this, an order makespan target is set at nine days, matching the constraint used by the case study AM user to achieve their promised lead time of 10 days; and then the minimum number of material preparation, AM and de-powder machines necessary to meet this target is compared between the facility layout approaches. Table 6.3 and Table 6.4 show the respective results for the cellular and process layouts, and the percentage of orders for which the makespan target is met.

Table 6.3 shows that a minimum of one, two, three, and six AM machines are required to provide sufficient build capacity for the incoming orders at the production scales of 1, 2, 5, and 10, respectively. In line with the grouping of each AM machine with one material preparation and one de-powder machine in each cell, an equal number of these ancillary machines are also required at each production scale. In the process layout, a similar number of AM machines are required at each production scale, as shown in Table 6.4. The minimum number is identical to the cellular layout, aside from the baseline production scale 1. In this scenario, the makespan target is met in only 62.9% of orders when using just one AM machine, which is deemed unsatisfactory.

Table 6.3: Minimum number of machines required to meet makespan constraint in experiments using cellular layout

Production Scale	Order Inter-arrival Rate	Minimum Machines in Cellular Layout			Makespan Target Met
		Material Prep.	AM	De-powder	
Scale = 1	21.5 hours	1	1	1	73.8%
Scale = 2	10.7 hours	2	2	2	84.5%
Scale = 5	4.3 hours	3	3	3	81.4%
Scale = 10	2.1 hours	6	6	6	90.9%

Table 6.4: Minimum number of machines required to meet makespan constraint in experiments using process layout

Production Scale	Order Inter-arrival Rate	Minimum Machines in Process Layout			Makespan Target Met
		Material Prep.	AM	De-powder	
Scale = 1	21.5 hours	1	2	2	71.5%
Scale = 2	10.7 hours	1	2	1	80.8%
Scale = 5	4.3 hours	1	3	1	89.4%
Scale = 10	2.1 hours	1	6	1	92.3%

To further confirm that the number of AM machines is suitable for each production scale, Figure 6.1 illustrates the change in mean and spread (note: error bars span one standard deviation) in the order makespan as the number of machines is varied for each facility layout. For production scales 2, 5, and 10, there is a clear demarcation between insufficient and sufficient production capacity, depending on whether the order makespan exceeds nine days or not (Figure 6.1b, Figure 6.1c, and Figure 6.1d, respectively). In each case, this point coincides with the number of AM machines required for the given production scale, as per Table 6.3 and Table 6.4. On the other hand, for production scale 1, the makespan target is met less than 80% of the time, despite Figure 6.1a showing that the mean order makespan is consistently within the target value, even when using the minimum possible number of machines. The reason for this discrepancy is that the threshold full build capacity utilisation, of 3.2%, for releasing and packing a batch of incoming orders takes longer to meet at the baseline production scale. As a result, orders may spend up to five days waiting in the batching queue in experiments at production scale 1. In reality, the case study AM user mitigates the time lost to this delay by releasing batches for packing earlier but with a lower full build capacity utilisation, which may even be as low as <1%, in spite of the cost effectiveness penalty associated with poorer utilisation of machine capacity (see Section 5.4).

Shifting focus to the ancillary equipment, the number of material preparation and de-powder machines can be varied freely in the process layout. With this in mind, Table 6.4 shows that the absolute minimum number of each machine, one each, is sufficient to support the AM workflow in all but one case, production scale 1. Therefore, from an equipment investment perspective, the cellular layout is more economical for lower scale production. Whereas, on the other hand, the greater flexibility afforded by the process layout avoids the cost of excess ancillary equipment as the production scale increases.

Expanding upon this intuitive finding, the role of ancillary equipment in the responsiveness of the workflow can be further examined via a sensitivity study to provide insights that support investment decisions therein. Figure 6.2 and Figure 6.3 illustrate the relative effect of investing in material preparation and de-powder machines, respectively, on the time taken for each build to progress through the corresponding steps under the process layout.

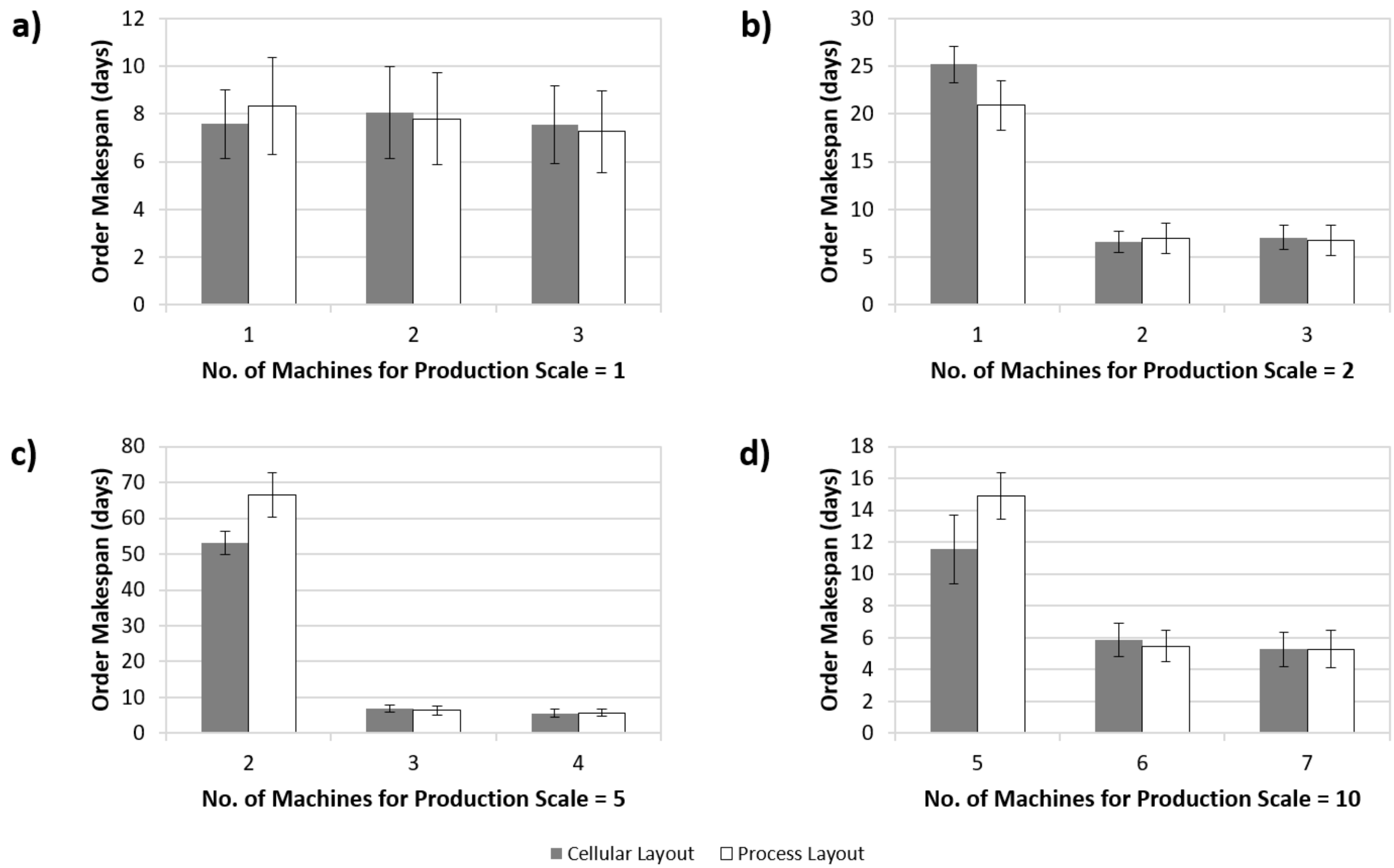


Figure 6.1: Effect of facility layout and number of machines on order makespan for production scales a) 1, b) 2, c) 5, and d) 10

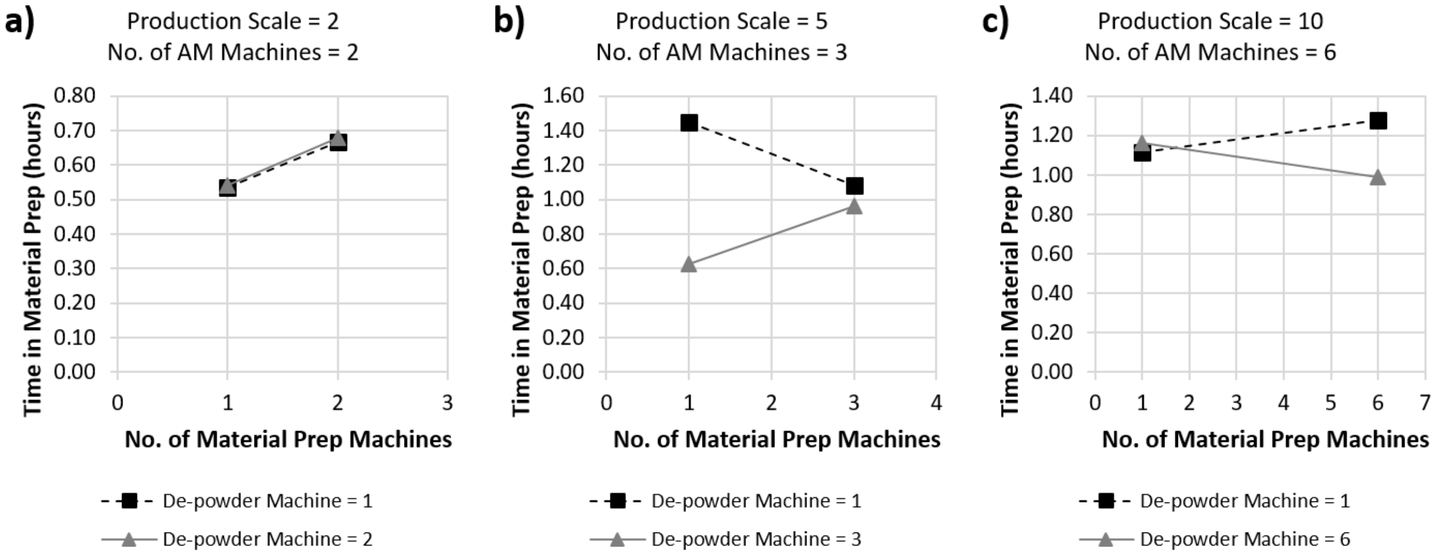


Figure 6.2: Effect of number of material preparation machines on time spent in this section of the workflow for production scales a) 2, b) 5, and c) 10

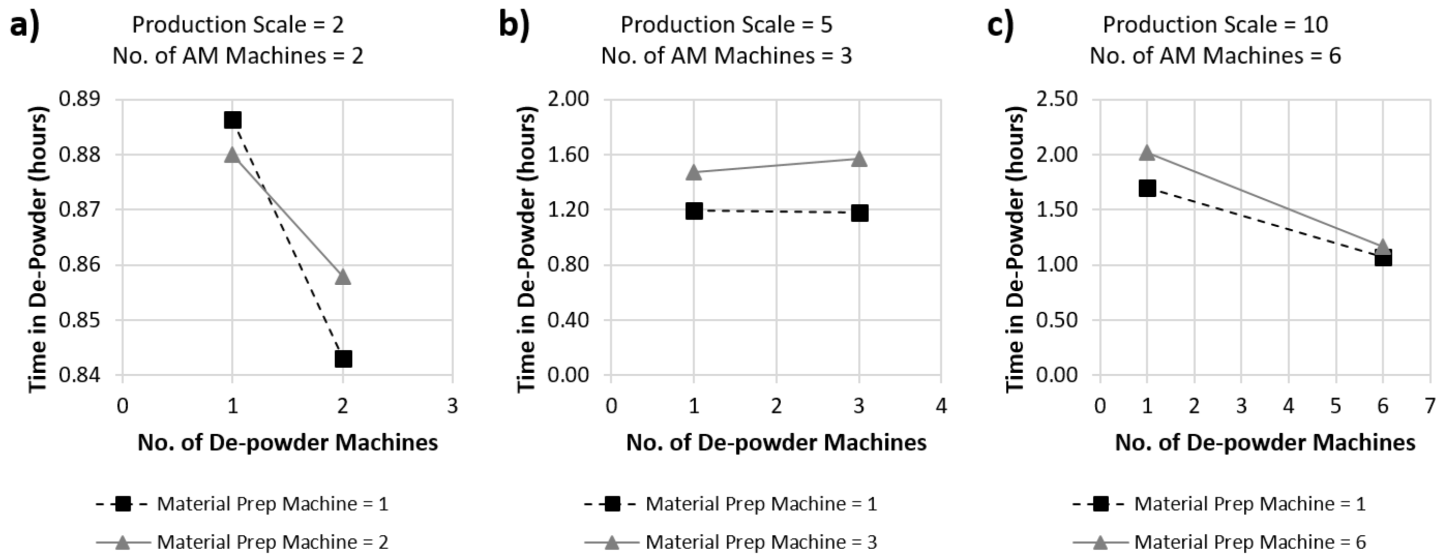


Figure 6.3: Effect of number of de-powder machines on time spent in this section of the workflow for production scales a) 2, b) 5, and c) 10

Contrary to expectations, Figure 6.2 and Figure 6.3 indicate that investing in additional material preparation and de-powder machines does not guarantee faster progression through the respective parts of the workflow in all scenarios. The effect of the number of either ancillary machine varies with both the production scale and number of other machines in the workflow. First, Figure 6.2 shows that the time taken for the material preparation step improves when increasing the number of material preparation machines in only two cases: alongside minimum de-powder machines, i.e. one, at production scale 5; and alongside maximum de-powder machines, i.e. six, at production scale 10. In the other cases, the process step time actually increases, in the most extreme case by 53.6% (Figure 6.2b, at three de-powder machines).

On the other hand, the time taken for the de-powder step decreases in line with adding de-powder machines to the workflow in five out of the six cases, by up to 42.4% (Figure 6.3c: alongside maximum material preparation machines, i.e. six, at production scale 10). Whereas, in the single non-improved case (Figure 6.3b: alongside maximum material preparation machines, i.e. three, at production scale 5), the process step time increases by a mere 6.8%.

Therefore, the sensitivity analysis shows that increasing the number of de-powder machines more consistently improves the respective process step time, and thus responsiveness of the workflow, than increasing the number of material preparation machines. Given that the de-powder step also takes approximately twice as long, on average, as the material preparation step, it is more prudent to invest in additional de-powder machines first when expanding capacity whilst aiming to minimise the process makespan.

6.4 Effect of Facility Layout on Production Losses

Having explored the initial setup investment for equipment, the second part of the exploratory simulation investigates the operations performance of the AM workflow under each facility layout. This section presents the operations performance from the perspective of production losses, including value-added and non-value-added time in the workflow.

For a concise comparison, the production losses (and also cost in Section 6.5) are assessed for the minimum number of machines for the two layout options, and also the equal number of machines in the process layout as the cellular layout, at each production scale; this is summarised in Table 6.5 for clarity.

Table 6.5: Production scale, facility layout, and equipment combinations for operations performance simulation experiments

Production Scale	**Cellular Layout: Minimum Machines**			**Process Layout: Minimum Machines**			**Process Layout: Equivalent to Cellular Layout**		
	MP	**AM**	**DP**	**MP**	**AM**	**DP**	**MP**	**AM**	**DP**
Scale = 1	1	1	1	1	2	2	1	1	1
Scale = 2	2	2	2	1	2	1	2	2	2
Scale = 5	3	3	3	1	3	1	3	3	3
Scale = 10	6	6	6	1	6	1	6	6	6

Note: MP denotes “Material Preparation”, and DP denotes “De-powder”

6.4.1 Value-Adding and Non-Value-Adding Time

Following the framework for value-adding time (see Section 2.2.1), the makespan can be split into value-adding and non-value adding activities to indicate the effect of the facility layout on time-efficiency of production. Accordingly, Figure 6.4 shows the time each build spends in the AM workflow divided into four parts: automatic steps, requiring no operator intervention; manual steps, carried out by operators; travel between equipment; and waiting for the aforementioned steps. Of these four components, the automatic and manual steps can be considered either value-adding or necessary-but-non-value-adding, depending on the activity and sub-steps therein. Automatic and manual activities include, among others, packing parts, the AM build, and de-powdering the parts. Both the mean and spread in the time taken for these activities is relatively unchanged across the facility layout approaches, which again affirms that the minimum capacity across the equipment is sufficient for the production throughput. However, the waiting and travel time, which align with two of the seven lean wastes, are entirely non-value-adding, and vary across the facility layouts at each production scale. Therefore, it is pertinent to explore the scope to reduce or eliminate the waiting and travel time.

Assessing the effect of the facility layout on the travel time first, Figure 6.4 confirms that the cellular layout is capable of virtually eliminating travel time in the workflow. Across all four production scales, the travel time is less than one minute per build in the cellular layout, as compared to 14 minutes on average for the process layout. The difference is simply cause by the proximity of the material preparation, AM and de-powder machines in each cell, minimising the time taken to transfer the material and build cartridges from one machine to the next. While the travel time in the process layout is still two orders of magnitude smaller than the largest time contributor, automatic steps, it inflates the operator-dependent time (i.e. manual steps and travel) by up to one-fifth. Therefore, the cellular facility layout can significantly reduce the operator load in the AM workflow, freeing up time for alternative value-adding activities.

However, shifting from the operator's perspective to the overall time taken for the build to progress through the manufacturing system, Figure 6.4 shows that the waiting time is a far larger contributor to the makespan. The waiting time ranges from 25.7 hours in the cellular layout at production scale 2 (Figure 6.4b) up to 43.3 hours in the process layout at production scale 5 (Figure 6.4c), which is of the same order of magnitude as the time taken for automatic steps. As a result, the overall makespan of each build is extended by between 30.6% and 42.3% due to the waiting time alone.

Within the experiments at each production scale, the waiting time is consistently greater in magnitude when using the process layout. Switching from the cellular to the process layout, using the minimum number of machines, increases the waiting time by up to 26.8% (Figure 6.4d). Moreover, even where the number of machines remains unchanged, switching from the cellular to the process layout amplifies the waiting time by up to 40.7% (Figure 6.4c). Thus, as for the travel time, opting for the cellular layout reduces the non-value-adding waiting time, regardless of the scale of production. This improves the achievable lead time for fulfilling orders, by minimising the non-value-adding time in the AM workflow.

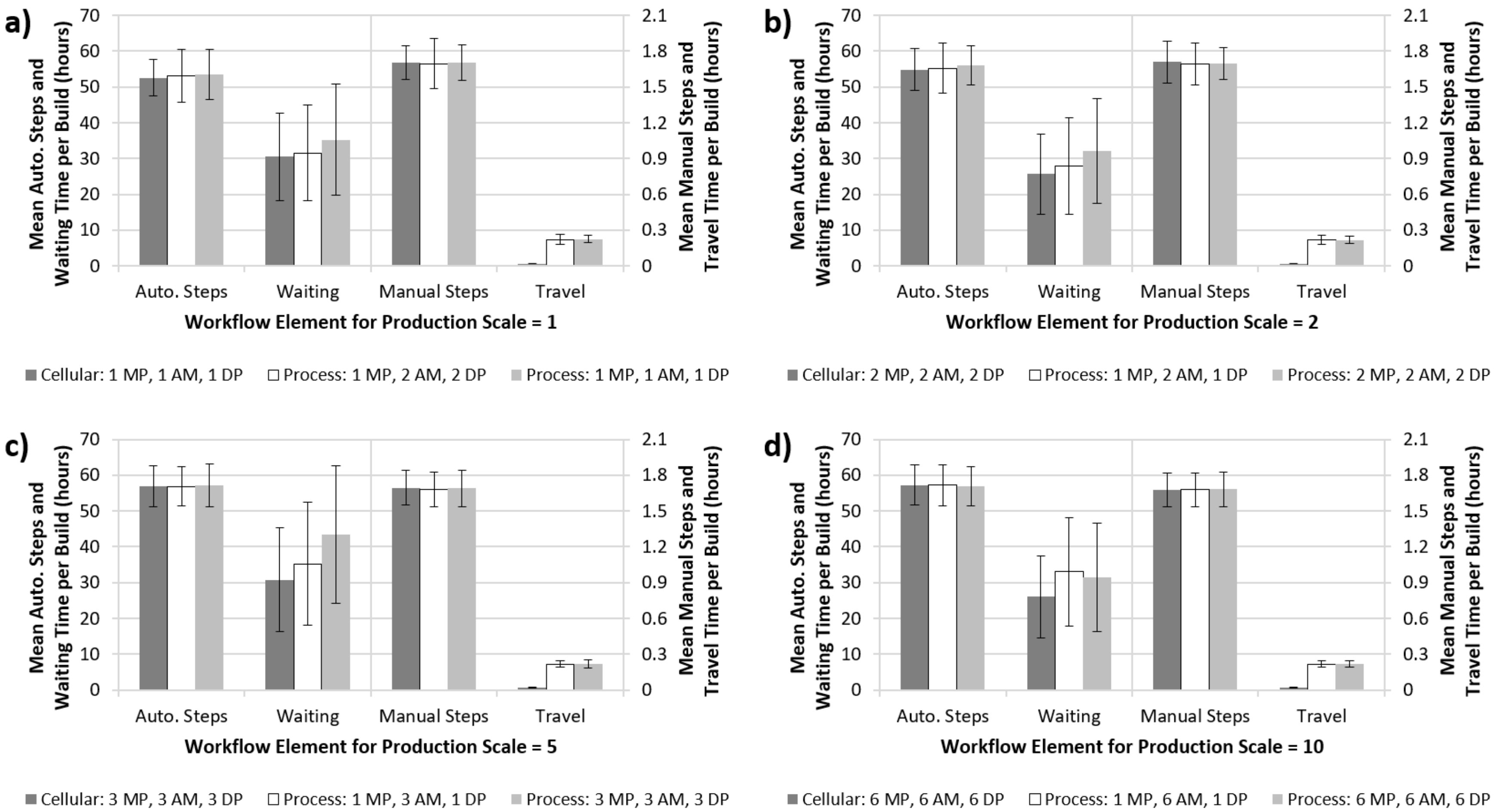


Figure 6.4: Value-adding and non-value-adding time in workflow for production scales a) 1, b) 2, c) 5, and d) 10

To help explain the underlying reasons for the waiting time advantages of the cellular layout, Figure 6.5 illustrates the waiting time incurred by each build in the different parts of the AM workflow: starting from batching orders into builds, through production, and ending with separating the cleaned parts into their respective orders again. Across all four production scales, waiting time at the AM machine is the largest in magnitude; this comprises of waiting for the machine itself, operators for loading and unloading, and prepared material and build cartridges. At the higher production scales, the AM waiting time entirely dominates, at over 90% of the total (Figure 6.5c and Figure 6.5d); whereas, at the lower production scales, between one-fifth and two-fifths of the waiting time is also spent at the build packing step (Figure 6.5a and Figure 6.5b). The rate of incoming orders at production scales 1 and 2 is low enough (at one order every 21.5 hours and 10.5 hours, respectively) that the capacity threshold for batching orders is often not met inside of working hours, and so batches await packing until the next operator shift.

Refocusing on the AM waiting time, workflows in the process layout incur a 25.5% higher waiting time than the cellular layout, on average; in the most extreme comparison, at production scale 5, switching to the process layout while maintaining the same number of machines increases the AM waiting time by 60.8% (Figure 6.5c). The difference in time between the two facility layout approaches comprises mainly of waiting time for the portable resources, the build and material cartridges, and the build waiting in the machine for unloading. In the cellular layout, it follows that the downstream de-powder machine within the cell is more likely to be ready and available for the finished build; and, notably, that the build and material cartridges circulate between the machines in the cell, in alignment with the progress of each build. Therefore, the cellular layout reduces waiting losses by exerting tighter constraints on the movement of WIP and portable resources across the manufacturing workflow.

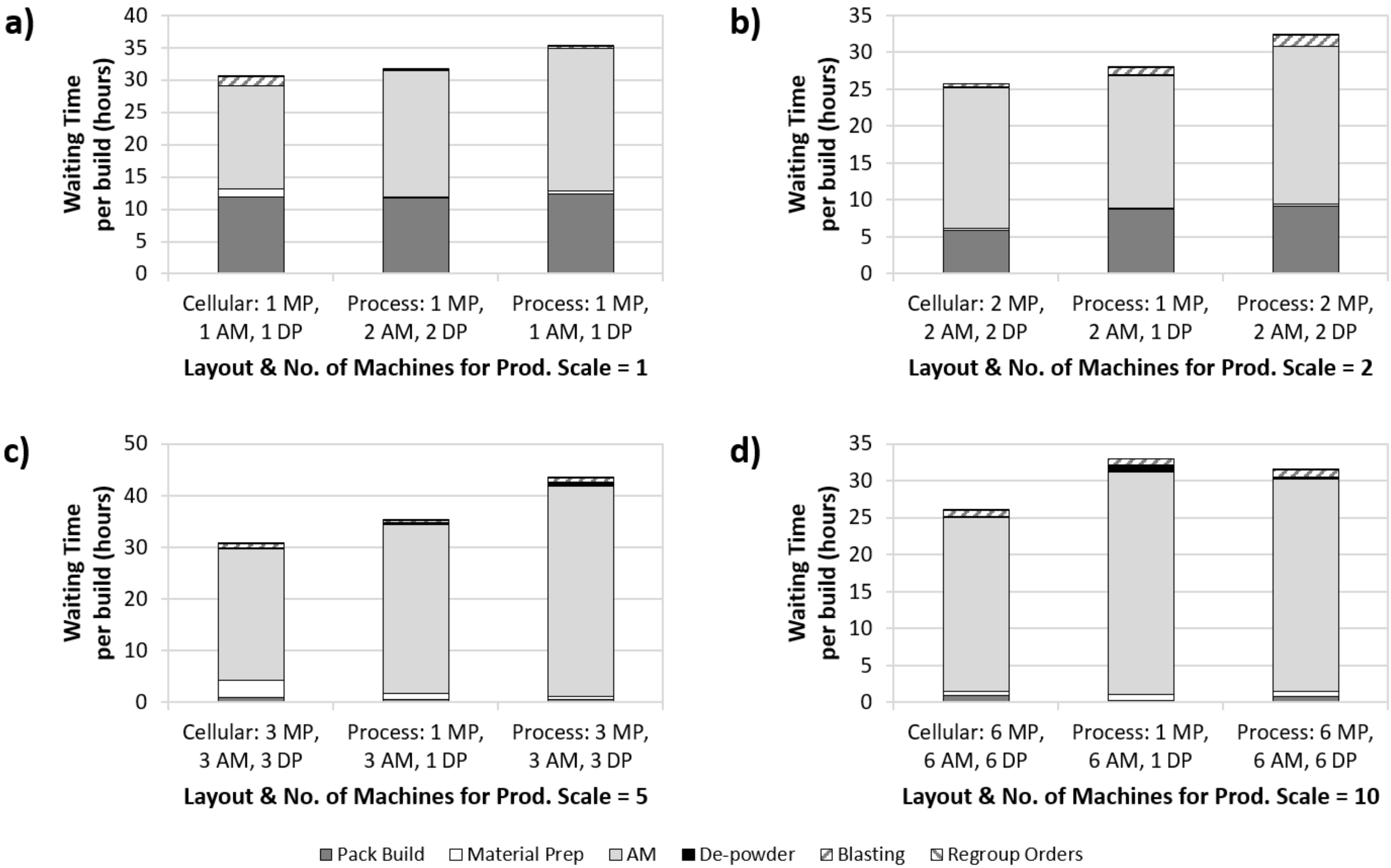


Figure 6.5: Waiting time in each part of the workflow for production scales a) 1, b) 2, c) 5, and d) 10

6.4.1.1 Influence of Operator Availability

Given that the waiting time at the AM machine is such a significant source of non-value-adding time, external influences on this time are explored for added context, such as the availability of operators to complete manual loading and unloading tasks. Figure 6.6 shows the effect of the AM build finishing inside or outside operator shifts on the waiting time at the AM machine. Across the board, the waiting time is significantly lower when builds finish during operator shifts. For the cellular layout, the waiting time is eliminated almost entirely at all four production scales. The same occurs for the process layout at production scales 1 and 2; whereas, at production scales 5 and 10 (Figure 6.6c and Figure 6.6d), the availability of the portable build and material cartridges does not keep up with the rate of builds, and so a portion of the waiting time remains.

Nevertheless, this highlights the importance of scheduling builds to synchronise manual upstream and downstream activities with operator availability. It should be noted that the case study AM user already applies a simple scheduling scheme for staggering builds across the working week, such that the automatic processes predominantly occur off-shift. However, as the production scale increases, it may become necessary to apply more sophisticated approaches to avoid large fluctuations in the operator workload.

6.4.1.2 Influence of Unplanned AM Machine Maintenance

This section explores a second external influence on waiting time for the AM machine, sensitivity to unplanned maintenance. Unplanned AM machine maintenance occurs in between builds to reactively rectify issues as they arise; separate to build failure events, which occur during the build. Figure 6.7 shows that unplanned maintenance extends the waiting time for the AM machine, that is, the time between the completion of material preparation and loading the AM machine. As expected, this is because the machine is not available for the next build while maintenance is ongoing. It should be noted that unplanned maintenance did not coincide with builds progressing through the workflow at production scales 1 and 2, hence the absence of results for these cases.

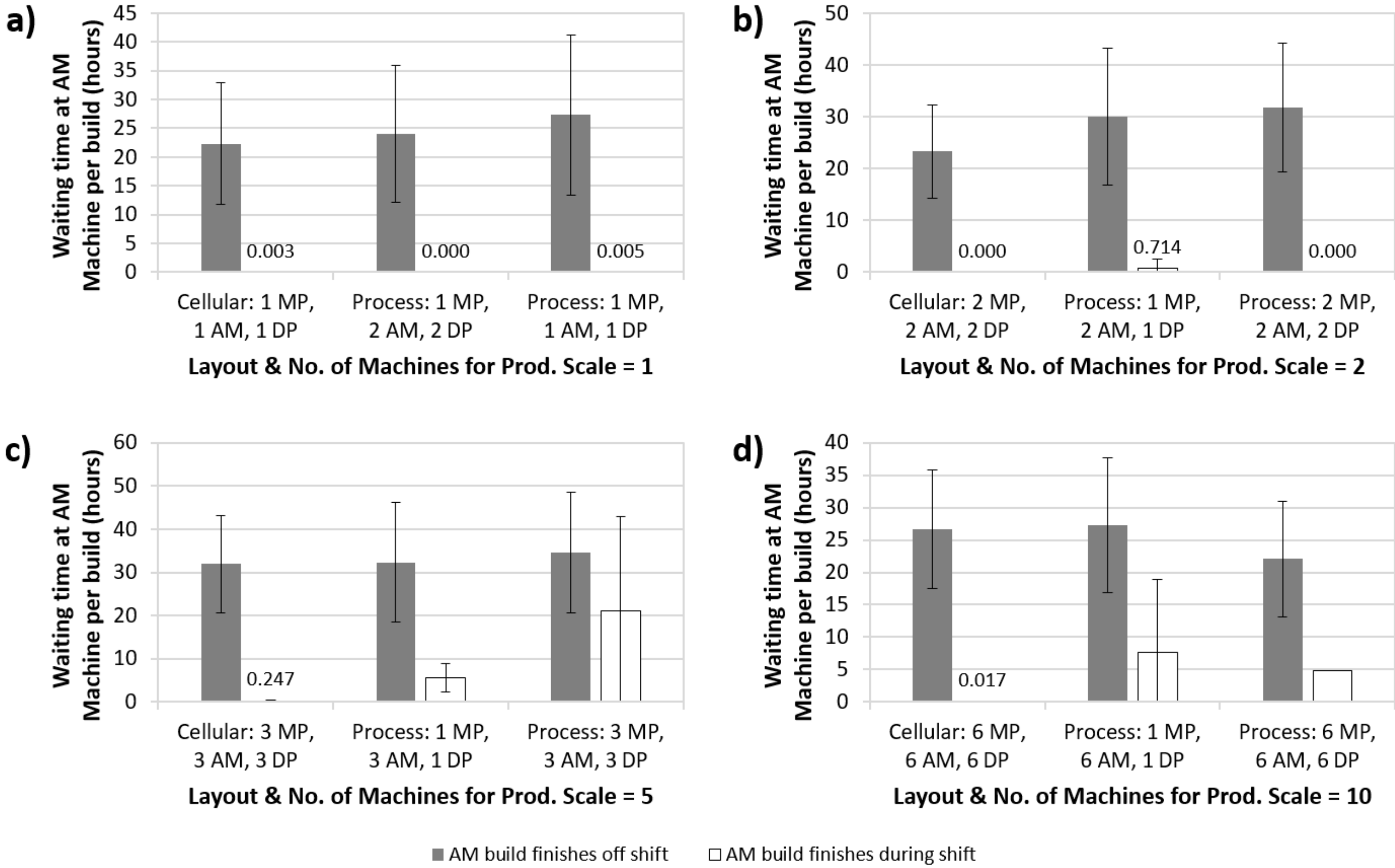


Figure 6.6: Influence of operator shift availability on waiting time per build at AM machine for production scales a) 1, b) 2, c) 3, and d) 4

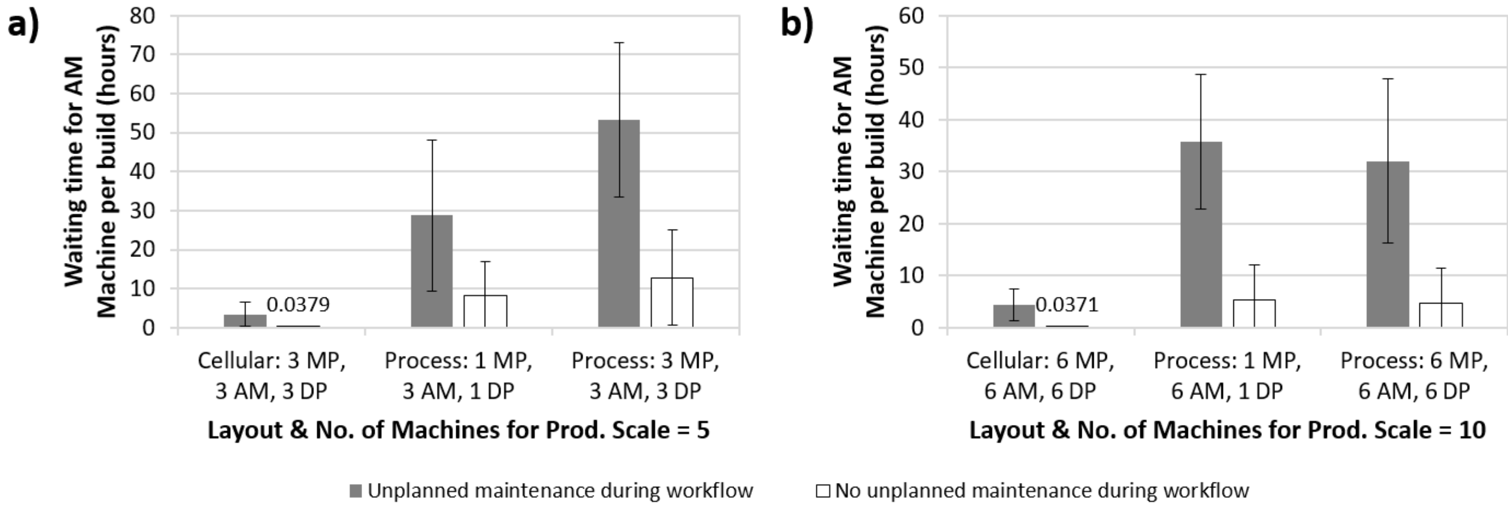


Figure 6.7: Influence of unplanned maintenance on waiting time for AM machine for production scales a) 5, and b) 10

Two notable comparisons can be made between the facility layout approaches, with respect to the influence of unplanned machine maintenance. First, Figure 6.7 emphasises the extent to which the cellular layout reduces non-value-adding time in the AM workflow: for both production scales 5 and 10, the average waiting time with unplanned maintenance in the cellular layout is up to three-fifths lower than the average waiting time without unplanned maintenance in the process layout. Second, the relative adverse effect of unplanned maintenance on the waiting time is actually higher for the cellular layout than the process layout. That is to say, the waiting time at the AM machine increases by 100-fold when unplanned maintenance occurs in the cellular layout; whereas the relative increase in the process layout is limited to seven-fold, at most. This aligns with the additional flexibility in the process layout to switch to the next available machine, rather than being constrained to the equipment within the same cell, as for the cellular layout.

6.4.2 Overall Equipment Effectiveness

Departing from the assessment of value-adding and non-value-adding time in the overall workflow, this section examines the production losses at the AM machine itself, using the OEE metric from Chapter 4. Figure 6.8 shows the OEE and constituent metrics for the facility layout approaches over the four production scales. It is immediately apparent that both the mean and spread in the OEE results are uniform across both the production scales and facility layout approaches. The availability is 76.3% on average, the performance is 76.2%, the quality is 95.4%, and the OEE is 55.3%. It should be noted that the performance metric is significantly higher in this study than in Chapter 4, because the reduced speed losses during the build are neglected as the theoretical volumetric process rate for the AM machine in this case study is unknown.

The uniformity in the values of each metric matches expectations, given that the build properties are relatively consistent across the board (see Table 6.1 and Table 6.2). Therefore, the facility layout does not influence production losses at the AM machine, unlike elsewhere in the production workflow.

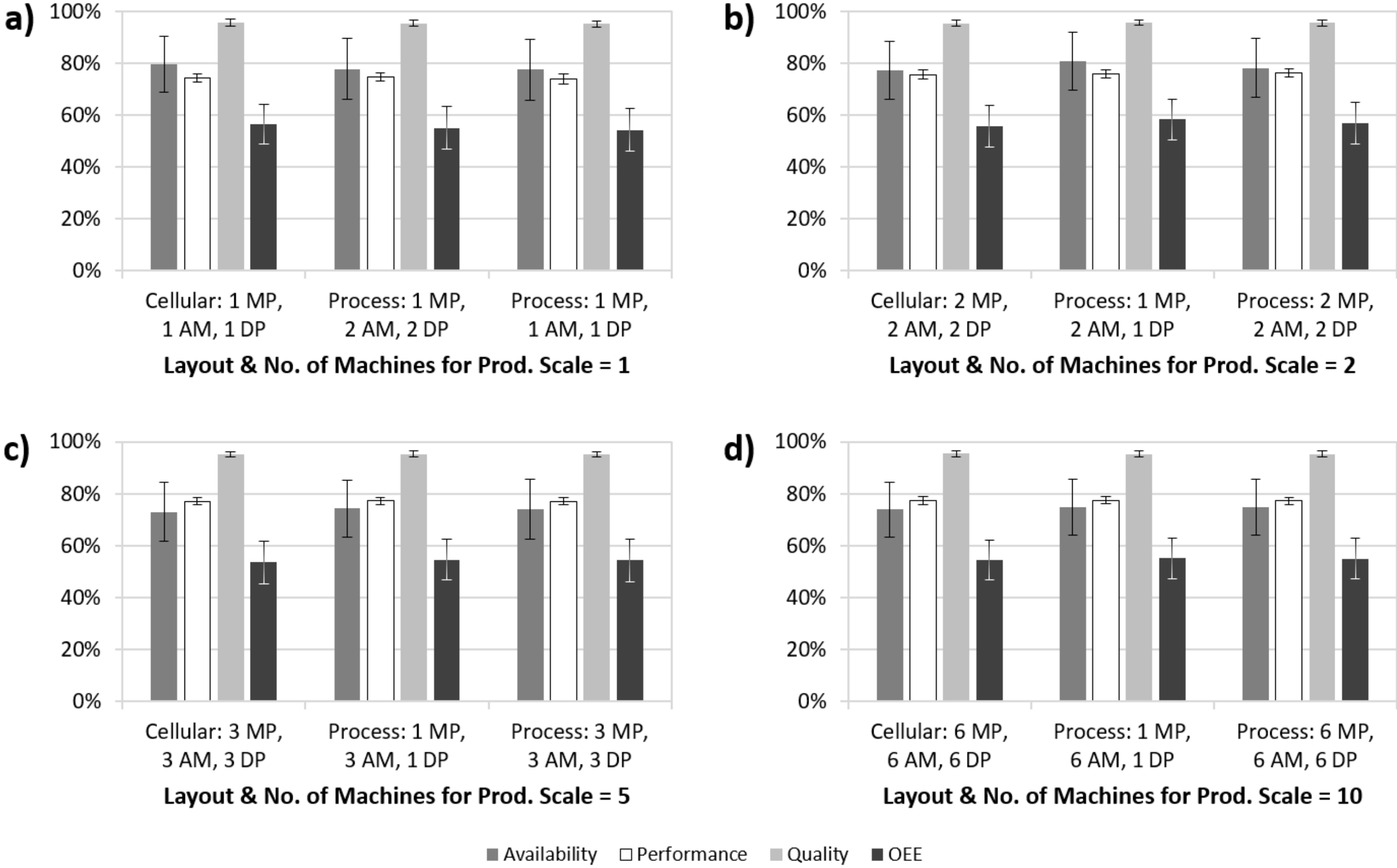


Figure 6.8: OEE and constituent metrics for AM machine for production scales a) 1, b) 2, c) 3, and d) 4

6.5 Effect of Facility Layout on Production Cost

The examination of operations performance for the two facility layout approaches shifts to the production cost. In this section, the key well-structured and ill-structured cost contributors are evaluated on a per-order or per-part basis, as appropriate. Given that the case study AM user's cost rates are not available for commercial sensitivity reasons, the time consumed in the cost-incurring steps is used as a proxy for cost. Like the previous section on production losses, a subset of the possible combinations of production scale, facility layout, and number of equipment is investigated (see Table 6.5).

6.5.1 Well-Structured Cost Contributors

Among the well-structured cost contributors (material, energy, labour and indirect costs), this section focuses on the latter two elements. The conversion of orders into builds is relatively uniform in these experiments and that the incoming stream of orders is also identical, and so the material and energy costs are consistent across the facility layouts. Similarly, the assessment of value-adding time (Section 6.4.1) suggests that facility layout does not affect the machine time, which influences the indirect cost. Figure 6.9 confirms that the AM machine time is uniform across the facility layout approaches; and this is used as a baseline for the analysis of ill-structured costs in the following section.

In contrast, the production loss results demonstrate that the facility layout affects the operator workload, which directly relates to the labour cost. Figure 6.10 shows the labour-incurring time in each part of the AM workflow. The four parts (build packing, AM machine and material setup, AM machine unload, and de-powder and post-process) align with the workflow stages covered by the total cost model. Across the production scales, the AM setup and de-powder steps incur the highest labour time, at 21.4% and 46.7% of the total labour time, respectively. While the total costed labour time decreases as the production scale increases, demonstrating economies of scale in operator input, the relative contributions of each step stay consistent within each facility layout.

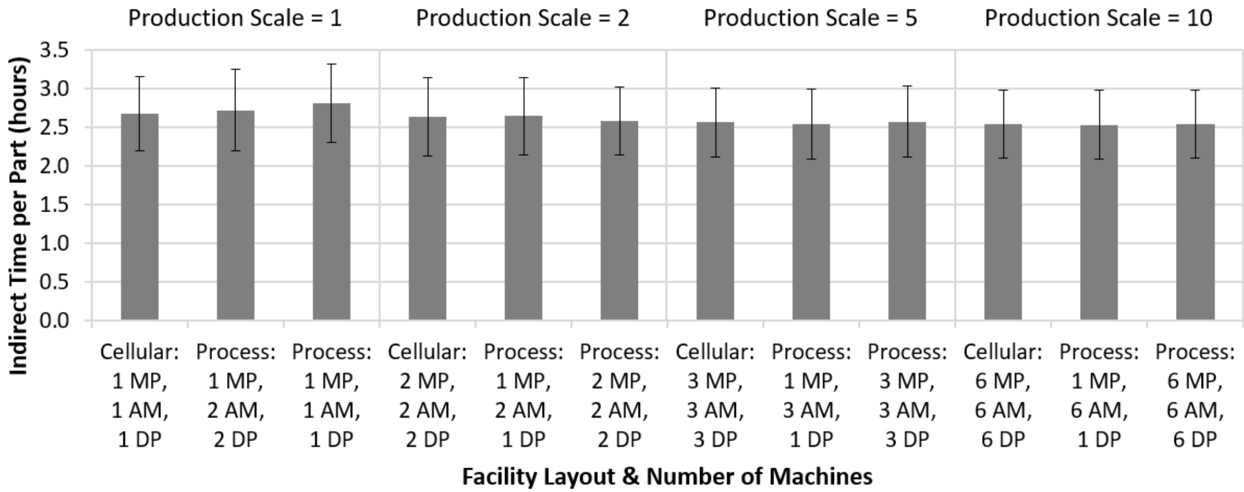


Figure 6.9: Costed indirect time for each facility layout approach at each production scale

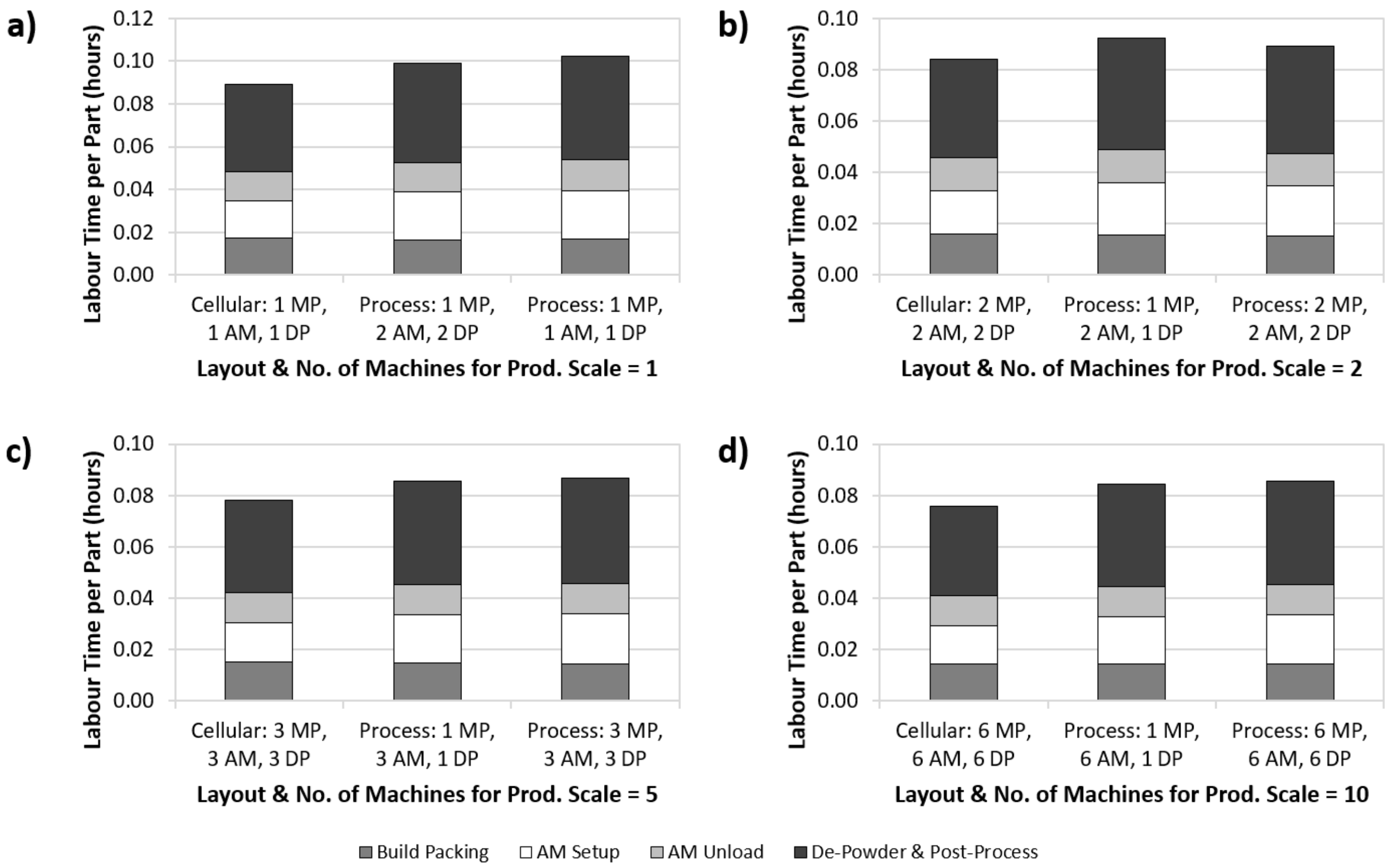


Figure 6.10: Costed labour time in different parts of the AM workflow for production scales a) 1, b) 2, c) 5, and d) 10

In addition, the setup and de-powder steps are the two most affected by the facility layout. Switching from the cellular layout to the process layout increases the setup labour time by 16.5% – 30.7%, and the de-powder and post-process time by 9.5% - 18.0%, depending on the production scale. Connecting this with the findings for non-value-adding time in Section 6.4.1, more time is expended in the process layout on travel between the manual steps, and waiting for the required resources. Therefore, the use of the cellular layout can significantly improve both the time and cost incurred for manual tasks in the AM workflow.

6.5.2 Ill-Structured Cost Contributors

From the total cost model, the two ill-structured cost contributors that feature in this research are the impact of late delivery and build failure. As for the well-structured costs, the time domain is used as a proxy for the cost. To this end, the proportion of orders that are delivered late, along with the mean and spread in their delay, is shown in Figure 6.11. To assess the cost-incurring time for build failure, the effect of failed builds on the two key well-structured costs, labour and indirect costs, is observed; this is shown in Figure 6.12 and Figure 6.13, respectively.

Exploring the late delivery first, Figure 6.11 indicates that the production scale has a greater influence on late delivery than the facility layout. This is caused by the time spent waiting in a backlog for batching the incoming orders at the low production scales, due to the minimum full build capacity utilisation allowed, as explored in Section 6.3. Nonetheless, the cellular layout reduces both the prevalence of late orders and the magnitude of the delay by up to two-fifths at production scales 1 and 2. On the other hand, the process layout experiments perform better at production scales 5 and 10, reducing the rate of late deliveries by up to half, as compared to the cellular layout. Therefore, the cellular layout is better for responsive, time-sensitive fulfilment up to medium-scale production, whereas the increased flexibility afforded by the process layout is best suited to high-scale production.

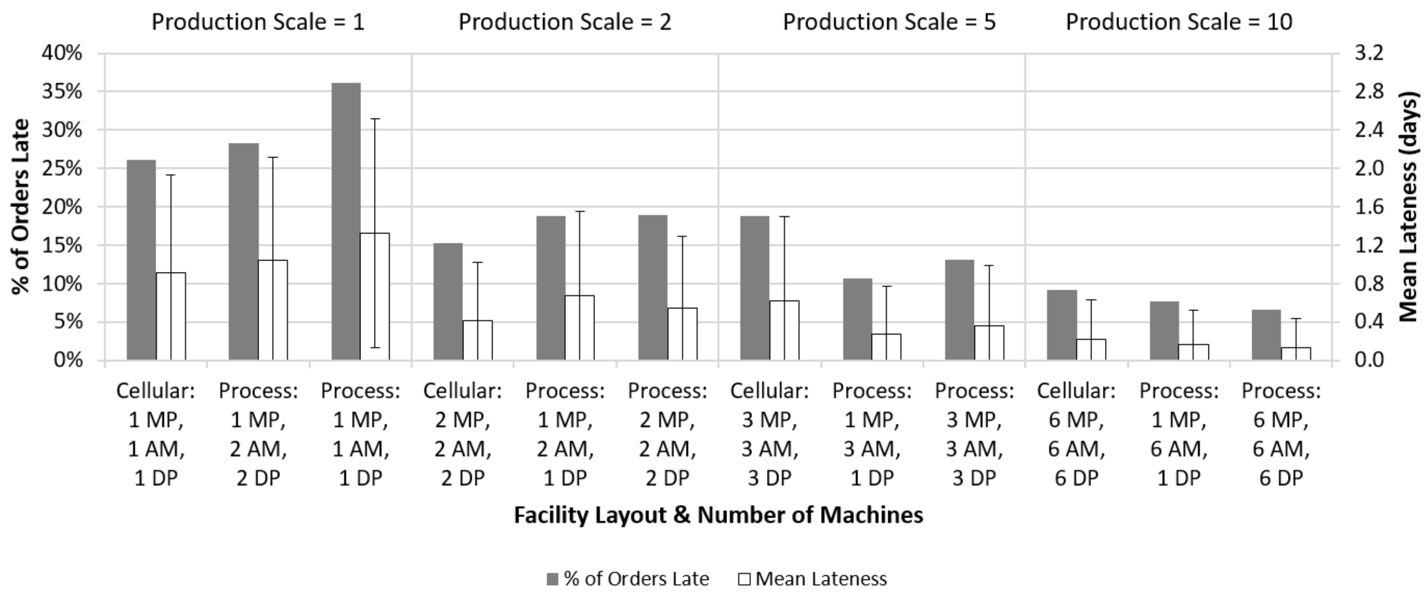


Figure 6.11: Late delivery of orders for each facility layout approach at each production scale

Shifting attention to the impact of build failure, Figure 6.12 and Figure 6.13 show that the response of labour and indirect costs, respectively, to build failure events follow similar patterns. This reflects the sequence of events in the AM workflow, whereby a failed build triggers a repeat of the entire AM workflow from material preparation through to de-powdering; which multiplies the time incurred for the well-structured cost contributors uniformly. Across the production scales and facility layout approaches, build failure causes a 68.1% increase in the labour time, and 73.8% increase in the indirect time.

The facility layout influences the costed time where build failure has occurred in a different way at production scales 1 and 2, than production scales 5 and 10; this is seen from the grey bars for both the labour time (Figure 6.12) and indirect time (Figure 6.13). At the lower production scales, 1 and 2, the costed time upon failure is highest for the process layout when using the minimum number of machines (middle bar in the group at each production scale); and yet, the process layout outperforms the cellular layout when the number of machines are identical. This suggests that there are two influences operating in tandem. First, the process layout has added flexibility to route builds to the next available machine across the entire facility, helping the repeat builds progress through the workflow faster than in the cellular layout, when the number of machines are the same. Second, introducing extra material preparation and de-powder machines, as compared to the scenario with the minimum number of machines in the process layout, improves the ability to turn around portable resources, the build and material cartridges, without delay; this reduces the amount of time that repeated builds spend in the workflow.

In contrast, at the higher production scales, 5 and 10, the cellular layout incurs the lowest costed labour time upon failure (Figure 6.12). Here, the extra labour time for travel in the process layout accumulates over the higher number of workflow repetitions, leading to a consistent disadvantage over the cellular layout. Whereas, all three layout-machine combinations perform similarly for the costed indirect time (Figure 6.13), indicating that layout-related effects on the aforementioned resource delays even out over the higher number of builds.

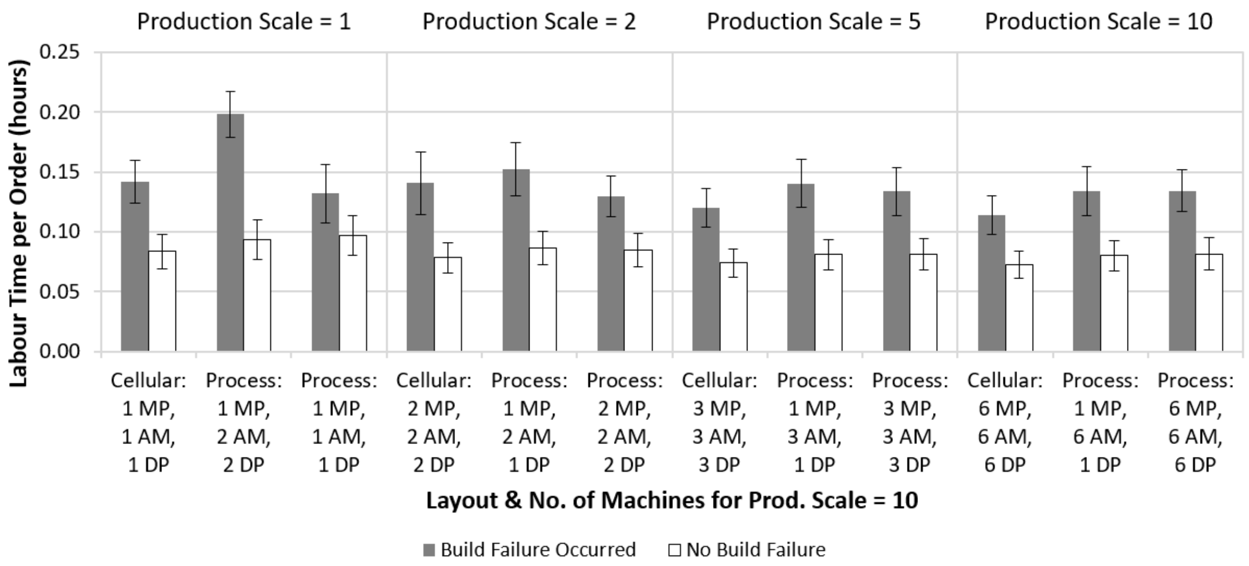


Figure 6.12: Effect of build failure on costed labour time for each facility layout approach at each production scale

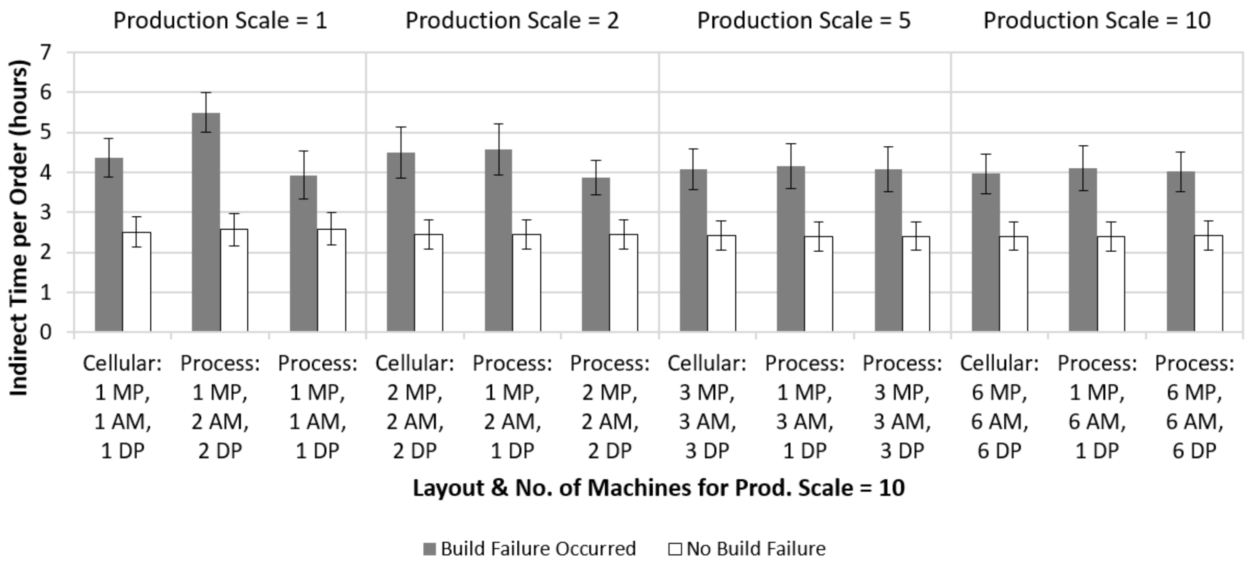


Figure 6.13: Effect of build failure on costed indirect time for each facility layout approach at each production scale

Interestingly, when the number of machines are equal, the facility layout has opposing effects on the two ill-structured costs (due to late delivery and build failure) depending on the production scale; this is outlined in Table 6.6. At production scales 1 and 2, the costed time penalty for build failure is higher for the cellular layout, whereas the penalty for late delivery is lower. In contrast, at production scales 5 and 10, the costed time penalty for build failure is lower for the cellular layout, and the penalty for late delivery is higher. Therefore, the robustness of each facility layout to disturbances, such as build failures, and ability of each facility layout to consistently deliver timely production changes as the scale of production increases. This contradicts the pattern observed for the well-structured cost contributors and the non-value-adding time, where the cellular layout consistently outperforms the process layout with lower cost and production losses.

Overall, the cellular layout is more time- and cost-efficient on average than the process layout, when considering the non-value-adding time, well-structured and failure-related cost contributors. Notably, however, the process layout achieves better adherence to the makespan constraint at higher scales of production, minimising both the fraction of orders delivered late and the delay therein (Figure 6.11). Therefore, the results suggest that the cellular layout performs less consistently at production scales 5 and 10, leading to poorer schedule adherence; and so the process layout may be a better option here.

Table 6.6: Summary of effects of production scale and facility layout on ill-structured cost contributors

Production Scale	**Effect on magnitude of losses due to Late Delivery**		**Effect on magnitude of losses due to Build Failure**	
	Cellular Layout	**Process Layout**	**Cellular Layout**	**Process Layout**
Scale = 1	↓	↑	↑*	↓*
Scale = 2	↓	↑	↑*	↓*
Scale = 5	↑	↓	↓	↑
Scale = 10	↑	↓	↓	↑

Note: ↑ and ↓ denote increase and decrease in cost-incurring time, respectively; * refers to an effect that changes when the minimum number of machines are compared instead

7 Discussion

This chapter presents a discussion of the findings of this research in order to contextualise and ascertain its wider implications for scaled-up AM operations. To this end, the chapter is divided into two distinct parts. The first part, in Section 7.1, compares and contrasts the results from the three preceding chapters to the related literature, explaining the key themes that emerge. The second part, in Sections 7.2 and 7.3, provide an integrated synthesis of the research findings along separate discussion themes that fall into two categories: operations management and technology adoption of scaled-up AM.

Together, the discursive analysis helps identify the advances in understanding of process efficiency and transparency of AM operations that arise from this research. Thus, the mechanisms for improving production losses and cost when managing scaled-up, make-to-order AM, with its associated product and process variety, become clearer – to the benefit of current and future AM users.

7.1 Contextualisation of the Results

7.1.1 Production Losses

Building on the limited discourse about production losses and OEE in AM, the results from Chapter 4 confirm that the fundamental logic of targeting the six big production losses is just as important in AM as in the realm of conventional, tool-based manufacturing. In addition, a novel approach to the calculation of OEE is presented in this research (see Section 3.4.1), which is discussed first.

7.1.1.1 Novel Calculation of OEE for AM

The original OEE formulations (Nakajima, 1988) are adapted in this research to better suit the process characteristics and product variety found in AM-based workflows. The approach for achieving this fit aligns with the work of Jauregui Becker et al. (2015), who retain the equation structures for OEE and the constituent metrics, but adjust the terms to suit their manufacturing system and product variety characteristics. In this case, the use of a cubic volume frame of reference (in the equations for performance and quality) is particularly well-suited to the geometric freedom for parts and fungibility of build space for process planning when using AM (Baumers *et al.*, 2017).

The implications of the novel OEE calculation method in this research can be ascertained by comparing the exploratory simulation results with OEE results for similar processes and operations approaches (Table 7.1). Of the few studies related to OEE in AM, only one provides quantitative values (Parshawanath Jain, 2022). For an equivalent comparison, Parshawanath Jain's results are adapted from measuring the time lost relative to 24 hours per day (calendar time base) to measuring the time lost relative to the planned production time i.e. when the machine is scheduled to run (as in this research). From the change in Parshawanath Jain's results upon switching the calculation method, it is apparent that the OEE calculation method in this research affects the availability and performance metrics, but not the quality metric.

Table 7.1: Comparison of OEE results for powder-bed fusion reported in literature, with this study highlighted in grey

Metric	Parshawanath Jain (2022)		IB-MtS operations approach
	Base: Calendar Time	Base: Planned Production Time	
Availability	12.2%	90.2% *	91.0%
Performance	86.0%	63.5% *	42.4%
Quality	75.0%	75.0% *	97.7%
OEE	7.8%	43.0% *	31.5%

Note: * denotes values calculated from available data & equations (3.5) – (3.7)

The availability metric is inflated in the novel calculation method, due to the use of a planned production time base rather than calendar time. On the one hand, a calendar time base allows the effect of unscheduled time and planned downtime to be captured (Muchiri and Pintelon, 2008). However, in Parshawanath Jain's work, this is currently indistinguishable from the time lost to poor demand and under-feeding the existing capacity, which availability already captures (De Ron and Rooda, 2006). Therefore, the use of calendar time does not provide clear additional information for the AM user. In contrast, the availability metric in this work more accurately reflects how the machine capacity is being managed with respect to the production workload, i.e. planned production. This can provide a better indication of non-value-adding activities within the planned uptime.

In contrast, the performance metric decreases when using the novel calculation method, since idle periods (e.g. machine cool-down) are classed as necessary-but-non-value-adding time rather than part of the machine's productive time. Additionally, Parshawanath Jain's calculations only implicitly account for delays and minor stops, via the change in machine uptime versus calendar time in the availability metric; whereas this should be explicitly included as time lost during machine operating time (De Ron and Rooda, 2006; Muchiri and Pintelon, 2008). As such, the performance metric in this work provides a more complete measure of equipment efficiency and effectiveness during its productive time.

The OEE and constituent metric values in this research and Parshawanath Jain's study are comparable when the same planned production time base is used (third and fourth columns in Table 7.1). While the performance and quality values deviate by 21.1% and 22.7%, respectively, this can be attributed to differences in machine operations due to the metal laser sintering process in Parshawanath Jain's work, such as shorter machine cool-down time and higher part rejection based on sample testing. Thus, the comparison of the studies suggests that the OEE calculation method is valid, and that the simulation results in this research satisfactorily reflect empirical build experiments.

7.1.1.2 Theoretical Framework

The theoretical framework for production losses in AM presents the notion of inherent and non-inherent losses in the AM workflow (Section 4.2.1), extending prior understanding of non-value-adding and necessary-but-non-value-adding time (Hines and Rich, 1997) during a generic manufacturing process. Moreover, a systematic mapping is provided between the AM operations characteristics and their influence on production losses in Table 4.1 and Table 4.2, guiding AM operations managers towards drivers of process efficiency in the workflow.

It is pertinent to emphasise that the theoretical framework demonstrates that all six production losses apply to AM. This contradicts previous assertions that reduced speed losses and start-up yield losses are not found in AM (Fera *et al.*, 2017). Referring to empirical studies involving laser sintering, this conflict can be further explained. Across 10 build experiments on the same machine with identical process parameters, contents and part packing, the build time varies by up to 55 minutes, or 37% (Baumers and Holweg, 2019). This does not agree with Fera et al.'s (2017) suggestion that the actual process time always matches the predicted time, which would be uniform in the aforementioned case. For start-up yield losses, process control studies identify layer-wise thermal variation arising from the interaction between the part geometry and whether sintering occurs over unsintered powder or previously sintered regions (Abdelrahman and Starr, 2015). Therefore, conditions within the AM machine are not uniform across the build process, as stated by Fera et al. (2017), and so start-up yield losses may arise.

7.1.1.3 Influence of Operations Approach

The results of the exploratory simulation study for OEE (Figure 4.5) and itemisation of the planned production time (Figure 4.6) show that the operations approach is a strong determinant of the process efficiency in AM.

Of the operations approaches investigated, the Identical Batch Make-to-Stock (IB-MtS) approach outperforms the alternative make-to-order options in terms of the OEE achieved, followed by Capacity Maximising Make-to-Order (CM-MtO), and lastly, Lead Time Minimising Make-to-Order (LTM-MtO). This pattern is largely driven by idle time losses, with complementary influences from reduced speed losses and setup losses (Figure 4.6). The fulfilment of production using as few builds as possible in IB-MtS means that the setup and idle losses associated with switching from one build to the next are minimised. Also, from closer examination of the build properties, the IB-MtS approach is also found to achieve the highest utilisation of machine capacity, as measured by the full build capacity utilisation, which leads to lower reduced speed and better amortisation of idle time losses. Extending this to the two make-to-order operations approaches, the CM-MtO approach leads to higher full build capacity utilisation and fewer builds than LTM-MtO; and so the associated setup and idle losses are almost half in CM-MtO than LTM-MtO.

In comparing the IB-MtS and CM-MtO approaches, both of which prioritise maximal use of the available machine space, it is important to acknowledge that the part size and geometry affects the achievable packing efficiency (Oh *et al.*, 2020). The test parts in this research coincidentally lead to well-packed builds in the IB-MtS approach, at close to 10% full build capacity utilisation. An alternative study that follows the same approach only realises builds with 2% full build capacity utilisation, due to the thin-walled and hollow nature of the parts therein (Alogla, Baumers and Tuck, 2019). Therefore, in practice, CM-MtO may outperform IB-MtS if the given selection of products can be packed more tightly in mixed batches than in identical part batches. Indeed, this is demonstrated by Ruffo and Hague (2007) from a cost perspective. Hence, the use of a hybrid approach, a standard batch of mixed parts with higher full build and occupied cuboid capacity utilisation, may be more appropriate than IB-MtS to minimise performance-related production losses, depending on the parts.

More generally, the underlying mechanism for the production loss results is similar in logic to quantity-cost relationships observed for single-machine AM operations (Figure 7.1). In the saw-tooth cost-quantity pattern (Ruffo, Tuck and Hague, 2006a), fully occupying each horizontal layer with parts gives a local cost minimum, whereas the fixed cost increment for each new build leads to a local cost maximum. In this research, the analogous production loss contributors are reduced speed and idle losses during the deposition of each layer; and setup and idle losses during changeover, warm-up and cool-down time between builds. Notably, the single-part builds for rework observed in the CM-MtO operations approach are equivalent to the aforementioned peaks in the saw-tooth quantity-cost relationship, with no economies of scale to amortise fixed production losses. Therefore, non-value-adding and necessary-but-non-value-adding time contributes towards cost-efficiency of production as well.

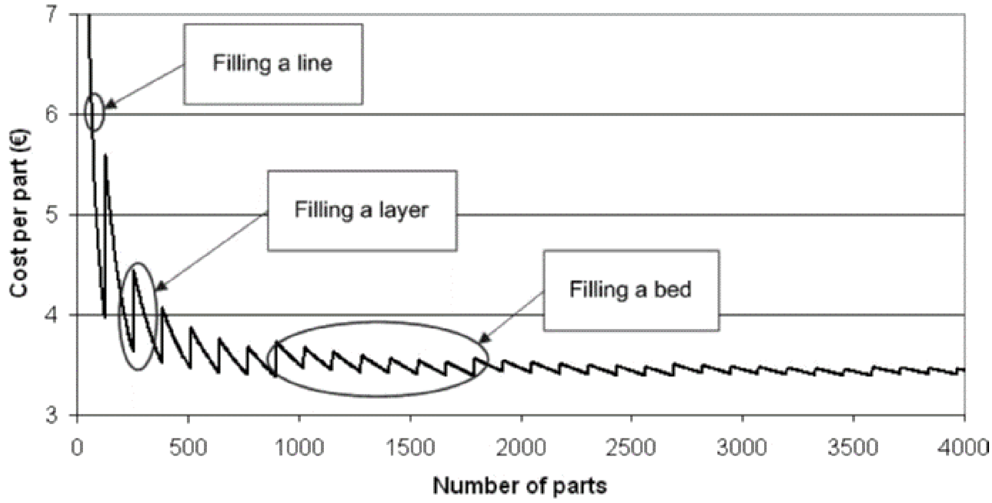


Figure 7.1: Quantity-cost curve for production of small parts using identical batch make-to-stock operations approach, taken from Ruffo et al. (2006a)

Across the operations approaches, the OEE values indicate that there is significant room for improvement in the production losses for laser sintering: the range in OEE of 16.4% - 35.1% straddles the lower bound (30%) of commonly-accepted values for conventional manufacturing (Dal, Tugwell and Greatbanks, 2000). This aligns with Parshawanath Jain (2022), who estimates a very low OEE of 7.8% when production losses are measured relative to calendar time (or 43.0% relative to planned production time, as per Table 7.1).

The constituent metrics help identify the reasons for high production losses, and help direct AM managers towards potential solutions (Dal, Tugwell and Greatbanks, 2000; Muchiri and Pintelon, 2008). The results of this research strongly suggest that the performance metric should be improved by targeting idle and reduced speed losses. To this end, the ability to cool down one build while simultaneously starting the next would significantly improve idle losses (Šoškić *et al.*, 2019); as would parallelisation in the layer-by-layer deposition process, such as through the adoption of multiple energy sources (EOS GmbH, 2021). Alongside these technological improvements, the operations approaches point towards the first two (of four) driving propositions that AM users should consider when planning production to minimise production losses:

1. To maximise OEE in AM, the foremost priority should be to minimise the number of builds.

This increases the ratio of productive deposition time to inherent fixed losses per build. Yet, the adverse consequence is to increase time lost to breakdown in the case of build failure, which may lead to unacceptable further outcomes, such as late delivery and wasted overhead costs during downtime.

2. The allocation and packing of parts should seek to achieve high full build and occupied cuboid capacity utilisation.

This depends on a consistent distribution of size and shape in the parts, appropriate to the AM machine. For the machine and parts in this study, homogeneous part size and shape are most favourable (IB-MtS), but similar space-efficient packing is achieved when mixed parts fit well together in a given build volume (CM-MtO). This minimizes uncertainty in the reduced speed losses and improves the confidence in the performance metric recorded.

7.1.1.4 Influence of External Factors

The two external factors, lead time and part size variety, are found to influence the production losses and OEE in different ways (Figure 4.13). Extending the lead time improves the OEE by increasing the volume of parts available to process at any one time, which in turn increases the ability to maximise use of machine capacity. This reduces setup and changeover losses between builds, and increases the amortisation of reduced speed and idle losses during builds. Importantly, however, the benefits of extending the lead time can only be realised when the operations approach allows taller, more time-consuming builds, as in CM-MtO. On the other hand, changing the part size variety affects the achievable packing density. For the test parts used in this study, moderate variety (PSV = 50) results in less dense packing (lower occupied cuboid capacity utilisation) than the scenarios involving no variety (PSV = 0) and higher variety (PSV = 100). Where the occupied cuboid capacity utilisation is higher, the productive proportion of the build time increases (Ruffo, Tuck and Hague, 2006a; Dirks and Schleifenbaum, 2020) and so performance losses are lower.

Therefore, two further propositions arise for AM users to consider when planning production to minimise production losses, completing the set of four:

3. Efforts to extend the order lead time will reduce changeover and idle losses, when applied in conjunction with the first two propositions.

While short lead times are a competitive advantage for AM, it is possible to manage customer expectations to balance this against effective use of machine capacity. For example, direct digital manufacturers may advertise a lead time range, to allow more time for the order book to fill when variation in production demand is at a low point, without missing customer delivery targets.

4. Efforts to constrain the part size variety during the allocation and packing of parts will reduce performance losses, in line with the full build and occupied cuboid capacity utilisation.

Process planning and packing algorithms can be adjusted to account for part size, alongside schedule constraints, when allocating parts to build jobs to mitigate the effect of part size variety on the capacity utilisation.

It is important to acknowledge that the external factors are somewhat beyond the control of AM users: lead time is dictated by the competitiveness of the make-to-order service in the chosen market (Cotteleer and Trouton, 2016), while part size variety is set by the product mix across the incoming orders. Nevertheless, this research has shown that the external factors can be viewed as “levers” that complement the operations approach to maximise the value-adding use of available capacity, within reason.

7.1.2 Workflow Optimisation and Production Cost

The second study builds upon the AM cost literature that explores AM process planning optimisation. The results from Chapter 5 highlight the importance of appropriate workflow optimisation approaches for achieving both effective use of the equipment capacity, and timely delivery of orders. In particular, it is shown that an integrated workflow optimisation approach can outperform simpler alternatives; and the discussion thereof opens this sub-section.

7.1.2.1 Cost-Effectiveness of Integrated Optimisation

The results for the exploratory simulation for workflow optimisation show that accounting for both packing and scheduling, whether separately or via integrated optimisation, reduces both the mean and spread in the cost of production (Figure 5.1). The effect of switching from separate optimisation (approach D) to integrated optimisation (approach E) on the specific cost of production is found to be marginal, with an improvement of just 0.01 GBP/cm^3 for approach E. As explained in Section 5.5, the difference arises from better utilisation of the available capacity, with more compact builds (higher occupied cuboid capacity utilisation) and higher consistency in the build contents (lower spread in full build capacity utilisation).

With respect to make-to-order operations at scale, the improved uniformity of build properties that integrated optimisation achieves has the potential to significantly alter the predictability of production cost. This is a known issue for AM operations management, particularly for AM bureaus that must provide cost estimates without prior knowledge of the properties of the builds in which orders will be fulfilled (di Angelo and di Stefano, 2010; Rudolph and Emmelmann, 2018). However, these prior studies into predicting AM part cost with limited build information focus on well-structured costs only; and so the findings of this research are novel in establishing consistency among ill-structured costs as well. Therefore, the use of integrated optimisation can increase the confidence in estimates of expected build properties for given incoming order rates, or throughput rates. As order price estimates improve in accuracy, AM users can achieve increased profitability and competitiveness.

7.1.2.2 Validation of Cost Drivers

By comparing the specific cost of production with other polymer laser sintering cost studies, the underlying cost drivers can be validated. This also helps to identify mechanisms by which workflow optimisation approaches that involve both packing and scheduling outperform alternatives on cost-effectiveness. To this end, Table 7.2 gives the production cost from a selection of studies over the past two decades, and the results of this study for approaches D and E.

Table 7.2: Comparison of specific cost results reported in polymer laser sintering literature, with this study highlighted in grey

Machine	**Specific Cost (GBP/cm^3)**	**Source**
EOS P100, novice operator	1.27 *	(Baumers and Holweg, 2019)
EOS P100, expert operator	0.87 *	(Baumers and Holweg, 2019)
EOS P100	0.84 *	(Baumers and Holweg, 2016)
EOS P770	0.80 *†	(Alogla, Baumers and Tuck, 2019)
EOS P100: Approach D	0.54	This study
EOS P100: Approach E	0.53	This study
EOS P100: Approach D, excluding risk-related costs	0.35	This study
EOS P100: Approach E, excluding risk-related costs	0.34	This study
3D-Systems Vanguard	0.31 *†	(Ruffo, Tuck and Hague, 2006a)

Note: * denotes specific cost that is inferred from data provided, and † denotes currency conversion using average historical exchange rate from reference year

Referring to Table 7.2, the cost of integrated optimisation in this study is at least 0.31 GBP/cm^3 lower than two previous studies into the same EOS P100 system (Baumers and Holweg, 2016, 2019), and 0.27 GBP/cm^3 lower than a study into the newer EOS P770 system (Alogla, Baumers and Tuck, 2019). Despite differences in the cost models, whereby the P700 costs have no risk-related component, the full build capacity utilisation emerges as a key driver for the large specific cost disparity. The 3DPackRAT software used in this research packs parts more densely than the conservative manual packing approach in the previous P100 studies, at 12% (mean) versus 9% full build capacity utilisation respectively. In the P770 study, the full build capacity utilisation is lower still, at approximately 2%, due to the part geometry. The full build capacity utilisation influences the indirect and material costs through the build time and unsintered material consumed per unit volume of output. In this research, these cost drivers are lowest when using integrated optimisation. Ruffo, Tuck and Hague (2006a) report a similar specific production cost to approaches D and E in this study, while operating a different laser sintering machine at 12% full-build capacity utilisation. However, this comparison relies on neglecting the risk-related cost from the results of this study for equivalent cost model assumptions. Nonetheless, across the different comparisons, the importance of sufficiently filling the machine capacity for cost-effective AM operations is underlined, in agreement with previous studies.

7.1.2.3 Trade-Off between Capacity-, Failure-, and Schedule-related Costs

Expanding upon the importance of process planning to towards efficient use of machine capacity, the detailed study of the cost drivers in this research reveals a trade-off between the indirect, failure, and lateness costs (Figure 5.6). These in turn relate to managing effective use of capacity, the risk of failure, and adherence to schedule constraints. This extends and combines two separate pairs of trade-offs that have been explored in the AM operations management discourse: capacity versus risk of failure (Baumers and Holweg, 2016), and capacity versus timeliness of delivery (Khajavi *et al.*, 2018).

Baumers and Holweg (2016) introduce a trade-off between indirect and failure costs, driven by capacity utilisation and build height, respectively. This leads to optimum cost performance at sub-maximum full-build capacity utilisation. The pattern in indirect and failure costs, plotted against build height in Figures 5.5 and 5.6, show that this research aligns with the previous work. Furthermore, Figure 5.7 highlights that this phenomenon strongly influences the performance of the optimisation approaches in terms of specific production cost. In particular, moderate height builds in optimisation approaches C, D and E occupy the most cost-effective region of operation, at less than 0.55 GBP/cm^3.

In the other half of the three-way trade-off, Costabile et al. (2017) note that capacity utilisation cannot be wholly prioritised at the expense of part lateness when managing the delivery of an incoming order stream. This captures the overarching process-planning challenge for make-to-order AM operations. To this end, the results of this research can be contrasted with the work of Khajavi et al. (2018), who include penalties for non-timely delivery in their study on digital kitting in AM workflows. The relevant workflow results are summarised in Table 7.3. Comparing equivalent optimisation approaches (Experiment 1 and approach B, Experiment 5 and approach E), integrated optimisation results in 13% higher specific production cost than packing optimisation in Khajavi et al.'s work, despite a similar proportion of parts delivered late (20% in approach B, 26% in Experiment 1). This contradicts the results from this research, where the specific production cost difference is 55% in the opposite direction.

Table 7.3: Comparison of AM workflow results in this study, highlighted in grey, against Khajavi et al. (2018)

Workflow Optimisation Approach	**Mean Specific Cost (GBP/cm^3)**	**% of Parts Late**	**Mean Build Height (mm)**
Packing Only (Experiment 1)	0.10	26	292.7
Packing and Scheduling, Integrated (Experiment 5)	0.13	0	195.0
Packing Only (Approach B)	0.82	20	288.7
Packing and Scheduling, Integrated (Approach E)	0.53	0	259.3

However, the build heights explain this contradiction. Given a lower volume of parts in Khajavi et al.'s order schedules than in this study, integrated optimisation (Experiment 5) generates builds that are 195mm tall on average. These builds fall below the optimum moderate range (225 – 315mm, see Figure 5.6), which leads to higher indirect costs. Alongside this, packing only optimisation (Experiment 1) leads to builds that fall within the aforementioned optimum range. Moreover, Khajavi et al.'s cost model does not include failure-related costs, as this is outside the scope of their work. If the risk-of-failure model from this research is applied to their results, the unit cost difference between Experiments 1 and 5 drops to 3%, and importantly, integrated optimisation (Experiment 5) is cheaper.

Therefore, the results in this research extend previous work to show that the production cost depends on a trade-off between all three major cost drivers: build productivity derived from capacity utilisation, the risk of failure, and timely delivery. The workflow optimisation approaches lead to builds that fall in different regions of this trade-off. Thus, cost-effective production is achieved not only by generating productive, low-risk builds on-time, but doing so consistently; which integrated optimisation is able to do most successfully.

7.1.3 Facility Layout

The third study extends the AM capacity management and scheduling discourse to include the impact of facility layout on AM operations efficiency, evaluating this with respect to a real AM user's facility. To this end, the results of Chapter 6 uncover and explain the sources of non-value-adding time and workflow inefficiency that arise from the cellular and process layout choices for AM.

The findings confirm that the facility layout sufficiently impacts the ancillary steps in the AM workflow so as to influence the time- and cost-efficiency of production. It is also shown that the facility layout influences the robustness of the workflow to disturbances, such as unplanned maintenance and machine breakdown. Notably, the effect of facility layout on the average makespan and timeliness of delivery can change, depending on the production scale. Therefore, AM operations exhibit a link between production throughput and appropriate facility layout, in a similar manner to conventional manufacturing.

7.1.3.1 Influence of Production Scale

Expanding upon the summary above, the results for setup investment (Section 6.3), production losses (Section 6.4), and cost contributors (Section 6.5) can be brought together to provide a mapping between facility layout and production scale, specific to the AM context. This is shown in Table 7.4. Notably, the mapping extends the generic characteristics of the facility layout approaches (Table 2.11), as developed for conventional manufacturing. Outlining the observed strengths and weaknesses of each AM facility layout approach in this way provides a guide for AM users to make the appropriate choice for their direct digital manufacturing application by considering process efficiency, in both time and cost, and adherence to external constraints.

Table 7.4: Characteristics of facility layout approaches for AM

Characteristic	**Facility Layout Approach**	
	Process	**Cellular**
Orientation	Segregated workflow steps	Integrated workflow steps
Product-Process Mix	Independent of product mix or variety	
Production Scale	Higher scale (> 10,000 parts per year)	Lower and higher scale (1000s – 10,000s parts per year)
Advantages	Higher flexibility in setup investment Higher flexibility in scheduling Better for schedule adherence at higher scales of production	Negligible travel time within the manufacturing cell Lower labour load Better for schedule adherence at lower scales of production
Disadvantages	Higher travel time Higher waiting time More time lost to unplanned maintenance More time lost to build failure	Lower flexibility in setup investment Lower flexibility in scheduling

Two significant differences are found between the AM-specific (Table 7.4) and the generic facility layout characteristics (Table 2.11). First, the facility layout choice is independent from the product variety. In other words, neither layout incurs changeover inefficiencies for fulfilling a high variety of products. This is due to the non-dedicated nature of AM machines and ancillary equipment, and the fungibility of AM machine capacity (Baumers *et al.*, 2017). However, it should be noted that, where production regularly involves parts made using different materials, equipment and workspaces can be dedicated to each specific material to avoid contamination issues (Kang *et al.*, 2018).

Second, the process layout in AM exhibits higher vulnerability to disruptions such as unplanned maintenance and build failure, which is a characteristic of the line layout paradigm. However, the underlying cause is different in each case. In the line layout, disruption from downtime arises from the inflexibility of the workflow to adjust around the unavailable machine (Radford and Richardson, 1977, p. 133). On the other hand, in the AM process layout, while production can easily be switched from an unavailable machine to an available alternative operating in parallel, inefficiencies in the workflow around the machine accumulate. For example, extra delays arise in the workflow from waiting for ancillary resources (such as build and material cartridges) and extra travel time between machines (Figure 6.7 and Figure 6.12, respectively).

Overall, there is a trade-off between process efficiency across the workflow, and flexibility in both capacity management and scheduling (Table 7.4). The process layout is able to fulfil production using fewer ancillary machines than the cellular layout, incurring a lower setup investment. However, this is at the expense of a higher non-value-adding time in the workflow, due to waiting and travel between machines, along with the labour load incurred. Nevertheless, the additional flexibility in routing offered by the process layout improves its consistency in the time domain, leading to better schedule adherence than the cellular layout. Therefore, while the cellular layout is the better choice to minimise production losses across the AM production facility, the process layout offers better stability in the time domain at higher production scales.

7.1.3.2 Impact on Value-Adding and Non-Value-Adding Time

The impact of facility layout on the value-adding and non-value-adding time in the AM workflow has been explored in depth in Section 6.4.1, particularly the impact of non-value-adding travel and waiting time on process efficiency. Given the paucity of facility layout studies in the AM management discourse, the results from Chapter 6 are contrasted with one study only, Kellner et al. (2019), which focuses on the process layout. Table 7.5 presents the results of this research and Kellner et al.'s optimised process layout for metal laser sintering.

Both sets of results confirm that non-value-adding time is a significant proportion of the overall production makespan. However, the impact of travel and waiting time is noticeably higher in Kellner et al.'s work, at 84.0% of the makespan, compared to 37.7% or less in this research. There are two main reasons for this difference. First, the metal laser sintering process in Kellner et al.'s work requires a much shorter production time than polymer laser sintering, particularly given the large machine used by the case study company. The difference is 25-fold, at 2.1 hours for metal laser sintering versus 55.3 hours on average for polymer laser sintering. Therefore, the production time inevitably dominates the overall makespan length in this research.

Table 7.5: Comparison of value-adding and non-value-adding time with results for powder-bed fusion reported in literature, with this study highlighted in grey

Facility Layout Approach	**Production Scale**	**Fraction of Makespan**			**Source**
		Production	**Travel**	**Waiting ***	
Process	-	16.1%	41.7%	42.3%	(Kellner *et al.*, 2019)
Cellular	1	64.0%	0.0%	36.0%	This study
Process	1	63.3%	0.3%	36.5%	This study
Cellular	2	68.7%	0.0%	31.2%	This study
Process	2	66.9%	0.3%	32.8%	This study
Cellular	5	65.5%	0.0%	34.4%	This study
Process	5	62.3%	0.2%	37.5%	This study
Cellular	10	69.4%	0.0%	30.6%	This study
Process	10	62.1%	0.2%	35.8%	This study

Note: * “Waiting” is equivalent to “Storage” in Kellner et al. (2019)

Second, the production facility in Kellner et al’s study uses slow-moving conveyors between machines, which themselves act as a work-in-progress buffer between process steps. In contrast, the case study company in this research rely on operators to transfer parts and builds between the machines manually, but as quickly as possible. As a result, the travel time is shorter in this study, and its impact on the makespan is minimal. However, it is important to acknowledge that automating the manual loading and unloading process for the material preparation, AM and blasting machines would improve the labour load in the workflow, particularly at higher production scales – albeit at the expense of potentially higher travel-related non-value-adding time.

7.2 Operations Management of Scaled-Up AM

Shifting focus to the AM practitioners’ perspective, this section discusses the results in the context of operations management of scaled-up AM.

7.2.1 Systems Perspective of AM Operations

The importance of a systems perspective towards industrial AM is highlighted by Eyers and Potter (2017), who seek to expand the perspective of AM management beyond the control of AM processes in individual machines. The AM system definition proposed by the authors covers the full production value chain: design, pre-processing, production, and post-processing (see Figure 7.2). This perspective underpins operations management and the pursuit of efficient and effective use of resources across full AM workflows.

To this end, the research studies in this thesis investigate the system demands, resources, disturbances and outputs for the pre-processing and production elements of the chain. Notably, the results inform operations management decision making at different levels of abstraction in the AM system: from single-machine productivity (Chapter 4), through production cost control for discrete multi-machine systems (Chapter 5), to workflow productivity and cost across entire AM facilities (Chapter 6). These levels of abstraction correspond to Muthiah and Huang's (2007) structure of analysis: machine, workflow sub-system, and factory. Expanding Eyers and Potter's (2017) evaluation of the impact of the AM systems perspective on manufacturing competitive objectives, Table 7.6 shows how the results in this thesis provide new, practical insights in each dimension for AM users.

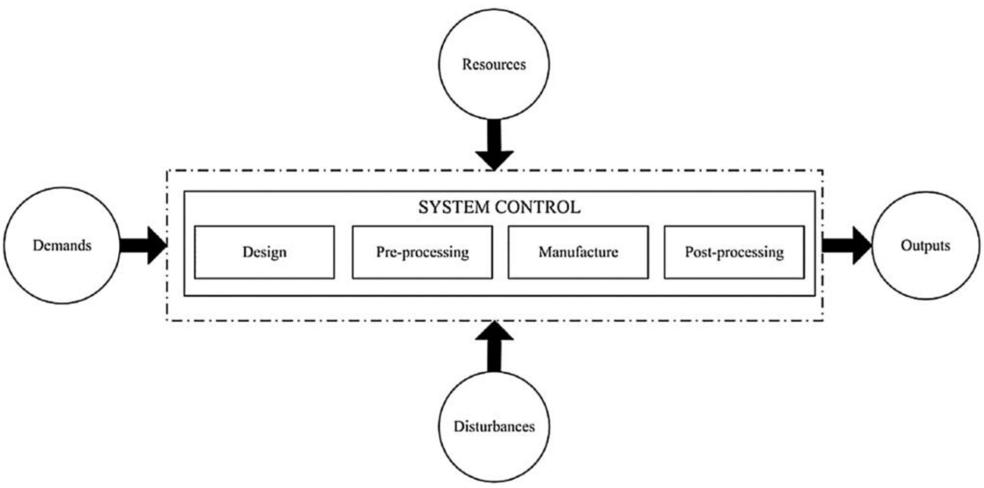


Figure 7.2: Industrial AM system definition, taken from Eyers and Potter (2017)

Table 7.6: Systems-level AM operations findings with respect to manufacturing competitive advantages

Competitive Objectives	**Definition ***	**Findings at Level of Systems Abstraction**		
		Single AM machine	**Network of AM machines**	**AM Production Facility**
Cost	Expense incurred by manufacturing operations in the satisfaction of demand.	(Not explored in this research.)	Integrated control of the AM workflow improves cost through efficient allocation of shared resources (i.e. each AM machine) to input orders.	The process layout allows ancillary machine resources to be shared more efficiently, improving setup costs for scaled-up AM systems.
Dependability	Correct satisfaction of demand at the expedited time.	Inherent production losses at the AM machine exacerbate the time lost when disturbances affect the system, leading to build failure.	Limited to AM machine reliability, consistent allocation of demand across the AM machine network reduces deviations in reliability.	The cellular layout improves system dependability, at the expense of redundant capacity in ancillary machines; although facility layout effect diminishes at higher scale.
Flexibility	Ability to change attributes of the production system and/or its outputs with little penalty.	(Not explored in this research.)	(Not explored in this research.)	The process layout is more amenable to system-level flexibility in production capacity and scheduling.
Quality	Manufacture of products that conform to a predetermined specification.	The pursuit of acceptable quality can diminish the most efficient use of AM machine capacity (e.g. through packing constraints).		The impact of AM machine quality issues cascade via repeated steps required elsewhere in the workflow.
Speed	Time taken to respond to customer demand.	Inherent production losses at the AM machine limit the scope for compressing lead times.	Appropriate production planning control (a pre-processing step) is paramount for achieving acceptable lead times.	As for dependability, the cellular layout improves lead time, at the expense of redundant capacity. Although, the process layout excels for scaled-up AM via its flexibility.

Note: * Definition of competitive objectives as per Eyers and Potter (2017)

7.2.2 Transparency of AM Operations

As compared to conventional manufacturing, the use of AM leads to better transparency and understanding of resource efficiency, by simplifying and condensing multiple, distinct manufacturing processes into a single AM workflow (Baumers *et al.*, 2013). Despite this, the understanding of process efficiency in AM has been restricted to date, due to unsuitable metrics and measures for manufacturing performance – particularly in relation to productivity. There is a myriad of "partial" metrics, which apply to either specific (and sometimes unrealistic) machine conditions, such as complete defect mitigation in-situ (Reid, 2019); or to specific use cases, such as utilisation measured against incoming orders (Gopsill and Hicks, 2018) and throughput measured against batch size (Stittgen and Schleifenbaum, 2020). Such metrics give an incomplete picture of machine productivity, and importantly, the potential value being generated by the expensive AM process.

In this research, the development of coherent and comprehensive productivity metrics (namely, OEE, and also the use of value-adding time) improves the transparency of AM operations further and supports decision-making to maximise AM machine performance. While OEE and value-adding time are applied to isolated machines and workflows within a single production facility in this thesis, others show that OEE can provide decision-support even when operations span across different, distributed facilities (Antônio Mendonça, Da Piedade Francisco and De Souza Rabelo, 2022).

As a further consequence, purposely-designed performance metrics for AM make it easier for users to understand the system, without needing to delve into its intricacies (Melnyk, Stewart and Swink, 2004). On the one hand, while it is important for AM operations researchers to find the deeper, underlying mechanisms behind effective and efficient AM workflows, the target for AM users is to maintain proper performance of their systems quickly and effortlessly. Well-designed metrics therefore provide easier paths for AM users to find the proper solution to issues as they arise, increasing confidence in AM deployment and operations management in industry.

From a wider perspective, Melnyk et al. (2004) provide a typology of metrics that are of interest to operations managers, shown in Figure 7.3. The research in this thesis focuses on the outcomes tense (rather than the predictive tense), whereby actual production data is used to provide an indication of performance after the event – and inform future AM operations decisions. Additionally, the total cost estimation and OEE metric together capture the financial and operational (or productivity) focuses, leading to a holistic appraisal of AM operations. The evaluation of production loss drivers in laser sintering has uncovered common relationships between the financial and productivity-related performance, such as the dependence on efficient use of machine capacity, and trade-offs between minimising changeovers and reliability-related costs and downtime. Nevertheless, it could be useful for future research to focus on formalising the relationships between cost and productivity to further improve the transparency of AM operations.

		Metrics Tense	
		Outcome	**Predictive**
Metrics Focus	**Financial**	Return on Assets	Overtime Dollars *(predictive for budget overrun)*
	Operational	Elapsed Lead Time	Number of process steps and setups *(predictive for lead times)*

Figure 7.3: Typology of operations metrics, from Melnyk et al. (2004)

7.2.3 Production Strategies and Trade-Offs

A common theme that has emerged in the results is that of trade-offs that arise in both cost-, quality- and time-related performance when pursuing different process planning strategies in AM. Depending on the priority pursued by the AM user, which in turn is informed by the business model and customer needs, the results have illustrated which process planning approach would be best.

This is summarised in Figure 7.4. To further clarify, the closing remarks of this section cover the key features, metrics, and pitfalls of each approach for operations management of scaled-up AM.

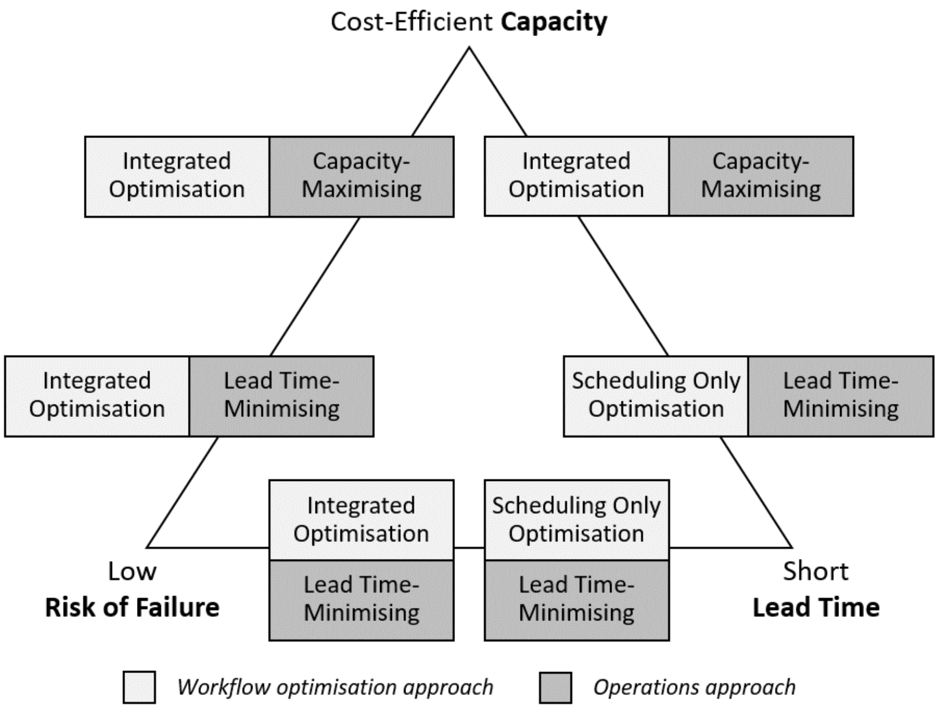


Figure 7.4: Overview of production strategies and trade-offs in outcomes

Looking at the operations approach first, the capacity-maximising approach leads to more cost-efficient use of machine capacity at the expense of lead time and risk of failure, which are both driven by build height. Minimising the production cost would be the expected strategic driver for this approach; and additionally, the production losses are lower here, as per the availability and performance sub-metrics of the OEE. On the other hand, the lead time-minimising approach prioritises the responsiveness of production, and so the makespan would be an appropriate metric. Short lead time (and lower risk of failure) are achieved through short builds with low full build capacity utilisation. This leads to poor amortisation of fixed time and cost elements, which accrue mainly on a per-build basis. Given that the time and cost per part would be higher, AM bureaus can typically charge a premium for short lead times.

Following a similar logic, the Scheduling Only workflow optimisation approach minimises the lead time at the expense of inconsistent cost. Here, only parts to be delivered imminently are manufactured in each build job, and so depending on the production scale (and, thus, use of machine capacity), this optimisation approach may lead to a mix of short and tall builds, with fluctuations in the risk of failure and amortisation of fixed costs. In contrast, integrated optimisation of packing and scheduling generates builds with balanced capacity utilisation, trading off the risks of failure and late delivery with the fixed costs. Integrated optimisation is most suited to a cost- and production loss-driven strategy, and particularly to the management of unpredictable order streams in AM bureaus.

It is worth noting that as the production scale increases, the role of facility layout in cost-, time- and quality-efficiency also becomes important (Huang *et al.*, 2021). Referring to the facility layout characteristics for AM workflows (see Table 7.4), the cellular and process layouts can be assessed against the three-way trade-off. The cellular layout reduces the impact of failures on the makespan, and minimises non-value-adding time (waiting and travel); whereas the process layout sees shorter makespans at higher production scales. Thus, the cellular layout is suitable when the quality is prioritised, and for short lead times at low production scales. The process layout favours cost-effective use of workflow capacity (across all equipment), at the expense of adequate lead times and lower redundancies to failure, at higher scales of production.

7.3 Technology Adoption of Scaled-Up AM

In the second of the two cross-cutting discursive themes, this section explores how the results can influence the technology adoption of scaled-up AM.

7.3.1 Towards Digital Factories

AM is a distinctly digital manufacturing process, which should inherently support the benefits of digital factories such as increased responsiveness to changing customer demand and improved process optimisation capabilities for efficiency (Araújo, Pacheco and Costa, 2021). However, AM sits within a workflow that depends on manual labour in the upstream and downstream ancillary steps, such as build file preparation and post-processing (see Figure

2.1). Therefore, suitable digital tools and solutions must be developed to elevate the AM workflows towards fully digital factories.

Focusing first on the upstream steps, there are two key challenges for computational decision-making support in this area. One, the optimisation of production planning in AM is a highly complex and multi-dimensional problem, which is entirely infeasible to solve through brute-force exploration of possible solutions (Araújo *et al.*, 2018; Framinan, Perez-Gonzalez and Fernandez-Viagas, 2023). Two, it is important to capture the rich, tacit knowledge held by AM operators when developing decision-support tools to help ensure their suitability and practicality (Mandolini *et al.*, 2020). In this thesis, the study of workflow optimisation approaches has attempted to reconcile these challenges. The cost results in Chapter 5 demonstrate that heuristic optimisation, with an integrated approach to the packing and scheduling dimensions, outperforms operator-led workflow optimisation approaches.

Increased digital control and automation is also emerging elsewhere in the AM workflow, for example: auto-mixing and loading of feedstock material in Multi Jet Fusion printing, and new post-processing machines that require minimal operator intervention. Despite this, the facility layout results in this thesis (see Chapter 6) show that a significant proportion of the production lead time still depends on operators. This is either in the form of manual workflow steps, such as transferring material and parts from one machine to the next, or time spent waiting for available operators for such steps. Thus, novel technologies are required to address this gap in the digitalisation of the AM workflow.

To this end, the facility layout could be leveraged to improve the ability to automate more elements of the AM workflow. In the cellular layout, the shorter distance and fewer infrastructure obstacles between different machines in the workflow simplifies the challenge of automating, for example, the transfer of feedstock material to, and ready-to-post-process parts away from AM machines. This is reflected in the prevalence of robotic arm and conveyor systems in demonstrator facilities that use the cellular layout (Boivie *et al.*, 2011; Lehmhus *et al.*, 2016; Kang *et al.*, 2018), while futuristic alternatives for the process layout, such as automated guided vehicles (EOS GmbH, 2023), have yet to be fully developed. Furthermore, the facility layout simulations suggest that the physical distance between different machines influences the transfer time between them, which would apply regardless of the manual or automated method of transport. Therefore, facility layout will continue to be an integral factor in the success and efficiency of future digital AM factories.

With respect to implementing manufacturing digitalisation, it is argued that the change process is easiest and most effective when the workflow is simple, for example in make-to-stock fulfilment with low product variety (Strandhagen *et al.*, 2016). From the perspective of production losses, the exploratory simulations in Chapter 4 show that identical batches of parts, leading to consistent and repeatable production, are indeed the most efficient operations approach for AM. On the other hand, suitable methods to manage the effect of product and process variety are also demonstrated in this thesis, from both productivity and cost perspectives. Importantly, digital production planning tools are at the heart of this, for example, integrated workflow optimisation.

Taking a broader perspective, the remit of integrated workflow optimisation could be expanded to include networks of material preparation and post-processing machines (in addition to AM machines). By covering more of the AM workflow, digital production planning tools of this nature could lead to unified and simplified control of the AM workflow. This would further increase the transparency of AM operations, seen at the AM machine level, to an overarching "AM operations overview" of order streams through AM production facilities as a whole. Complementary innovations to support this could include adopting more sophisticated optimisation algorithms based on machine learning, and adapting suitable facility-level productivity metrics, as explored by Muchiri and Pintelon (2008), for AM. Moreover, it would become possible to investigate the implementation of AM in novel product-centric digital factory configurations, such as "One Touch" control of production routing and scheduling (Lyly-Yrjänäinen *et al.*, 2016), and product-based material flows, such as digital kitting (Khajavi *et al.*, 2018).

7.3.2 Improving Technology Adoption Determinants

To date, evaluations of AM against the various determinants of technology adoption have focused on the relative advantages of AM and its compatibility with existing manufacturing environments (Oettmeier and Hofmann, 2017; Schniederjans, 2017; Khorram Niaki, Torabi and Nonino, 2019; Handfield *et al.*, 2022). However, the crux of this research has been to explore coordinated changes in operations – as espoused by Milgrom and Roberts (1990) – and their influence on productivity and cost in AM. It is therefore expected, and pertinent to verify, that the AM operations insights impact varied technology adoption determinants. Table 7.7 summarises the research findings against these determinants, as defined by Rogers (1983) and Oettmeier and Hofmann (2017).

The development of suitable cost and productivity metrics in this research, and their application in identifying underlying mechanisms of efficiency in AM operations, has a notable effect on the observability and complexity determinants. This is because the performance of AM systems becomes much more transparent and visible, as explained in Section 7.2.2, and also more digestible for the AM user. Moreover, by translating production loss frameworks and the OEE metric from its widely-used conventional manufacturing context to the AM context, this research improves compatibility of AM with existing manufacturing management systems.

The results for AM operations approaches, workflow optimisation approaches, and facility layout approaches in this research also contribute to the progress of AM as a GPT. While the AM industry awaits further improvements in the technology, the AM operations mechanisms can be applied to improve cost and productivity in the short-to-medium term. The operations management levers and AM workflow trade-offs can be captured in complementary innovations (e.g. software tools) for process planning, eventually leading to highly product-centric production management platforms to support scaled-up AM.

Table 7.7: Mapping of the research findings against determinants of adoption for AM, as per Rogers (1983) and Oettmeier and Hofmann (2017)

Determinant of Adoption	**Description**	**Influence of this Research**
Relative advantage	Perception of the innovation as better (economically, or status-wise) than previous options	AM cost modelling is expanded to include trade-offs in ill-structured costs (failure, late delivery); and the role of complementary innovations such as integrated workflow optimisation in improving the cost-benefit balance is demonstrated.
Compatibility	Perception of the innovation's consistency with the adopter's existing systems and experience	Compatibility of AM operations management (with wider manufacturing concepts) is improved through the adaptation of commonly-used productivity metrics (OEE, value-adding time) for AM, in a manner that resolves previous conflicts in definition.
Complexity	Perception of difficulty in use and understanding of the innovation	Underlying mechanisms of AM operations that emerge from the exploratory simulations help AM users understand how to design and operate their systems efficiently in the appropriate context (e.g. production scale, product variety, lead time constraints).
Trialability	Extent to which the innovation can be experimented with, to reduce the adopter's uncertainty	(Not explored in this research.)
Observability	Extent to which the innovation and its impacts can be observed and communicated by the adopter	The OEE metric is adapted for AM to improve the transparency of productivity and effective use of capacity. Further, the impacts of workflow operations on AM machine productivity are clearly observed.
Absorptive capacity	Ability of the firm to develop, utilise, evaluate, and apply relevant new knowledge	(Not explored in this research.)
External pressure	Influence of regulation, competition, other innovations, and customer needs on the firm	(Not explored in this research.)
Perceived outside support	Training, knowledge, and support to reduce uncertainty about the innovation	Quantitative insights into the influence of key AM operations decisions (operations approach, workflow optimisation, and facility layout) provide new knowledge to support the adoption of efficient workflows in scaled-up AM.

8 Conclusions

This concluding chapter presents a summary of the thesis, with a focus on the key findings and contributions to the relevant discourse. Alongside this, the limitations in the research are acknowledged and recommendations for future work are provided.

8.1 Summary of the Thesis

The overarching aim of this thesis is to uncover drivers of process efficiency, affecting both cost and production losses, for direct digital manufacturing applications that use AM in a make-to-order fulfilment context. To this end, the research focuses on uncovering suitable guiding frameworks and systematic mechanisms to make AM operations more transparent and more efficient, from the machine to production facility. This leads to the three research objectives, as outlined in Section 1.3, which have been addressed as follows.

8.1.1 Production Losses in AM

The extant literature is marked by poor transparency regarding AM process efficiency, with conflicting understanding of value-adding time (Totah *et al.*, 2017; Pushparaj *et al.*, 2019; Kurdve *et al.*, 2020). To this end, this research has developed a novel OEE metric, which adapts the original formulation by Nakajima (1988) to better suit the product and process variety found in AM workflows and technologies, respectively. Therefore, the ability to compare the performance of AM equipment, both against its theoretical capacity and alternative machines, is vastly improved. Even in the absence of further process improvement, the application of this metric positively impacts AM adoption via better observability and understanding of its relative advantage (Rogers, 1983).

In the discussion of OEE in AM, prior studies offer only partial explanations of sources of production losses (Fera *et al.*, 2017; Reid, 2019; Parshawanath Jain, 2022). Notable omissions from the assessment of process efficiency using OEE include: thermal inconsistencies across the build (Bourell *et al.*, 2014), the assumption of perfect process planning, and defects that cannot be corrected in-situ (Baumers and Holweg, 2019). The formation of a systematic production losses framework for AM in this research addresses this gap, highlighting the prevalence of necessary-but-non-value-adding time (Hines and Rich, 1997) in the AM workflow. More importantly, the evaluation of production losses with respect to the operational characteristics of AM (Baumers and Holweg, 2019) shows that all six production losses apply to AM, which contradicts Fera et al. (2017). This is further extended by identifying sources of process efficiency (and inefficiency) in line with both production loss and AM operations characteristics frameworks, which provides implementable insights for AM users to improve their process planning towards better process efficiency.

The exploratory simulation studies that build on the theoretical framework expand and elaborate on the link between process planning and production losses, which are only alluded to via narrow metrics by Gopsill and Hicks (2018), and Stittgen and Schleifenbaum (2020). The results (see Chapter 4) demonstrate that minimising the number of builds and, concurrently, maximally filling the available space in each build are key to improving the ratio of value-adding time to production losses in polymer laser sintering production. This provides quantitative evidence to link underlying factors, such as capacity utilisation and height-dependent risk of build failure, with setup and performance-related production losses.

While the production loss drivers may be different in alternative AM processes, particularly outside the powder-bed fusion category, the OEE metric is constructed in such a way that it is entirely generalisable to other AM technologies. Most importantly, by formalising the production loss drivers, it is possible to guide AM users towards more productive and efficient use of the available machine capacity, in line with their existing workflow constraints, such as order lead time and part size variety.

8.1.2 Workflow Optimisation in AM

While a variety of ill-structured costs have been explored in the extant literature, such as failure (Baumers and Holweg, 2016), quality-systems (Schmid and Levy, 2012), flexibility (Alogla *et al.*, 2021), and inventory (Khajavi *et al.*, 2018); the assessments have been limited to exploring each in isolation, which precludes identifying any trade-offs therein. The total cost model developed in this research addresses multiple ill-structured costs for the first time, pertaining to the cost of failure and penalties for late delivery. The choice of these two ill-structured costs relates to two separate cost trade-offs noted in the literature, between capacity utilisation and, respectively, failure-related costs (Baumers and Holweg, 2016) and timeliness of delivery (Costabile *et al.*, 2017). Extending the aforementioned work, this research shows that a three-way trade-off emerges between these elements, whereby process planning approaches must satisfy scheduling constraints using moderately-filled builds to both amortise fixed costs and avoid excess risk-of-failure.

Importantly, this research is unique in exploring the above with relation to multi-build, multi-machine operations. While various operations research studies have begun to progress from sequential optimisation of packing and scheduling in the AM workflow (Baumers, Özcan and Atkin, 2017; Kapadia *et al.*, 2021), the potential improvements in cost drivers from alternative but more complex integrated optimisation approaches lacked attention. The cost results (see Chapter 5) show that integrated optimisation is able to balance the competing influences on production cost across networks of AM machines more effectively than alternative, simpler workflow optimisation approaches. Therefore, integrated workflow optimisation delivers lower cost and better predictability of cost for scaled-up AM production. While these findings relate to polymer laser sintering, the logic is readily applicable to other powder-bed fusion processes where 3D packing is achievable.

By systematically exploring the cost impact of different workflow optimisation approaches, the relative importance of time-dependent indirect costs, build height-dependent failure costs, and schedule-dependent late delivery costs have been emphasised, as explained above. This can help focus future development of process planning optimisation algorithms for scaled-up AM. This research has also demonstrated the benefits of integrated optimisation of packing and scheduling: not only on the cost-effectiveness of production but also on the predictability of cost, which helps businesses improve their competitiveness as production scale and volatility in demand increase (Deradjat and Minshall, 2017).

8.1.3 Facility Layout in AM

Despite the importance of the facility layout and organisation of the AM workflow for the success of scaled-up AM (Huang *et al.*, 2021), the extant literature provides little justification for facility layout choices or assessment of best practice therein. This research therefore contributes a novel quantitative assessment of production losses and cost contributors arising in the AM workflow due to the implementation of different facility layout approaches. By identifying the key sources of non-value-adding time in the workflow for each facility layout approach, and the relative magnitude thereof, the results provide a stepping stone towards future optimisation of scheduling across the AM workflow to improve process efficiency.

By modelling the production facility and operations of a real AM user, the results (see Chapter 6) show that the cellular layout outperforms the process layout in terms of non-value-adding time (and labour costs) arising from travel, waiting and disturbances such as unplanned maintenance and build failures. However, the production scale also affects the results; and the process layout delivers on-time production more consistently at higher volumes of throughput (>10,000 parts). Therefore, while the cellular layout minimises production losses, the process layout is a viable alternative for high-scale AM.

While capacity management optimisation has been observed for single layout choices (Kellner *et al.*, 2019), the comparative nature of this exploratory study allows the development of a “best practice” guide for setting up AM facilities for different scales of production. This extends the previous frameworks for conventional manufacturing, such as the product-process matrix and product or process-oriented facility layouts, to the AM context. Thus, AM users can readily understand which layout option to pursue to satisfy their operational needs and production throughput.

8.2 Contribution of the Research

Reviews of AM from a technology adoption perspective point towards its potential to revolutionise and disrupt manufacturing and product-service industries. However, an oft-quoted barrier to this progress is the poor perception of process efficiency and production cost. Complementing core innovation within the technology and delivering immediate results, operations management can improve the performance of AM systems, shifting the operating frontier towards the ultimate asset frontier. This relies on holistic assessments of process efficiency and cost in AM, to resolve trade-offs and find optima therein. However, previous AM operations studies have often assessed relevant aspects in isolation, such as ill-structured failure costs, flexibility costs, availability and productivity.

Therefore, this research is designed around systematic studies into AM operations at different levels of abstraction. Consequently, this thesis attempts to provide thorough guidance for the AM user towards extracting the maximum value-adding capacity from the AM workflow, while fulfilling the product variety and process responsiveness required of direct digital manufacturing. This is based on exploring the underlying cost and production loss mechanisms, which are then collated into practicable overarching operations principles. As mentioned in the introduction, this helps answer the question, how should scaled-up AM be implemented and why? To this end, Table 8.1 provides a summary of the key contributions and research gaps addressed, which is followed by a discursive overview.

Table 8.1: Summary of research contributions against the literature gaps

<table>
<tr><th>Identified Gaps in the Literature</th><th>Contribution of this Research</th></tr>
<tr><td>Poor transparency of AM process efficiency, particularly with reference to well-established theories (value-adding time, production losses) and metrics (OEE) that can support the AM business case (Pushparaj et al., 2019; Kurdve et al., 2020).</td><td>New OEE framework and metric improves AM compatibility and observability, with respect to Rogers (1983) technology adoption determinants.</td></tr>
<tr><td>Absence of quantified estimates of production losses in the AM workflow, and evaluation of steps that can be taken to reduce these (Fera et al., 2017; Reid, 2019; Parshawanath Jain, 2022).</td><td rowspan="2">OEE used to quantify sources of production losses in the AM workflow, including “inherent” losses. Operations approaches and guidelines to minimise production losses are developed for AM practitioners.</td></tr>
<tr><td>Limited investigation of the link between AM process planning and production losses, despite studies that allude to its significance (Gopsill and Hicks, 2018; Stittgen and Schleifenbaum, 2020).</td></tr>
<tr><td>Studies into ill-structured costs are limited to individual machine operations (Schmid and Levy, 2012; Baumers and Holweg, 2016; Alogla et al., 2021). Extension of this to multi-machine scenarios is required to reflect realistic industrial AM operations (Khajavi et al., 2018).</td><td>Consistent production cost behaviour for machines working in parallel, a precursor to fully scaled-up AM, when optimising both packing and scheduling.</td></tr>
<tr><td>Ill-structured costs have been evaluated in isolation in the extant literature, which neglects potential trade-offs therein (Baumers and Holweg, 2016, 2019; Khajavi et al., 2018).</td><td>New total cost model for failure and flexibility-related costs is used to probe trade-offs in ill-structured costs.</td></tr>
<tr><td>Similarly, process planning factors that influence both well-structured and ill-structured cost drivers are typically optimised sequentially, in isolation (Freens et al., 2015). Integrated optimisation of these factors shows promise for improving cost-effectiveness of AM (Baumers, Özcan and Atkin, 2017), but the links to the cost drivers have not been explored.</td><td>Production cost is lowest and most consistent when using integrated optimisation, driven by trade-off in capacity, failure, and timeliness (flexibility) costs. This optimisation approach smooths cost of volatile flows.</td></tr>
<tr><td>Within the limited discussion of equipment organisation for AM workflows (Yoo et al., 2016; Avventuroso et al., 2017; Kang et al., 2018), the effect of different facility layout approaches on production efficiency from a time or cost perspective has not been explored.</td><td>Novel comparison of cellular and process layout in AM shows differing vulnerability to failures and sources of non-value-adding time in the workflow.</td></tr>
<tr><td>While the relationship between facility layout and production scale (and variety) is well-established for conventional manufacturing (Radford and Richardson, 1977; Naylor, 2002), and could be significant for scaled-up AM (Huang et al., 2021), both qualitative and quantitative investigation of this phenomenon is missing in the AM discourse.</td><td>Evaluation using case study company’s data provides evidence for AM practitioners about facility layout at different scales: cellular layout for low-medium scales, process layout for high scales, despite inefficiencies.</td></tr>
</table>

First, this thesis demonstrates that the success of scaled-up AM relies on exploiting the fungibility of capacity to maximise efficiency in both cost and value-adding-time. Notably, the prevalence of reliability issues, such as build failure and part rejects, must be managed by operating at sub-maximum capacity with respect to the AM machine and workflow. Second, the research into the management of multiple AM (and ancillary) machines operating in parallel shows that productivity and production cost are minimised through a combination of optimisation in the digital and physical realms. It is necessary to develop sophisticated, integrated workflow optimisation approaches to tackle the complexity of the production planning solution space; and this must be complemented by due attention to the facility layout to avoid sources of non-value-adding time, particularly as the scale of production increases.

Underpinning both contributions above is the transposition and adaptation of key productivity concepts from conventional manufacturing to AM – namely, production losses, OEE, and value-adding time. This has produced new tools for AM users to deploy towards proactive management of industrial AM systems. Furthermore, the monitoring and continuous improvement enabled by OEE in particular can act as a stepping stone towards data-driven, real-time optimisation of material flows and productivity in scaled-up AM.

To achieve such futuristic goals for AM operations, this research points towards the development of production planning platforms that encompass more steps in the AM workflow, greater automation of manual steps and transitions in the AM workflow, and skills development among AM operators to help them leverage digital decision-support tools for increasingly complex product-process flows.

8.3 Limitations and Recommendations for Future Work

While this thesis contributes to the understanding of AM operations and the onward impact on adoption of scaled-up AM, there are inevitably limitations to the methodology and findings. This section identifies notable constraints in the research, and offer recommendations of future work to help address these.

First, it is imperative to acknowledge the shortcomings of the exploratory simulation approach chosen for this research. Despite offering freedom to investigate a wide range of operational scenarios and generate generalised insights (Jahangirian *et al.*, 2010), it is not possible to capture the empirical and random variation within the AM workflow using controlled elements such as regression-based build time models, consistent order arrival rates, and fixed MTBFs. Therefore, targeted empirical experiments would be beneficial for validating the guidelines proposed in this study for production losses, workflow optimisation and facility layout in the specific contexts of application; this would help capture secondary influences from industry-, procedure-, and even machine-specific characteristics.

The simulation of order fulfilment in the production loss and workflow optimisation studies uses a static pre-determined delivery schedule to simplify the incoming order stream (Hedenstierna, Disney and Holmström, 2016). Shifting towards a dynamic stream of incoming orders would be more representative of make-to-order operations, as seen in the third, facility layout study. The influence of different operations approaches and workflow optimisation approaches on minimising production losses and generating cost-effective builds, based on incomplete information (Rudolph and Emmelmann, 2018), could then be explored. Regarding the workflow optimisation in particular, this research has shown that integrated optimisation delivers consistent capacity utilisation when the orders are known in advance. It is therefore important to establish whether this cost-effective pattern prevails under more variable product demand conditions, with limited information about future demand, to further support make-to-order AM operations.

In the facility layout simulation study, the influence of the production scale on the performance of the AM workflow suggests that the process efficiency, in terms of value-adding and non-value-adding time, could be further affected by workflow factors that have not yet been explored. The holistic assessment of the AM production facility could therefore be expanded to include factors such as bursts of demand, optimised build scheduling to align with operator availability, or investment in portable resources (build and material cartridges) rather than more expensive machines. Designing such future studies in a sensitivity analysis structure would promote understanding of the most impactful factors, further guiding AM users about appropriate operations management choices for scaled-up AM.

Throughout this research, the risk of build failure has been accounted for using a layer-based model, which simplifies the thermal basis of the laser sintering process. Part quality and successful build completion depend on appropriately controlling the temperature distribution in the build volume (Southon *et al.*, 2018). This distribution is influenced by laser printing parameters along with the sintered area of each layer and the surrounding layers, which together control the magnitude of heat input into local regions of the build volume and the rate of heat dissipation (Abdelrahman and Starr, 2015; Huang *et al.*, 2020). The layer-based function in this study is unable to capture these phenomena, and so shorter builds are systematically favoured in the production loss and workflow optimisation simulations, involving the EOS Formiga P100 machine.

Therefore, a new laser sintering build failure model could include stochastic and thermally influenced sources of cascading failure, such as foreign particles in the powder feed or part warpage increasing layer-on-layer. Modelling the likelihood of failure phenomena more accurately would enable more accurate research to probe the trade-off between different process planning strategies for deterministic cost and production losses versus the stochastic rework and failure events, which is particularly important for improving AM from a lean manufacturing perspective.

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Appendix

A.1 Explanation of Test Part Design

A set of test parts is used to populate incoming orders in the simulated make-to-order AM workflow. The part designs are inspired by industrial applications of polymer AM, with features that exploit the geometric intricacy and absence of support structures found in laser sintering. Part A is a device for guiding bone-cutting steps prior to knee surgery (Figure 3.4a). Part B is the front section of a plane-like unmanned aerial vehicle (UAV) with an internal helical core structure (Figure 3.4b). Part C is a semi-flexible assembly that behaves like a chainmail fabric (Figure 3.4c). Its longest dimension is 30 times larger than its shortest dimension, which means that the Z-height of the build would change significantly depending on how this part is oriented. Part D is a self-contained device for mixing and collecting the product of two chemical reagents (Figure 3.4d). It is inspired by cheap, custom chemical reaction devices that are made for out-of-lab applications (Kitson *et al.*, 2013). Part E is a ring-shaped mechanical compression support with a graded body-centre cubic lattice structure to allow a rocking motion about one axis (Figure 3.4e).

A further design consideration is the geometric complexity of the parts, as this a key value-adding motivator to adopt AM (Araújo *et al.*, 2015). The geometric complexity can be quantified using a metric first proposed by Valentan et al. (2011), and further endorsed by Araujo et al. (2015). Based on this metric, given in equation A.1, the test parts in this research are 10 times more geometrically complex on average than a previous set of industry-inspired parts from Baumers et al. (2013), denoted B2013. This is shown in Figure A.1.

$$k = \frac{f \times a}{v} \tag{A.1}$$

where:

k – part complexity
f – number of facets, or triangles, in the part mesh
a – surface area of the part (mm^2)
v – volume of the part (mm^3)

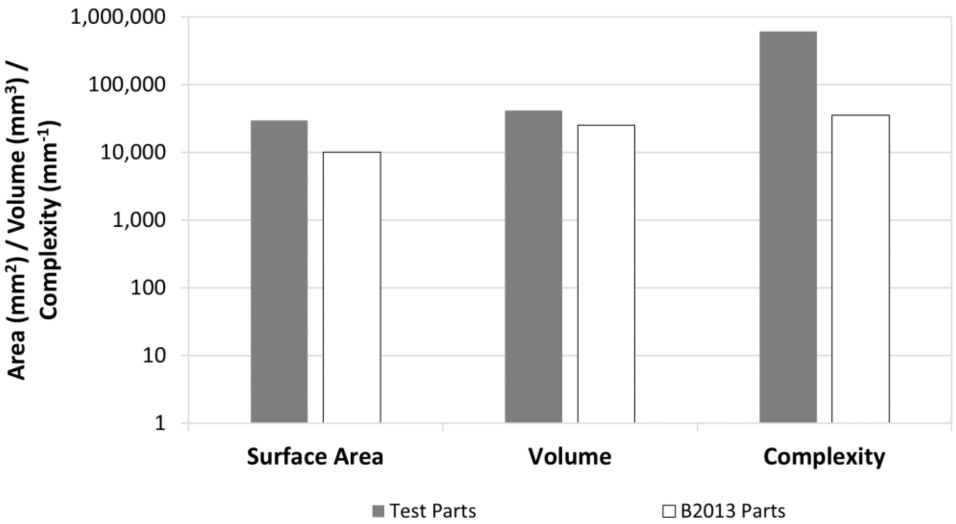

Figure A.1: Comparison of geometric properties between test parts in this research and Baumers et al. (2013)