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**The Impact Of Adopting Additive Manufacturing On Responsive
Supply Chain Performance**

By

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Abstract

Additive Manufacturing (AM), or 3D printing as it is frequently known, is an umbrella term for a collection of manufacturing technologies that enables products to be manufactured layer-by-layer from three-dimensional digital data. While the costs associated with AM represents a barrier to its wider adoption, its benefits outweigh its costs when considered in some contexts. Few studies have investigated the costs and benefits of this technology from a supply chain perspective, particularly in market environments characterized by demand uncertainty. In this type of scenario, it becomes necessary to adopt higher levels of internal competencies, find the optimal way to manage inventories and flexibly respond to sudden market requirements. This thesis therefore aims to address this gap by examining three key aspects: the learning effects offered by AM, the impact of AM on inventory-related costs and the impact of AM on the critical capability of flexibility.

To assess learning in AM, this thesis focuses on the experimental measurement of AM operator time and improvement in operator effectiveness as a result of learning. Learning is thus assessed by measuring the reduction of labour time through operator learning within a series of build repetitions and estimates a progress ratio which captures the learning effect within this series. To assess the impact of AM on inventory-related costs, this thesis develops a conceptual model that matches possible AM scenarios with demand volume level and severity of stockout penalty. It also conducts a case study to obtain insights into the resulting model which has been developed. In this case study, an inter-process comparison is undertaken by simulating a supply chain based on data collected from a plastic products manufacturing company that produces pipe fittings using Injection Moulding (IM) technology. The simulation model produced has been built using the Arena software package for three distinct scenarios: the current configuration with IM only,

a proposed configuration with AM only, and a proposed configuration that combines AM with IM. To evaluate the impact of AM on flexibility, a conceptual model has also been constructed that maps certain AM characteristics relevant to flexibility to key market disruption scenarios faced by managers. This aspect is also highlighted through the case study which assesses the impact of AM on four distinct supply chain flexibility types: volume, delivery, mix and new product using metrics obtained from the literature.

The results obtained on learning in AM suggest that AM exhibits a learning effect for both the novice and the expert operator with progress ratios of 67.73% and 80.42% respectively. Further, results on the impact of AM on inventory-related costs revealed that utilizing IM alone showed the lowest supply chain unit cost (€0.90) compared to utilizing AM as a stand-alone (€2.72) or in a combined approach (€0.94). With regards to AM's impact on flexibility, the supply chain employing IM showed greater volume and delivery flexibility levels (i.e. 65.68% and 92.8% for IM compared to 58.70% and 75.35% for AM, respectively). However, AM showed higher mix and new product introduction flexibility level, indicated by the lower changeover time and cost of new product introduction to the system (i.e. 0.33 hrs and €0 for AM compared to 4.91 hrs and €30,000 for IM, respectively). It is anticipated that these results can be used to inform practitioners and scholars on various contexts where AM can create value and the appropriate and timely investments needed to unlock that value.

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List of Abbreviations

Abbreviations	Description
AM	Additive Manufacturing
3D	Three-Dimensional
IM	Injection Moulding
SCM	Supply Chain Management
JIT	Just-In-Time production
EOQ	Economic Order Quantity
EPQ	Economic Production Quantity
RBV	Resource-Based View
TPS	Toyota Production System
SMED	Single-Minute Exchange of Dies
FMS	Flexible Manufacturing System
3D CAD	3-Dimensional Computerized Aided Design
STL	Standard Triangle Language
RNG	Random Number Generator
LS	Laser Sintering
SD	Standard Deviation
SOD	Standard Operating Procedures
CFAM	Centre For Additive Manufacturing

1. Introduction

The goal of this chapter is to deliver an introduction to the topic investigated in this doctoral project. Section 1.1 first contextualizes this research by briefly describing the field under study and the importance of taking a supply chain perspective when analyzing the costs and benefits of AM. Section 1.2 offers a discussion of the motivations for the doctoral project. This is followed by Section 1.3, where an introduction to the three research objectives examined in this research is made. Section 1.4 describes the structure of the thesis and followed by Section 1.5 which presents the published work.

1.1. Research context

1.1.1. Costs and benefits models of Additive Manufacturing

Additive Manufacturing (AM), or 3D printing as it is frequently known, is an umbrella term for a collection of manufacturing technologies that have been evolving since the 1980s and which enable the manufacturing of products from three-dimensional digital data, usually in a layer-by-layer fashion without tooling or moulds (ASTM, 2015). Over the recent decades, the adoption of AM technology has grown at a compound annual rate of around 30% in terms of industry revenue, and the industry is predicted to reach an annual revenue of approximately \$20bn - \$75bn in 2025 (UK Additive Manufacturing Steering Group, 2017).

Since the emergence of AM, various studies have been undertaken to investigate the costs and benefits of this technology. Son (1991) distinguished between two types of cost elements: well-structured costs (i.e. machine, material and labour costs) and ill-structured costs (e.g. inventory, build failure and machine set up related costs). Initial efforts in assessing the costs and benefits of AM were conducted by Alexander et al. (1998) and Hopkinson and Dickens (2003), who offered basic AM cost models as a solution. These initial cost models were followed by other

studies (e.g. Ruffo et al., 2006; Ruffo and Hague, 2007; Baumers, 2012; Rickenbacher et al., 2013) that examined additional aspects related to the cost of this technology. While these cost models succeeded, to some extent, in articulating the well-structured part of the AM cost model, it was not until recently that ill-structured cost elements of AM began to be investigated (e.g. Khajavi et al., 2014; Baumers and Holweg, 2016). With the increase of these cost models over time, it has become possible to make a more realistic assessment of the costs and benefits of this technology (Thompson et al., 2016). This thesis aims to increase the scope of these models yet further by examining this area from a supply chain perspective. Figure 1.1 describes the positioning of this thesis in relation to the extant AM literature.

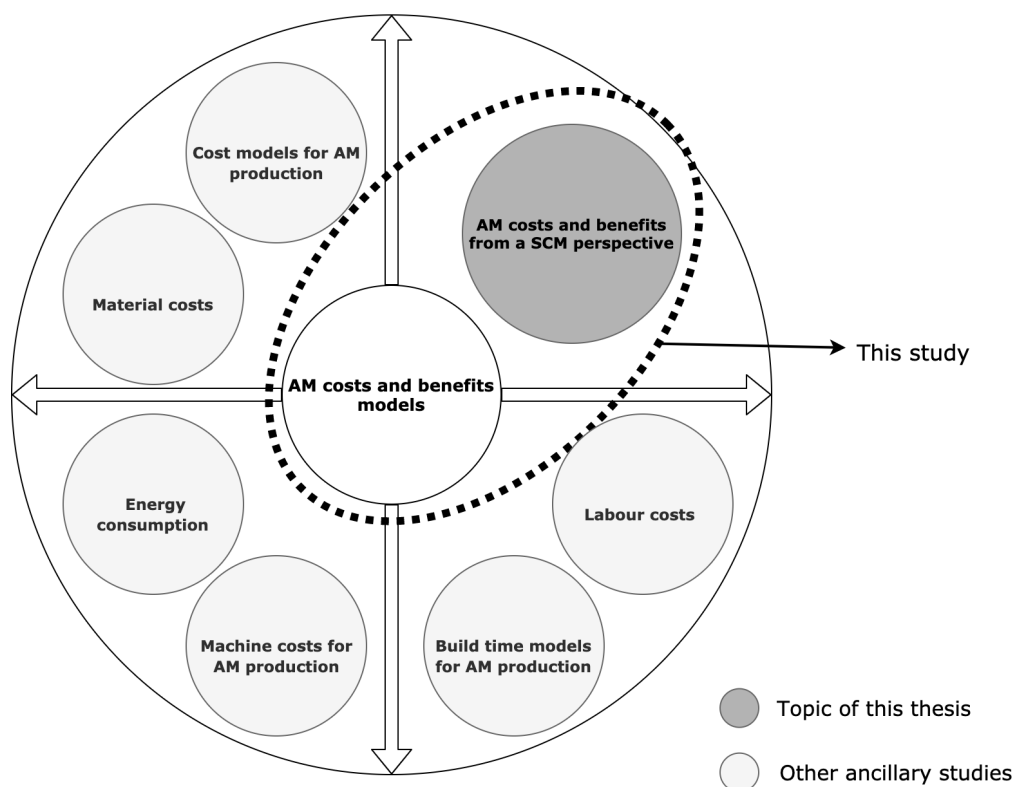


Figure 1.1: Positioning of this thesis in terms of the existing literature. The outward movement represents the expansion of the costs and benefits models with increasingly more ill-structured aspects taken into account.

1.1.2.Costs and benefits analysis from a supply chain perspective

To assess the costs and benefits from a supply chain perspective, it is imperative to review the distinct contexts where AM is adopted. AM adoption has progressed through different phases and can be grouped into four distinct categories based on various production settings. The first of these is the use of AM for toolmaking, where polymer moulds or metal dies, for instance, are rapidly fabricated using AM (Levy et al., 2003). The second category is where AM is utilised in the product development stage, specifically to produce prototypes (e.g. Kontio et al., 2012). The use of AM in products that require mass customisation (i.e. individualised) or complex geometries symbolises the third category, indicative of a gradual shift of AM towards direct manufacturing of end-use products (Bak, 2003; Huang et al., 2015). The first three production settings discussed above are appropriate for AM mainly because of the unique feature of the absence of tooling in this technology. The fourth and final category is where AM is employed in production settings to enhance the response to market demand volatility, representing a significant shift in the motivation for adopting AM. Although the ability to viably produce individualised parts has continued to be a key feature of this technology, its recent adoption in industries with higher production volumes has been evident, particularly in the spare parts industry (Gibson et al., 2010; Mellor et al., 2014). In such an industry, the main motivation for adopting AM is to address the unexpected disruptive customer orders; that is, to utilise AM for the production of products characterised by demand volatility. In this type of scenario, AM is employed to produce a variety of products with disparate production volumes.

This thesis contributes to the effort in this area (i.e. the fourth category) by investigating the value of AM on supply chain performance when it operates under demand volatility. A definition of demand volatility would

be useful at this juncture and therefore, Handfield et al. (2013) have described it as:

“major shifts in customer demand volume, product or service mix, government regulations, new competitors, substitute products, short product life cycles, and requirements for rapid network nodal changes and redesign”

From a supply chain perspective, AM represents only one small element involved in the fulfilment of products with demand volatility. Typically, the delivery of a final product in these end-use manufacturing settings requires a chain of supplementary activities and resources, known as the supply chain. The activities in each supply chain can be divided between upstream and downstream. Upstream activities are those close to the raw material side and manufacturing firms are typically located on this side of this chain (Anderson Jr et al., 2000) while downstream activities are those close to the end consumer (Singer and Donoso, 2008). Volatility in demand may typically first appear in the form of demand variability in the latest downstream node (i.e. retailers), with this volatility spreading upstream towards the manufacturing firms (Lee et al., 1997).

Responding to this type of demand volatility can be conceptualised from three supply chain levels, which typify the focus of Supply Chain Management (SCM), namely: operational, tactical and strategic (Muñoz et al., 2012). Operational decisions are intra-firm and cover short-term scheduling and planning activities within a specific function in the firm. Tactical decisions are also intra-firm but include medium-term planning activities that involve many, if not all of the functions in the firm. Strategic decisions tend to be longer term and pertain to the structuring and redesigning of the supply chain based on business scope. These three levels have also shaped the development of SCM literature from a focus on operational and tactical issues to wider strategic concerns (Hines, 2004).

1.1.3.Increasing the performance of responsive supply chains

Supply chains that operate in markets with demand volatility adopt responsive (i.e. as opposed to efficient) strategies (Reichhart and Holweg, 2007); hence, they are referred to as responsive supply chains. Within such supply chains, a complex set of processes and resources are required to transform raw materials into a finished product. There is a requirement, therefore, for a tactical intra-firm supply chain which must be configured into and incorporate all relevant departments and functions as far as production is concerned. For products characterized by demand volatility, a manufacturing firm seek to gain a competitive advantage by adopting an appropriate level of supply chain responsiveness in line with market needs (Sabath, 1995; Thatte, 2007). In this regard, firms with the capacity to fulfil volatile demand expediently would flourish. As supply chain managers in such manufacturing firms are continuously searching for steps to enhance their supply chain responsiveness (Malhotra and Mackelprang, 2012), researchers and companies across various industry sectors are gradually becoming aware of the potential benefits that AM technology may offer in this type of setting (Mellor et al., 2014; Brettel et al., 2016; Ben-Ner and Siemsen, 2017).

The performance of such a supply chain can be enhanced through the development of organizational learning capability (Asree and Rao, 2011), elimination of excess inventory (Etienne, 2005) and the increase of supply chain flexibility (Gunasekaran et al., 2007). Demand volatility has driven manufacturing firms to shift focus from resources that are characterized by cost-effectiveness (i.e. through economies of scale) and asset-based to flexibility, learning and skill-based resources to sustain their competitive advantage (Miller and Shamsie, 1996). In particular, Lau (1996) states that flexibility has become the most critical component in securing a competitive advantage in volatile markets. Recent research therefore, has proposed AM as a potential player in increasing supply chain responsiveness and

flexibility (Mellor et al., 2014; Brettel et al., 2016). However, from a supply chain perspective, success in being highly flexible, for instance, may lead to a failure in the chain's cost performance (Reichhart and Holweg, 2007).

1.1.4. Impact of adopting new technologies

Adopting new manufacturing technologies is not so straightforward and can bring an element of uncertainty to the orderliness of an established supply chain process (Lee, 2002). The job of the supply chain manager involves balancing a complicated set of processes and resources to ensure an optimal level of supply chain performance. Adopting new technology, therefore, may severely disrupt the delicate equilibrium of the entire supply chain. This means it is critical to view the supply chain in a holistic sense; a generic point that has been elucidated by Drucker (2003, p. 151) who states:

"Every discipline has at its centre today a concept of a whole that is not the result of its parts, nor equal to the sum of its parts, and not identifiable, knowable, measurable, predictable, effective or meaningful through identifying, knowing, measuring, predicting, moving or understanding the parts. The central concepts in every one of our disciplines, sciences and arts are patterns and configurations. [...] Indeed, the parts in any pattern or configuration exist only, and can only be identified, in contemplation of the whole and from the understanding of the whole. "

In the same vein, it is clear that the impact of adopting new technologies such as AM must be examined from a complete supply chain perspective if a realistic assessment of this technology is to be made. Any assessment of AM in isolation can only be regarded as transitory at best, as its overall effect on the performance of the supply chain must inevitably be examined.

This point is evident in many phenomena and has been illustrated in the words of Muller (1943, p. 107):

"Although parts and processes may be isolated for analytical purposes, they cannot be understood without reference to the dynamic unified whole that is more than their sum."

The other issue to consider is that causing a major disruption to the supply structure is highly likely to represent a significant capital investment which would need to be recaptured through increased buying orders and possibly increased costs to the customer. Customers, however, are not necessarily expected to reward those supply chains that offer products manufactured using advanced manufacturing technologies such as AM, nor may they be cognizant of it. For these reasons, supply chain managers may tend to embrace a rather conservative strategy by not investing in advanced manufacturing technologies such as AM (Olfati et al., 2020), notwithstanding its potential benefits and appeal to a firm. This judicious investment strategy and decision-making process as well as a general interest in enhancing the performance of supply chain have prompted a plethora of publications devoted to discourse on the evaluation and selection of advanced manufacturing technologies (e.g. Kulak and Kahraman, 2005; Evans et al., 2013; Boonman et al., 2015). Despite the circumspect approach taken by supply chain managers and firms, the case for such advanced manufacturing technologies appears to remain positive (Ghobakhloo and Azar, 2018). This indicates a clear gap in the literature that can correctly assess in detail the relevance of such technologies.

The relative dearth of studies in this domain has practical implications for manufacturing firms considering the adoption of AM. The lack of research knowledge hinders the commercial realisation of competitive advantage (Cook and Cook, 1994), especially in manufacturing settings that rely on responsive supply chain strategies. Understanding precisely *how* the

adoption of AM impacts the performance of these supply chains is critical and its importance cannot be underestimated.

1.2. Research motivations

In line with the increasing realisation of the costs and benefits associated with AM, this doctoral research aims to study the impact of adopting AM on the performance of responsive supply chains. The previous section discussed the context of this research, highlighting the significance of analysing various effects that new manufacturing technologies can cause from a wide, supply chain, perspective. Based on this context, this section presents the three key motivations underpinning the overall aim of this doctoral research.

The first factor stems from the current gap in research that neglects the process activities that surround the automated aspects of AM machine activity. These activities are heavily dependent on labour input. Up to this point, the AM literature has focused on various aspects related to machine activity including materials (e.g. Vasquez et al., 2011; Gu et al., 2012; Huang et al., 2015; Ning et al., 2015; Wang et al., 2017) and processes (e.g. Ram et al., 2006; Murr et al., 2012), but little or no research has considered the surrounding activities undertaken by operators. These activities link the AM production chain from the design phase to the shipping phase, hence representing a significant part of the whole supply chain. In particular, a responsive supply chain necessitates higher levels of internal strategic tangible resources (e.g. technologies) and intangible resources (e.g. knowledge), which are critical elements in the implementation of a responsive supply chain strategy (Cousins and Menguc, 2006). One of these internal resources is organisational learning, which refers to the capability of an organisation to learn through, for instance, learning curves exhibited by labour (Lapr   and Van Wassenhove, 2003; Argote, 2012). As some research into the cost structure of AM has highlighted (Ruffo et al., 2006; Baumer et al., 2017), significant labour inputs are required in the AM

process. Building on the wealth of knowledge concerning the learning effect and its relevance to supply chain performance, this research investigates the existence of the learning effect in this technology and highlights its significance to supply chain performance.

The second motivation comes from the lack of consideration given to the demand characteristics (to date) when attempting to examine the effects of AM adoption in the existing literature. The literature has shown that different demand environments require different supply chain strategies (Lee, 2002; van der Vorst, 2002), and so this research focuses on those environments characterised by demand volatility. A critical SCM practice under these conditions is inventory management and control; a discipline that relies primarily on the identification of demand characteristics. Baumer and Holweg (2016) have argued that realistic cost models for AM should be used as a basis for the statement of cost-quantity relationships in AM and should reflect ill-structured elements, such as inventory (Son, 1991). Therefore, evaluating AM from a supply chain perspective means that inventory-related costs must be considered. To date, no studies have addressed the cost-effectiveness of AM in production settings that require different production volumes while accounting for inventory-related costs and opportunity costs resulting from stockouts. This research, therefore, attempts to provide a valuable contribution in this regard as it seeks to realistically assess the commercial aspects of AM through the inclusion of the cost impact of inventory and stockouts.

This evaluation lays the foundation for the third motivating factor to consider: the supply chain's competitive priority of flexibility. Flexibility has been defined as the ability to respond to different changes in the market with little or no penalties in cost, time or effort (Upton, 1994). While a sizeable body of literature exists that has sought to define, classify and measure flexibility in manufacturing and SCM (Gupta and Somers, 1992; Shewchuk and Moodie, 1998; Tsourveloudis and Phillis, 1998; D'Souza and Williams, 2000; Stevenson and Spring, 2007), little research effort has

been extended to AM, even though it has been repeatedly suggested by some that it has positive effects on flexibility (e.g. Chimento et al., 2011; Hämmäläinen and Ojala, 2015). Probing for evidence of this positive effect would therefore help to shape this debate and provide some much-needed knowledge, particularly from a supply chain perspective.

1.3. Research objectives

The key overarching aim in this thesis is to assess the impact of adopting AM on the performance of supply chains when operating in market conditions characterized by demand volatility. Based on the motivations described in Section 1.2, three distinct objectives have been identified within this doctoral project:

1. To examine whether AM exhibits a learning effect for both expert and novice operators.
2. To evaluate the total cost of a responsive supply chain employing AM, including inventory-related costs.
3. To examine whether the adoption of AM increases the flexibility of a responsive supply chain.

These objectives were established based on structured reviews of the relevant literature conducted by the author. Engagement with the AM community at the Centre For Additive Manufacturing (CFAM) at the University of Nottingham in the UK also played a valuable role during the execution of this research.

1.4. Thesis structure

The six chapters contained within this thesis are structured as shown in Figure 1.2 below and are briefly outlined here:

- Chapter 1 introduces the project and its key topics, discussing the research context and significance of the research. It also describes the motivations behind the development of the research objectives as well as presenting the relevant published works.
- Chapter 2 reviews literature pertaining to the research objectives. Background literature related to SCM, its relevant theories and practices, and AM is then reviewed. This is followed by presenting a detailed review and discussion of the focal literature of each one of the research objectives.
- Chapter 3 provides a description and rationale for the methodology executed in this research. It explains the experimental work undertaken for the 1st research objective. This is followed by a description of the logic behind the construction of conceptual models of supply chain cost and flexibility in AM. It then describes the inter-process comparison model built using a case study undertaken in a plastics manufacturing company to address the 2nd and 3rd research objectives.
- Chapter 4 presents the findings of this research linked to the project's research objective(s). These are examined at three levels: (a) the findings obtained based on operator learning in AM, and; (b) findings related to the impact of AM on inventory-related costs, and (c) impact of AM on supply chain flexibility.

- Chapter 5 discusses the findings within their appropriate streams of literature. This chapter is divided into several sections, with each one addressing distinct aspects of the literature based on the study's findings.
- Chapter 6 concludes the research by drawing the work of the preceding chapters together. It summarises the findings and contributions to knowledge, as well as identifying the limitations of the research. Future recommendations based on these observations are offered at the end of the chapter.

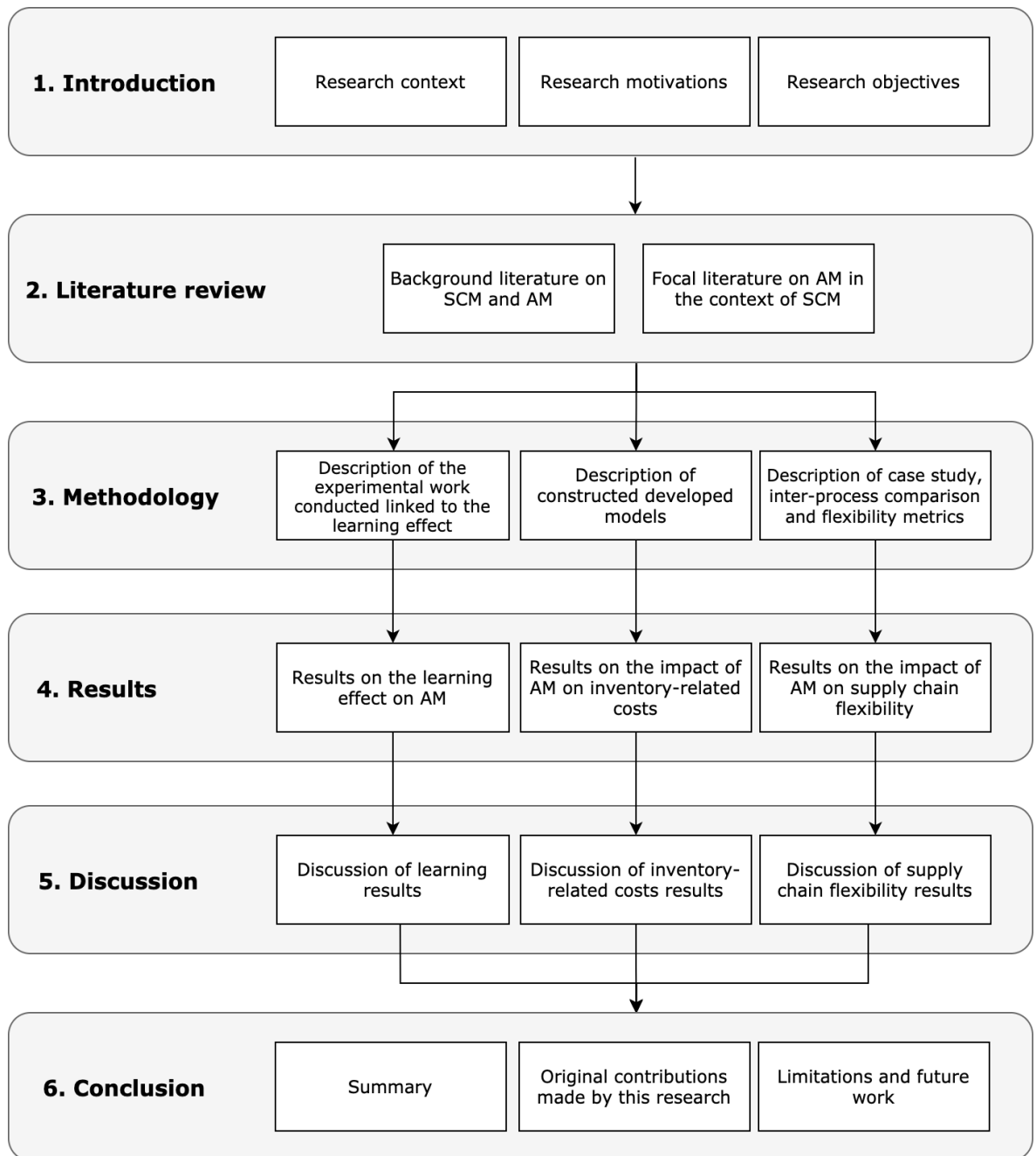


Figure 1.2: Thesis structure.

1.5. Published work

During the initial phase of this research, a contingency was made for it to be peer reviewed whenever possible. This has resulted in four separate research papers, each of which is described below:

1. The first research paper was submitted and presented at the 2019 Symposium on Logistics conference. This work is titled " The Impact of Adopting Additive Manufacturing On the Performance Of A responsive Supply Chain" (Alogla et al., 2019) and introduces the initial results obtained in examining the effect of AM on inventory-related costs and supply chain flexibility.
2. The second research contribution was written for the Journal of Mechatronics and Manufacturing Systems and is titled "Analysis Of The Effects Of Operator Experience And Learning In Laser Sintering" (Alogla et al., forthcoming). This work deals with the learning aspect of this thesis and was recently accepted by the journal and it is currently prepared for publication.
3. The third article that has been prepared during this doctoral project is titled "Characterizing The Cost Of Additive Manufacturing: Demand Volatility And The Absence Of Inventory" and presents in details the work related to the impact of AM on inventory-related costs. This manuscript represents the results obtained following the execution of the methodology pertained to the second research objective of this thesis. This work is currently undergoing additional preparation.
4. The fourth research paper that also has been prepared during this thesis is titled "The impact of Additive manufacturing on the flexibility of a manufacturing supply chain" (Alogla et al., 2021) and was published by the Applied Sciences journal.

2. Literature review

This is the theoretical chapter providing the basis upon which the overall research has been undertaken. As this thesis is interdisciplinary, merging theories and concepts from various fields of research is essential (Tan, 2001). Many areas of research have been developed independently but have been gradually included under the umbrella of SCM. These are research areas such as inventory management and control (Tempelmeier, 2011), lean manufacturing (Hines et al., 2004), agile enterprise (Croom et al., 2007), manufacturing flexibility (Stevenson and Spring, 2007) and organisational learning (Opengart, 2015). This chapter provides a coherent review of these areas as it relates to the responsive supply chain, which forms the background theory underpinning this research. The next part of this chapter provides focal literature sections that review the prevailing AM literature in reference to these areas; thus laying the foundation to address the research objectives. Figure 2.1 illustrates the logical relationship between the distinct areas/sets of literature reviewed in this chapter. A summary of the gaps identified and their link to the research objectives is presented in Section 2.11.

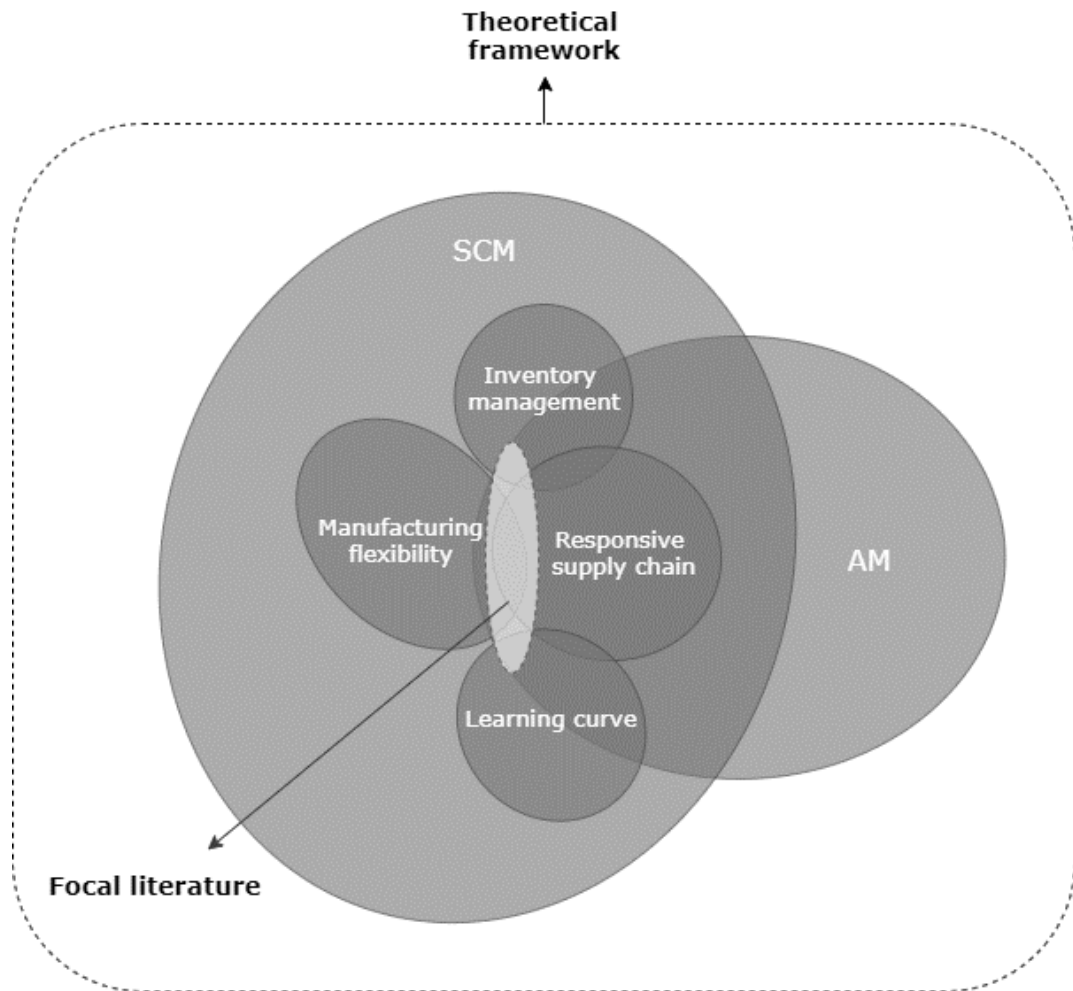


Figure 2.1: Relationship between the different areas reviewed in the literature.

2.1. Theoretical perspective

This section offers an outlook supporting the theories discussed in this research study. It also introduces and describes competing theories, which justifies why the research problem studied in this thesis exists.

2.1.1. Paths to competitive advantage

A central theme in the SCM literature is that the effective management of supply chains results in gaining a competitive advantage (Power, 2005). Competitive advantages describe a firm's capability to meet customer preferences more efficiently than a competitor's capability to achieve the same result, thereby elevating

the said firm above its competitors (Bendoly et al., 2007). While competitive advantage is often the principal aim of manufacturing firms (Barney, 2012), the strategies that may bring about this goal have been the subject of controversy, debate and much scholarly discourse in the literature. The main theories linked to these strategies are highlighted below.

2.1.1.1. Resource-Based-View and the Contingency theories

One of the main approaches to forming a competitive advantage is derived from the Resource-Based-View (RBV) theory of the firm. While this field of interest has been discussed by several scholars in strategic management literature (e.g. Chen and Huang, 2009), it has also been gaining interest among SCM scholars in the past two decades (e.g. Reuter et al., 2010; Hollos et al., 2012). The core concept of RBV is that the analysis of firms should be subject to the characteristics of their resources, where the utility, rarity, inimitability and non-substitutability are what classify these resources as competences, enabling sustainable competitive advantages for the firm (Wernerfelt, 1984; Barney et al., 2001; Galbreath, 2005). These competencies might include, for example, particular tangible resources such as specialised manufacturing facilities, or intangible ones such as trade secrets and labour experience (Teece et al., 1997). Initial research efforts in this area have focused on the heterogeneity of resources (Wernerfelt, 1984; Barney et al., 2001), followed by studies concentrating on the organization of these resources (Eisenhardt and Martin, 2000; Teece, 2007). Developing these heterogeneous resources per se, however, is not sufficient to gain a competitive advantage, but rather, evaluating the merits of its development and configuration are those elements that could lead to a competitive advantage (Allred et al., 2011).

The RBV theory, also, does not offer a prescriptive account for how these competencies lead to profits (Teece et al., 1997); an indication of its failure to consider the relationship between these competencies and the market. The Contingency theory has emerged, therefore, to fill this gap by building upon RBV theory, and posits that gaining competitive advantage is a result of the right alignment of endogenous competencies with exogenous market conditions (Donaldson, 2001). While this perspective is more inclusive to the variables that lead to competitive advantage, both of these theories tend to focus to a greater extent on internal competencies. Both also fail to offer any insights into how such internal competencies can lead to long-term (i.e. strategic) effects and in turn to economic outcomes (Bendoly et al., 2007). This illustrates that competencies (i.e. internal or external) certainly merit further academic research so as to be fully understood.

2.1.1.2. The role of competitive capabilities

To discern the connection between internal competencies and economic outcomes, Koufteros et al. (2002) proposed a framework that describes the relationships between competitive priorities, operational initiatives, competencies, and competitive capabilities, as shown in Figure 2.2 below.

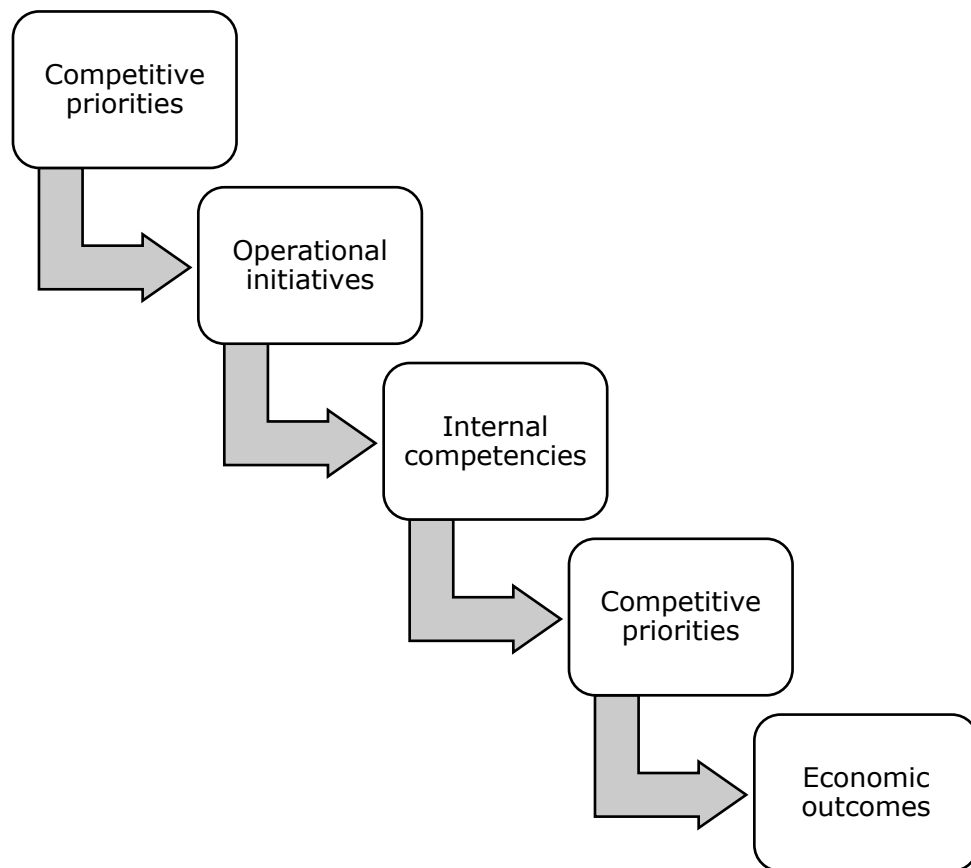


Figure 2.2: Link between competitive priorities, internal competencies, and competitive capabilities (adapted from (Koufteros et al., 2002)).

Competitive priorities are goals (e.g. lower unit costs) that direct decision-making when setting action plans from a tactical level. These action plans may include (but are not limited to) vertical integration, quality improvement, capacity expansion, and/or production planning and control. These action plans, if successfully executed, lead to the development of internal competencies. Internal competencies describe the development of resources that are hard to imitate, as described by the RBV theory in Section 2.1.1.1. It is through the development of these competencies that external competitive priorities are achieved. These priorities may manifest themselves to the customer in the form of capabilities such as quality, cost, dependability (i.e. delivery) or flexibility. Eventually, these competitive capabilities should result in improved performance leading to better economic outcomes in the form of increased profits.

2.1.1.3. Relationships among competitive priorities

The recognition of the importance of competitive priorities has led to the development of other streams of literature with a focus on external capabilities rather than internal competencies. One of these streams is the dynamic capabilities theory (Eisenhardt and Martin, 2000). Dynamic capabilities indicate the capacity of the firm to incorporate, construct, and reconfigure inimitable and non-substitutable internal and external competencies to respond rapidly to changing markets (Teece, 2007). What distinguishes the dynamic capability perspective from the RBV theory is its recognition to the inevitability of facing volatility in markets, especially in the long-run. As described by Teece (2007, p. 1320):

“If an enterprise possesses resources/competences but lacks dynamic capabilities, it has a chance to make a competitive return (and possibly even a supra-competitive return) for a short period; but it cannot sustain supra-competitive returns for the long term except due to chance.”

Dynamic capabilities, therefore, help realize competitive priorities by continuously aligning/positioning competencies in response to market needs. This, however, does not guarantee the realization of all competitive priorities, due to their relationship with each other. The relationship among these competitive priorities has been the subject of debate in the literature. The first theory that attempts to clarify the nature of this relationship is related to the trade-offs theory, which was first developed by Skinner (1969). According to Skinner (1969), the theory of trade-offs is founded on the premise that there is an inevitable compromise or trade-off(s) to be made between competitive priorities in planning or managing a manufacturing system. Therefore, a manufacturing system cannot deliver the highest level in all competitive capabilities, particularly

while designing new manufacturing systems where several dimensions such as cost and flexibility will conflict with one another (Skinner, 1996). While the trade-offs theory has been supported by empirical studies (e.g. Boyer and Lewis, 2002), a number of other studies have suggested a more harmonious (i.e. combined) rather than opposing nature in the relationship among competitive capabilities. This has led to another strand of research that examines how capabilities exhibit a cumulative nature.

The concept of cumulative capabilities was initially discussed by Nakane (1986) and later by Ferdows and De Meyer (1990). Nakane (1986) indicates that a cumulative progression exists for the development of competitive capabilities. This cumulative progression can be likened to a pyramid or, as widely known, the sand cone model, as shown in Figure 2.3 below. This model consists of quality, delivery (i.e. also referred to as dependability in the literature), cost, and flexibility. According to this model, quality must first be assured. Contingent on the full development of quality as a capability, rapid and dependable deliveries would then follow and are pursued. Once quality and delivery have been controlled, cost efficiencies can be endured. At the end stage, flexibility is developed as a capability once quality, delivery and cost are under control. This model was later modified by Ferdows and De Meyer (1990), where flexibility was prioritised over cost in the order shown in Figure 2.3.

These two models developed by Nakane (1986) and Ferdows and De Meyer (1990) have gained significant interest from scholars, and there have been some attempts made to empirically validate them in the literature (e.g. Corbett and Whybark, 2001; Corbett and Claridge, 2002; Größler and Grübner, 2006). Notwithstanding this, there is no clear consensus in the extant literature on how, and in what manner cost and flexibility interact with each other. This gap indicates a lack of validity in the cumulative model. In addition, the

model's underlying assumption that there is only one right way to progressively develop competitive capabilities contradicts real-world settings where market conditions affect the prioritisation and focus of these competitive capabilities. This would also appear to tie in with what has been discussed in trade-offs theories, which suggests these two models oppose one another.

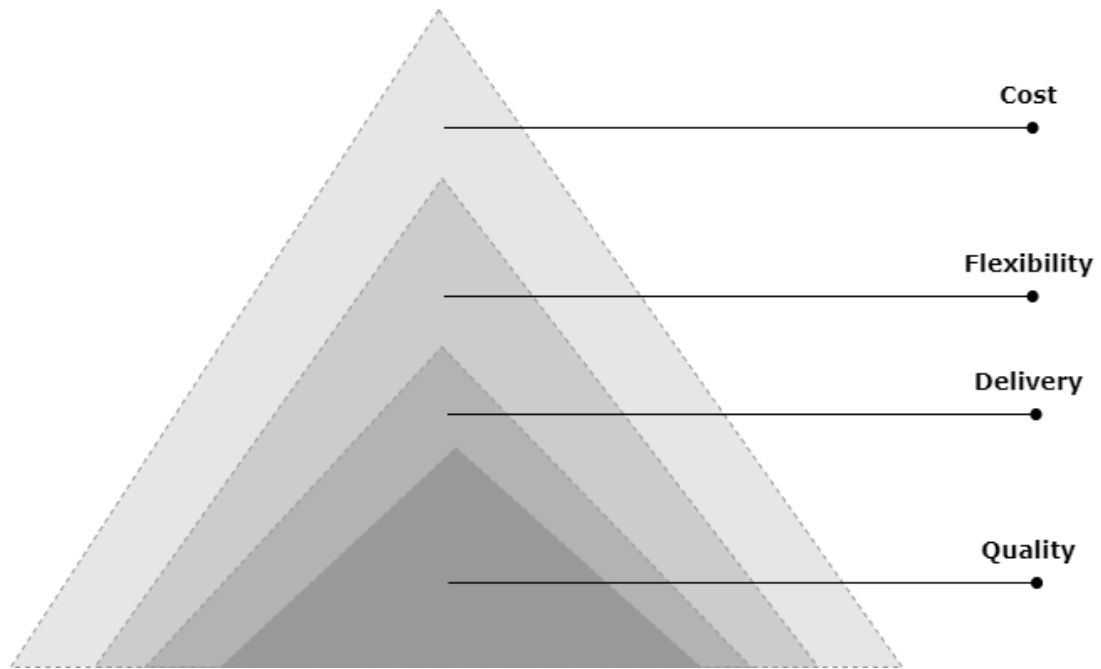


Figure 2.3: The sand cone model (adapted from Ferdows and De Meyer (1990)).

2.1.1.4. The performance frontier theory

In an attempt to resolve this conflict, Schmenner and Swink (1998) clarified two critical distinctions between the theory of cumulative capabilities and the theory of trade-offs. The first clarification is that these two theories are clearly of inherently different types. The theory of trade-offs, for instance, deals with performance difference across different competitors (i.e. inter-firm) while the theory of cumulative capabilities describes the performance difference within a manufacturing plant (i.e. intra-firm). The second clarification is that the theory of trade-offs is used when comparing between different competitors at a certain point in time, whereas the theory of cumulative capabilities looks at one (i.e. the same) manufacturing

firm over time. Building on these distinctions, Schmenner and Swink (1998) have asserted that these two theories are not in conflict and presented the performance frontiers theory, also known as the production function frontier theory, as a unifying theory which combines elements of the trade-offs theory and cumulative capability theory respectively.

Schmenner and Swink (1998) acknowledge the major classification in manufacturing strategy of "structural" and "infrastructural" decisions where the former represents decisions affecting operating policy and the latter reflects decisions related to physical assets. Along this line of distinction, the theory of performance frontiers distinguishes between the frontier of performance and that of the asset. The authors have defined the performance frontiers theory as follows:

"the maximum performance that can be achieved by
a manufacturing unit given a set of operating choices"

The asset frontier is determined by the types of investments that are reflected in the fixed asset part of the balance sheet, whereas the operating frontier is governed by adjustments in the operating policies and plans, based on the range of assets that has been installed. For the performance frontier, manufacturing firms improve one capability (i.e. cost) by trading off the deterioration of another (i.e. flexibility). Therefore, improvements are controlled in this frontier based on the competitive priorities of the firm. One major approach that can be used to overcome this trade-off necessity is through upgrading and adopting new manufacturing technologies.

Figure 2.4 below shows the operating frontiers within a performance area for two manufacturing firms that share the same asset frontier. Both firms adopt distinct management and operating policies despite their utilisation of the same technologies and physical assets. The

performance of each manufacturing firm is restricted by their operating policies, hence their operating frontiers. By adopting new management practices such as Just-In-Time (JIT) production, each firm can affect (i.e. move) their operating frontier. The degree of movement or progression for each firm, however, is ultimately constrained by the boundaries of the asset frontier.

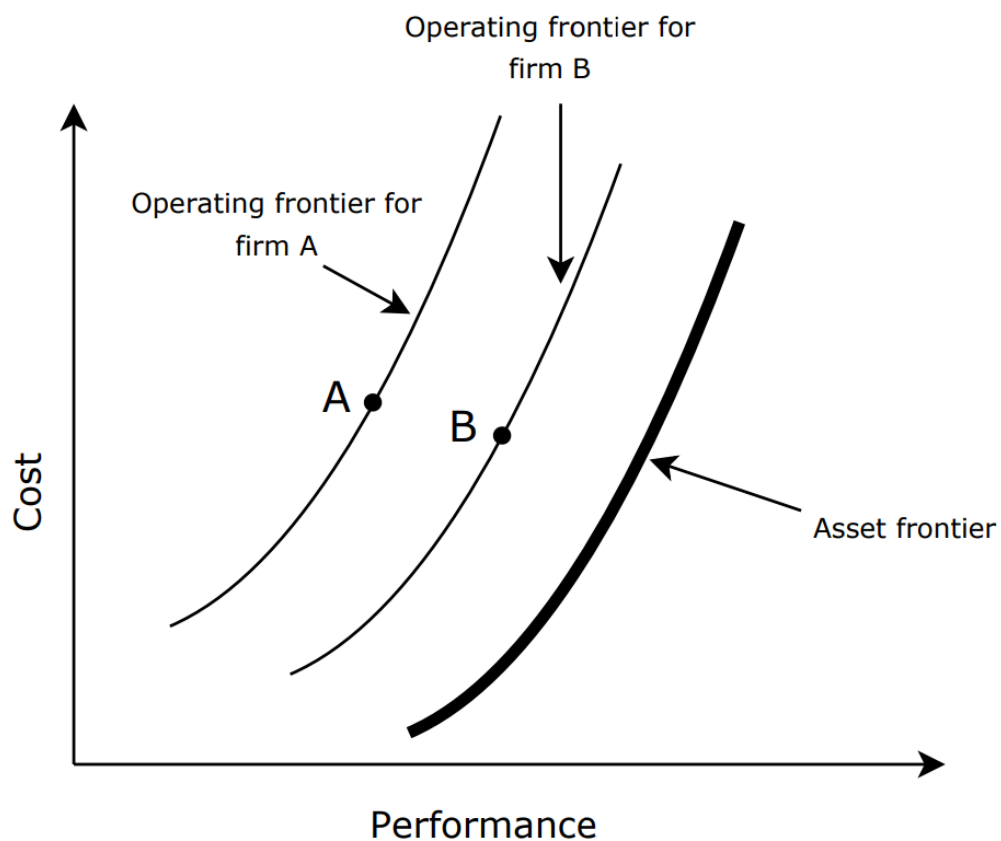


Figure 2.4: Operating frontiers for two hypothetical firms that share the same asset frontiers (adapted from Schmenner and Swink (1998)).

Schmenner and Swink (1998) make a distinction between two important kinds of movement within the performance space in Figure 2.4. The first kind is caused by improvements that cause higher levels of utilisation and efficiencies that do not cause a deterioration in the other performance dimensions. This is contrasted with the second kind of movement which may be caused, for example, by the adoption of new management philosophy. Figure 2.5 below shows three operating positions within the performance space of a

manufacturing firm. The first shows firm A's position due to underutilisation and inefficiencies. Once resources are utilised and efficiency improves, a transition to position A_1 occurs at which point the firm is further restricted by having reached its operating frontier. This is improved, however, once the firm adopts a new management philosophy such as JIT, thus gradually pushing the frontier further forward to position A_2 . Once this occurs, restrictions appear once more due to technologies and physical assets which start to substantially impact the performance of the firm.

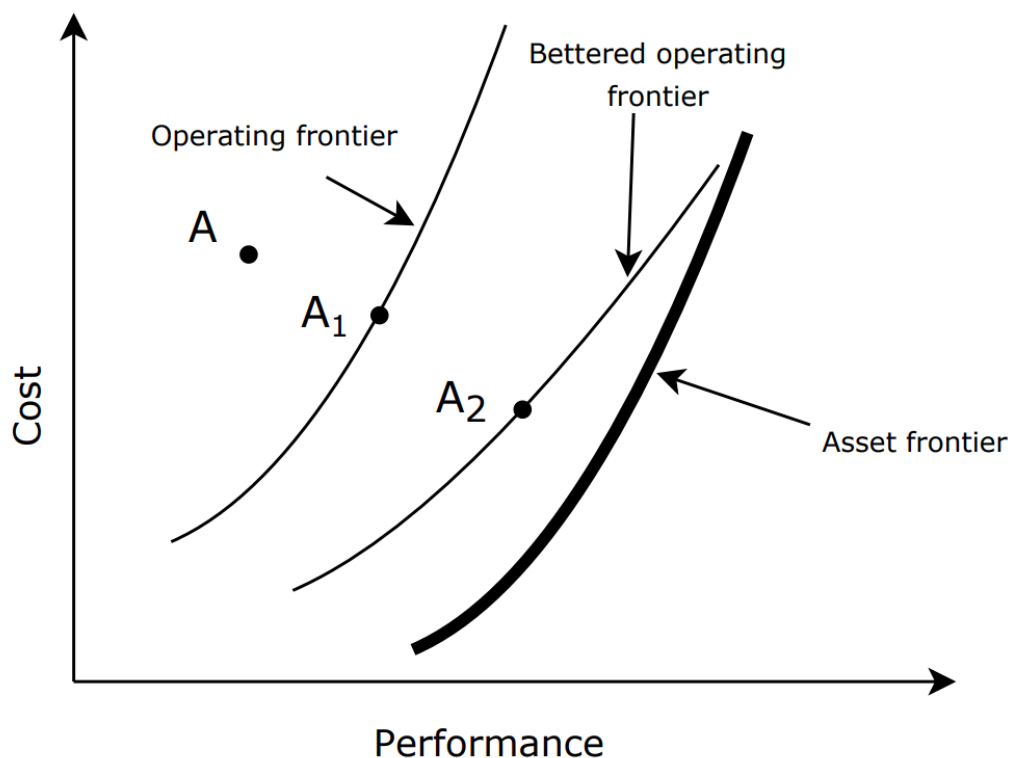


Figure 2.5: Three operating states for a manufacturing firm under the same asset frontier (adapted from Schmenner and Swink (1998)).

2.1.1.5. Order winning and order qualifying criteria

A third element of the literature concerned with relationships among competitive capabilities revolves around the order winner and order qualifier framework. The order winner and order qualifier concept emphasises that the strategic objective of a manufacturing firm should be to secure a competitive advantage by exploiting demand

volatility and trends, as this will lead to operational efficiency being achieved. Certain criteria linked to order-qualifying and order-winning have been established to enable this strategic objective to be achieved (Hill, 1995). Qualifying criteria are met when the firm satisfies the basic needs of its customers, and it is only after meeting them that the manufacturing firm can be considered as a possible supplier, as they are rendered as core requirements linked to market entry. Once achieved, the order-winning criteria that will help to distinguish the manufacturing firm from its competitors will be targeted.

Classic order winners and qualifiers are linked with distinct product attributes such as product type (i.e. customised vs standard), product variations ranging from wide to narrow, and demand volume ranging from low to high volumes. Linked to these attributes, quality and delivery are seen as order qualifiers (Hill, 1989, 2000; Hill and Hill, 2009). In particular, price is the order winner for standard products with narrow variations and high volumes. The main manufacturing priority, therefore, is cost-effectiveness. Customised products, on the other hand, that are characterised by wide variations and low demand volumes win orders contingent upon the uniqueness of their design and rapidity of delivery. For products with such attributes, flexibility in manufacturing is essential.

The primary notion of the order winner and order qualifier framework is that competitive capabilities are prioritised based on the two main types of products (i.e. standard and customised). Quality and delivery, however, are still considered order qualifiers for both product types, and this supports the consensus on quality and delivery as being the basic layers used to gain a competitive advantage according to the prevailing literature on cumulative capabilities. However, a trade-off still needs to be made between

cost and flexibility in these theories, which indicates a non-correlative relationship between the two competitive capabilities.

Based on the discussion above, it can be inferred that in order to gain a competitive advantage, a firm must develop a certain level of competency, which in turn will assist them in realising competitive capabilities. The performance of these competitive capabilities is constrained by the assets frontier (discussed in Section 2.1.1.4), which is affected by the adoption of new manufacturing technologies. This shows how important it is to get new technologies right if firms wish to expand the boundaries of frontiers and in doing so gain further financial benefits associated with improved income streams, as well as enhanced operating efficiency. In today's ultra-competitive marketplace, these are key aspects that firms are continually looking to achieve.

The next section moves on to consider the role of SCM and describes its development, as well as considering one of the key factors that hinder its efficacy.

2.2. Supply Chain Management (SCM)

SCM as a field of academic education, research, and commercial practice has advanced rapidly (Ellram and Cooper, 2014). It initially started with practices focused on efficiently managing inventory and planning and controlling production in a manner that guarantees a high level of capacity utilisation (Stevens and Johnson, 2016). Over time, logistical activities have been added to the field of SCM as a result of the emergence of high transportation costs (Ballou, 2007). Systemising these activities has led to the creation of Enterprise Resource Planning (ERP); a concept that has evolved from Material Requirements Planning (MRP) (Rondeau and Litteral, 2001). This phase was followed by the rise of the Japanese lean manufacturing

philosophy (Womack et al., 2007), which was later integrated with the process improvement practice known as Six-Sigma (Arnheiter and Maleyeff, 2005). This was combined with the intent of reducing waste and variation.

Up until this point, SCM has been focused on the efficient organisation of activities within the supply chain. These activities preclude the end-customer from being an integral part of this management process. Supply chain managers, however, gradually began to realise the increasing importance of having the end-customer's input into the management of their supply chains (Christopher and Towill, 2000). This more integrated approach (supplier-customer; customer-supplier) led to the emergence of agile supply chains that were symbolised by their ability to adapt to different changes in the market (Aitken et al., 2002). With the shift in markets and the notion of globalisation, this led to companies outsourcing non-essential activities to other developing countries to benefit from low costs (Gereffi, 1999), whilst trying to retain a focus on their core competencies (Hamel and Prahalad, 1990). Adaptation to the market with low-cost advantages has formed a consistent theme in the SCM literature.

From a manufacturing perspective, the purpose of SCM is to convert acquired raw materials into finished products that can be used by the end customer through executing successive processes throughout the chain (Singh et al., 2012). This also encompasses the required flow of information and materials, and the coordination of processes between the other links in the chain, i.e. factory, warehouse and/or customer (Christopher, 2012). Beyond this rather manufacturing-focused perspective, however, is the ultimate objective of profit which can be achieved by matching supply with demand, thus reducing the possibility of lost opportunities resulting

in stockout penalties whilst simultaneously enhancing customer satisfaction (Mason-Jones et al., 2000).

The one crucial component, however, that can severely disrupt the sometimes elusive achievement of matching supply and demand is uncertainty. Uncertainty in supply chains represents a perennial struggle for operations and supply chain executives (Hult et al., 2010). This uncertainty stems from the growing levels of complexity in global supply chains that consistently carry various risks, such as delivery interruptions and damaged products (Bhatnagar and Sohal, 2005). In order to mitigate the effect of such disruptions, successful supply chain redesign strategies can be established through the study and detection of the sources of such disruptions. These sources of uncertainty might disrupt a particular node in a supply chain, but the ripple effect or aftermath can potentially impact all participants in the supply chain. These sources are discussed in the following section.

2.3. Sources of uncertainty in the supply chain

The term uncertainty is occasionally used interchangeably with risk in the supply chain literature (Ritchie and Brindley, 2007). The key distinction between uncertainty and risk is that risk indicates or points to a potentially negative outcome, while uncertainty can arguably be referred to as either a negative or positive outcome. Simangunsong et al. (2012, p. 3) have provided an illustration of the difference between uncertainty and risk in the statement below:

“the risks associated with a natural disaster can only lead to supply chain problems; whereas uncertainty regarding customer demand can result in demand being either better or worse than expected. It can therefore be argued that the term “supply chain

uncertainty" is broader, and can be used to encompass issues that have sometimes only been referred to under the risk banner."

Before identifying the sources of supply chain uncertainty, it would be useful to delineate the term supply chain uncertainty so as to establish the context. Given the wealth of literature that has been devoted to this area (Simangunsong et al., 2012), it is curious that there seems to be a lack of consistency in its definition. Van Der Vorst and Beulens (2002, p. 413) have, however, provided a useful definition:

"Supply chain uncertainty refers to decision making situations in the supply chain in which the decision-maker does not know definitely what to decide as he is indistinct about the objectives; lacks information about (or understanding of) the supply chain or its environment; lacks information processing capacities; is unable to accurately predict the impact of possible control actions on supply chain behaviour; or, lacks effective control actions (non- controllability). "

While this definition implies broad possibilities, several successful attempts have managed to group these sources of uncertainty into general categories. In this regard, a pioneering piece of work on the uncertainty model has been developed by Davis (1993) who has identified three sources for supply chain uncertainty: supply, manufacturing process and demand disruptions. He described the expansion of information and processes, which resulted from the integration with other entities in the supply chain, as a cause of the uncertainty that can overwhelm the system. Furthermore, these system-induced uncertainties are magnified by the volatility that appears in marketplace demand. Mason-Jones and Towill (1998)

have elaborated on this work by adding another source: control uncertainty; which describes the ability of a decision-maker to translate customer orders into production targets and raw material needs.

Demand uncertainty, however, has attracted most research attention from the extant literature, as the other sources can be controlled using different techniques and practices, such as Six-Sigma for manufacturing process uncertainty and collaboration with key suppliers for supply uncertainty (Simangunsong et al., 2012). Furthermore, uncertainty in demand is considered to be the most severe source among all others (Van der Vaart et al., 1996; Gupta and Maranas, 2003), and it is caused by either demand amplification or demand unpredictability in the marketplace (Mason-Jones et al., 2000).

Demand amplification was first described by Forrester (1958), who was a system theorist and used computer simulations to observe the effect of different control policies on industrial dynamics. He conducted some studies to examine the disturbance to the supply chain caused by reordering patterns. He revealed, using computer simulations, how the information related to customer orders are distorted as they progress upstream, which in turn has an enormous effect on setting the optimum inventory level and production plans. In one scenario, he showed how a 10% increase in customer orders was amplified to 40% for the manufacturer, which entails a significant and unnecessary increase in inventory holding cost. This phenomenon is known as either the Forrester effect or the Bullwhip effect, the latter being a reference to the way in which the magnitude of a whip increases down its length (Lee et al., 1997). An example of this effect can be illustrated in Figure 2.6 below.



Figure 2.6: Illustration of the Bullwhip Effect (images taken from Lee et al. (1997)).

Another element - demand unpredictability, is considered to be the only source of uncertainty that cannot be directly controlled by supply chain executives (Mason-Jones et al., 2000). It is important here to distinguish between "inherent characteristics" of a product

that cause predictable fluctuations in demand and "exogenous phenomenon" that disrupts the supply chain. The former can be thought of as the weather changes that fluctuate the demand in seasonal patterns, whereas the latter is hard to identify and can manifest during technological advances or when new government regulations are placed (Van Der Vorst and Beulens, 2002).

If, for instance, one of these sources was identified, certain techniques might eliminate or at least mitigate the effect of uncertainty to the point where it becomes manageable. This, however, is not the case with demand uncertainty, which requires the redesigning of the whole supply strategy in a way that greatly fulfils different changes in demand.

The next section of this chapter discusses how different demand attributes affect the decision-making of supply chain strategy.

2.4. Supply chain strategy aligned with the nature of demand

In his influential work, Fisher (1997) began by raising the question of why the advances in strategies and technologies have not led companies to improve their supply chain performance. Before identifying the source of the problem, he offered a framework with which managers could choose the right supply chain strategy based on the market. He categorised products into two types based on the nature of their demand. Each type needs a distinct supply chain strategy. He believed that the main problem that most supply chains face is the mismatch between the type of product and the supply chain strategy adopted. A depiction of this categorization is shown in Figure 2.7 below.

Innovative products

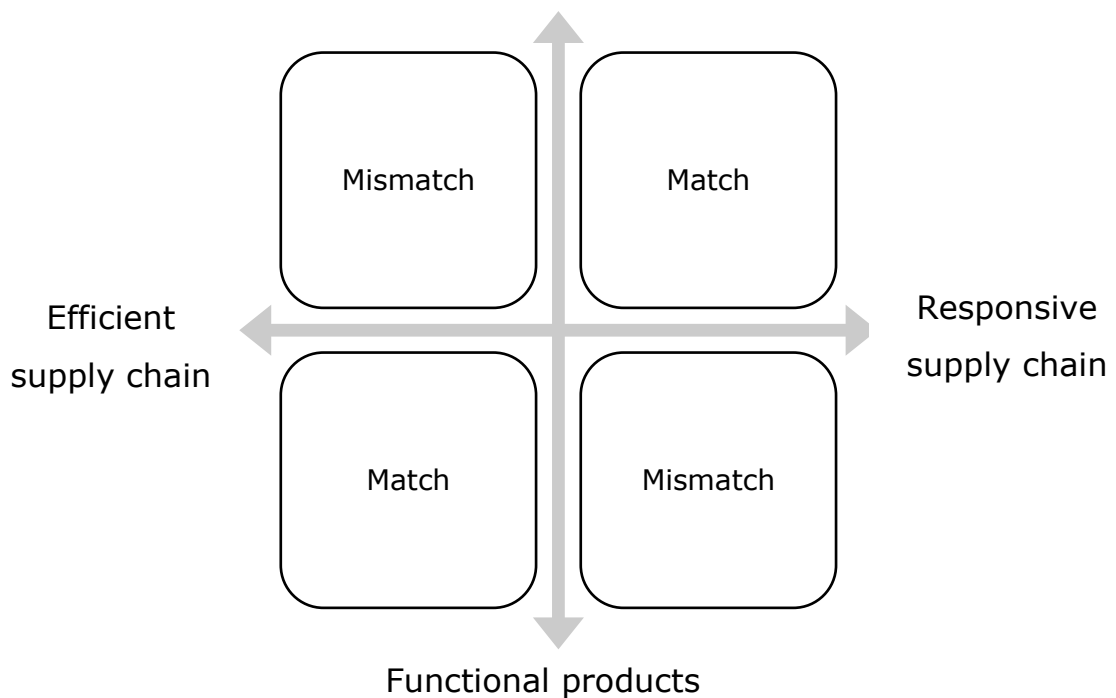


Figure 2.7: 2X2 matrix to match the right supply chain with products (adapted from Fisher (1997)).

The first type of products is functional products or common commodities. These are products that fulfil basic needs and are primarily characterized by their demand predictability and long life-cycle. The market for these products has low barriers to entry, which allows the market share to be divided and shared by multiple companies. Hence, only low margins can be achieved in this market segment. This occasionally leads companies to introduce new innovative products in the hope of attaining higher profit margins. The introduction of new innovative products, however, entails uncertainty in demand. This type of innovative or fashionable product represents the second type of product category, according to Fisher.

To choose the right supply chain strategy for a product, Fisher (1997) emphasises the importance of understanding the two main functions of a supply chain:

1. Physical function: converting raw material into finished products and all the transportation needed in between.
2. Market mediation function: ensuring all product requirements are matched with customer needs and wants.

Each one of these functions requires various cost elements. As the demand is predictable for the functional products, the cost of market mediation is not high, which allows managers to primarily focus on minimising the cost incurred by physical functions. This, however, is the incorrect strategy for innovative products where demand is uncertain and higher costs need to be invested in market mediation functions. These strategies that best fit functional products have been coined "physical efficient" strategies by Fisher, whereas others are "market responsive" strategies. It is only where firms fail to reconcile between the right supply chain strategy with the right product that a mismatch will occur and companies will fail to improve their supply chain performance. Fisher's general matrix was later empirically validated by several publications (e.g. Selldin and Olhager, 2007; Lo and Power, 2010).

While this distinction constitutes a useful starting point, functional products, in reality, are characterized by a degree of unpredictability in demand. The same also applies for innovative products which can be of a predictable demand nature, such as fashionable products, for instance, that may satisfy a social trend. A more accurate model of these distinctions would go beyond the four cells typology that has been discussed above and would measure the degree of the match in a continuous spectrum rather than a matrix. This type of model was successfully constructed by Wagner et al. (2012) and the impact of the mismatch was linked to financial performance.

Another key element in trying to determine demand uncertainty and proactively plan for future demand is inventory management and

this will be dealt with in the next section. It also sheds light on the impact of demand uncertainty on this practice.

2.5. Inventory management and demand uncertainty

In a perfect demand-fulfilment scenario, a whole supply chain is triggered to produce goods/products based on a forecast that precisely matches what is needed by the market. This is, however, far from reality. Demand in certain settings is difficult to forecast. Thus, firms in supply chains face the dilemma of either producing in batches and risking excess unsold inventory, or not producing enough inventory and consequently losing opportunities in the form of stockouts (Christopher, 2016). This section outlines the key literature that deals with the balancing of these two risks (i.e. excess inventory and stockout events) in the light of demand uncertainties.

To begin with, it would be prudent to discuss the conceptualisation of inventory management. Tersine (1988, p. 3) has defined inventory as follows:

"the stock on hand of materials at a given time, a tangible asset which can be seen, measured and counted. [It] may consist of supplies, raw materials, in-process goods, and finished goods."

Inventory is typically held for a variety of motives including hedging against uncertainty in supply and demand (Cachon and Terwiesch, 2008), the achievement of economies of scale (Chu et al., 2005), and speculating on an increase in future prices of raw materials or supplies (Berling and Martínez-de-Albéniz, 2011).

Managing inventory is an essential element of SCM, given its major effect on the performance of the participating firms in the supply chain (Shapiro and Wagner, 2009). This is typically carried out by

adopting an approach which ensures efficient management and control of inventory. These activities include, for instance, investing in supply chain software (Blankley et al., 2008), collaborating with supply chain participants by sharing vendor managed inventory (Yao et al., 2007) or implementing JIT methods (Green and Inman, 2005). It is well-established that effective inventory management enhances the overall performance of manufacturing firms (e.g. Koumanakos, 2008; Prempeh, 2015; Shin et al., 2015).

The effectiveness of inventory management is achieved through the application of various inventory models. The selection of an appropriate model is often undertaken based on three essential variables (Ziukov, 2016):

- The first variable considers the type of demand faced by the supply chain. Demand can be modelled as deterministic, implying exact anticipation of its volume and variability in advance, or stochastic whereby forecasting methods and techniques are utilised.
- The second variable is cost structure, which comes in the form of i) the order cost (i.e. set-up cost and transportation cost), ii) the inventory holding cost (i.e. space rent, insurance, maintenance, etc.), and/or iii) the stockout cost (i.e. lost profit of stockout events).
- The third variable is the inventory system structure and its physical aspects, such as whether it is held in a single location or several locations.

The conventional way of determining the appropriate inventory level to be ordered and produced in anticipation of customer demand usually comes in the form of distinct statistical methods, each aiming to answer two key questions: i) when to order (i.e. a reorder point at which replenishment is ordered) and ii) how much to order

(Nemtajela and Mbohwa, 2017). Setting the reordering point is based on the expected replenishment lead-time to produce or secure the new amount.

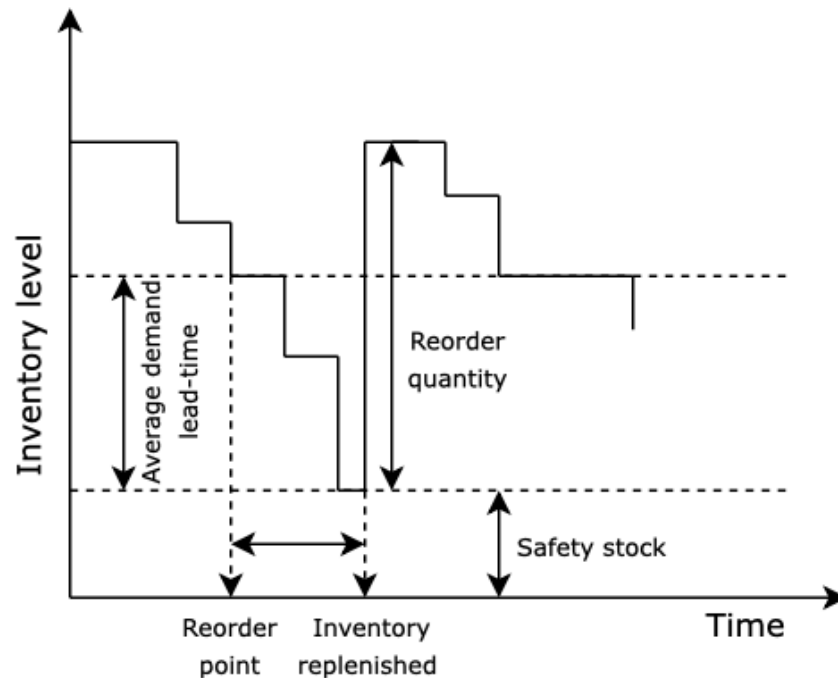


Figure 2.8: The reordering point technique of inventory control and management (adapted from Christopher (2016)).

As shown in Figure 2.8 above, the inventory starts at a certain level at the beginning of a business year. It then gradually decreases with each fulfilment of customer demand. At a certain point, known as the reordering point, an order is placed to replenish the inventory. The determination of this reordering point is dependent upon two main factors. The first is the average demand lead-time, which reflects how much time it takes on average for the remaining inventory to be depleted to a safety stock level. The safety stock level is decided based upon the target service level, which is the probability of not facing a stockout during the next replenishment cycle. The service level is determined subjectively so that the safety stock level is high enough to fulfil customer demand during the replenishment lead-time, but not so high that it incurs high carrying costs (Hoppe, 2006).

The second factor is the average lead-time needed for replenishment. This is shown in Figure 2.8 as the difference in time between the reorder point and the inventory being replenished. This lead-time is needed for the complete production of a new batch inside the factory or for the order to arrive from the supplier. Alternatively, as is shown in Figure 2.9 below, inventory is reviewed regularly with fixed periods between orders (Sarkar and Mahapatra, 2017). In this case, the amount to be ordered is the sum difference between the current inventory level and a predetermined target level.

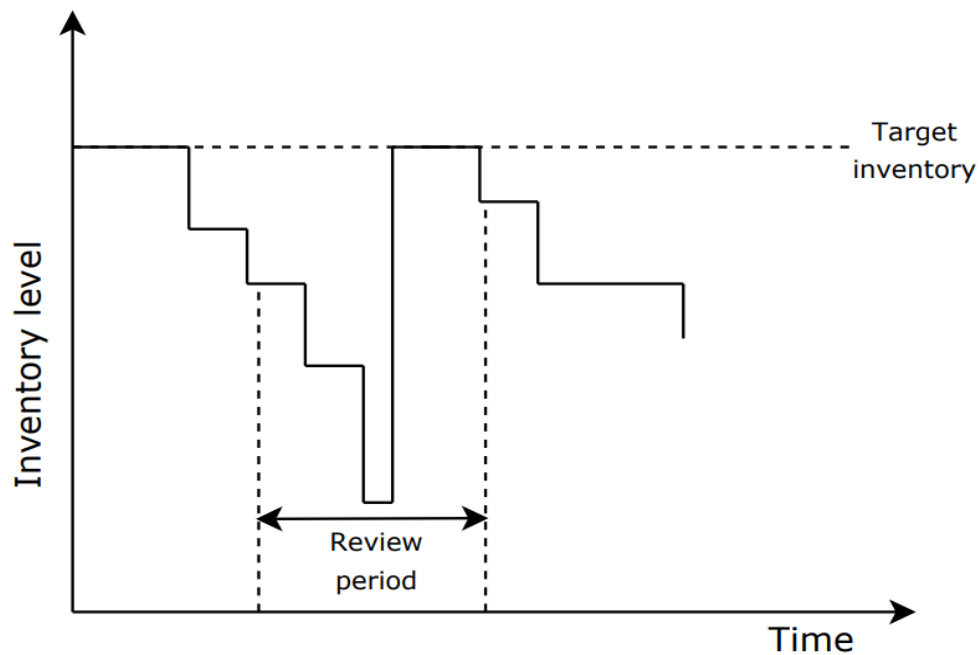


Figure 2.9: The regular review method of inventory control and management (adapted from Sarkar and Mahapatra (2017)).

A trade-off that always exists and affects the reordering point and the order quantity is the link between the inventory holding cost and the order/production set-up cost (Mekler, 1993). Realising an optimum balance between these two costs has been possible with a deterministic model known as Economic Order Quantity (EOQ) (Axsäter, 2015). To illustrate this, Figure 2.10 below shows the

optimum quantity to be reordered based on the total cost that considers the trade-off between inventory holding cost and ordering cost. The EOQ, representing the minimum point of the total cost curve, can be estimated using the equation:

$$EOQ = \sqrt{\frac{2AS}{H}} \quad 2.1$$

where A denotes the annual demand of the inventory unit, S indicates the order/set-up cost and H denotes the inventory holding cost. Another inventory model that considers a constant production rate instead of the single receiving of delivery in the EOQ is known as the Economic Production Quantity (EPQ), which can be estimated as follows:

$$EOQ = \sqrt{\frac{2AS}{H(x-1)}} \quad 2.2$$

in which x equates $\frac{A}{P}$ where P = production rate.

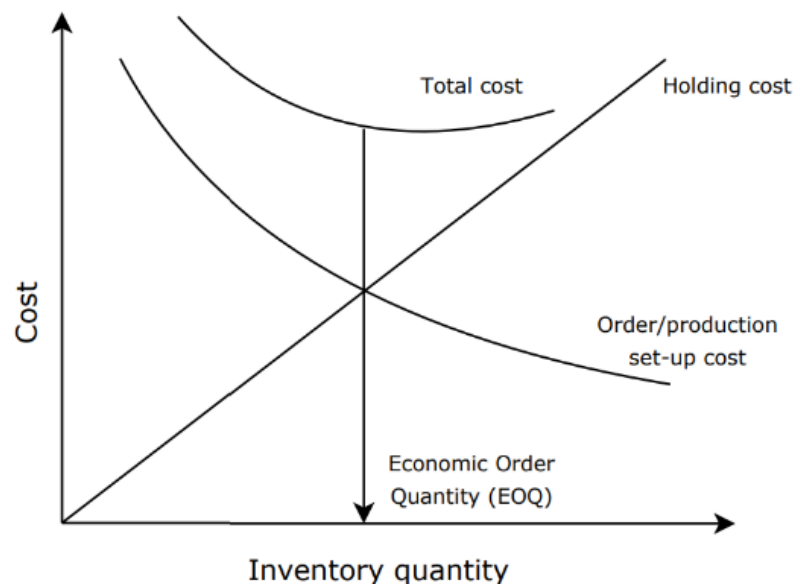


Figure 2.10: Achieving a balance between inventory holding cost and order cost through EOQ (adapted from Tersine (1988)).

A critical underlying assumption in both the EOQ and the EPQ formulas is that demand is predictable, as shown by the estimation A in Equation 2.1. Another assumption in these formulas is that stockout events are not permitted. This is generally inaccurate in real business settings, especially in the perishable goods/services industry where items lose their value over time (Chen et al., 2014), as demand is uncertain and firms face the critical dilemma of whether to overestimate demand and risk unsold products or underestimate and lose customers as well as the potential profits they may have yielded. This scenario has been referred to as the Newsvendor problem (Petruzzi and Dada, 1999). A newsvendor agent might order newspapers in excess of real demand and then find that he/she cannot sell the remaining quantity due to its lack of benefit or use outside its published day. If the newsvendor agent ordered fewer newspapers than what was actually needed on that day, a potential customer profit is lost. This phenomenon also applies to other industries that entail seasonal and trendy products such as the fashion industry (Song and Zhao, 2017). A considerable deal of literature has thus been devoted to developing and enhancing the newsvendor inventory model (e.g. Khouja, 1999; Petruzzi and Dada, 1999; Agrawal and Seshadri, 2000; Schweitzer and Cachon, 2000).

Despite the fact that the newsvendor inventory model considers stochastic demand and permits stockout or shortage costs, its planning horizon is a single period. A more accurate inventory model is the continuous review policy, denoted as the (Q,R) policy, that accounts for stochastic demand with multiple periods or repeating cycles (Tersine, 1988). Unlike the previous time-driven inventory models, whereby inventory is reviewed in regular periods with fixed order quantity, this model is event-driven, and so inventory is reviewed continuously (i.e. every day) and the decision of whether to order and how much to order is made correspondingly. The (Q,R)

inventory policy continuously checks if the inventory level reaches a predetermined reorder point R . Once this is triggered, an order of Q is placed to raise the inventory level back to the $R + Q$ level, as seen in Figure 2.11. In this model, Q is determined by using either EOQ or EPQ.

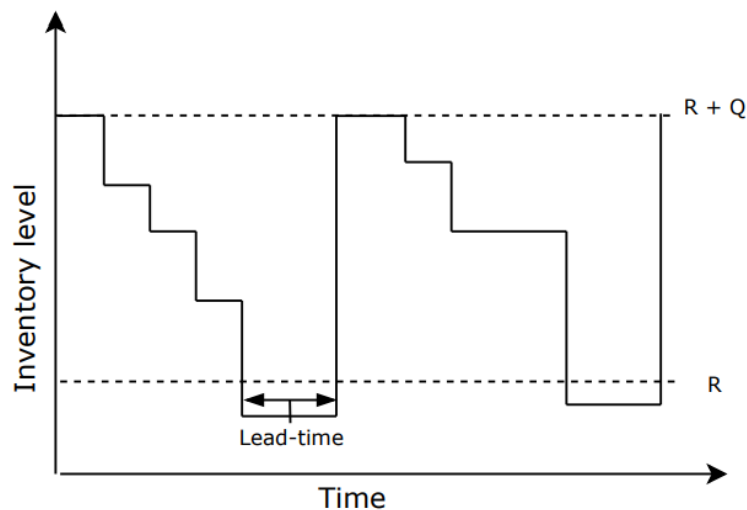


Figure 2.11: The (Q,R) inventory policy.

While these policies succeed to some extent in mitigating demand uncertainty, excess inventory will be held on a daily basis over the order cycle. For instance, if a product has been ordered in a batch of 500 units and a demand of 50 was requested on the first day, an inventory of 450 units will then be carried forward to the next day, which incurs cost in the form of holding cost. This does not include the additional safety stock (i.e. as a buffer against uncertainty) which adds to the daily residue of the inventory in the previous example.

It can be seen that despite several advances in the field of inventory management and control, the negative consequences of volatility in demand, manifested in the form of excess unsold inventory or stockout events, is still inevitable. Strategic initiatives to mitigate this effect are therefore justified. Such initiatives come in the form of designing, redesigning and reconfiguring supply chain strategies

to effectively respond to demand volatility. Basic responsive supply chain strategies are reviewed and discussed in the following section.

2.6. Responsive supply chain strategies

Tregoe and Zimmerman (1980, p. 17) define strategy as:

"the framework which guides those choices that determine the nature and direction of an organization"

Tregoe and Zimmerman (1980) stressed the importance of basing these choices on a single driving force, and recommended market needs as one major driving force. As discussed in Sections 2.3 and 2.4, demand volatility in the market is the greatest challenge that faces manufacturing firms. To meet this challenge, manufacturing firms redesign their supply chain strategies to enhance their responsiveness to the market. The next subsections review the generic responsive supply chain strategies under demand volatility.

2.6.1. Lean supply chain

Toyota Production System (TPS) is an integrative management system developed by Toyota in the 20th century and was later condensed and clarified by Womack et al. (1990). The purpose of the work of Womack et al. (1990) was to analyse why Japanese factories in the automotive industry have outperformed their competitors in the US and Europe in the 1970s and 1980s. By closely observing the Japanese factories, they identified three key reasons for this outperformance:

1. the consistent elimination of any non-added value activity (i.e. waste),
2. the continuous creation of a value stream where products flow smoothly through all production stages, and
3. the constant striving for perfection.

The observed eliminated waste, known as "Muda", manifests as overproduction, waiting time, unnecessary transportation, inappropriate processing, unnecessary inventory, unnecessary motion or defects. Womack et al. (1990) insisted that by focusing on the elimination of these types of waste and creating a smooth flow of products, companies can develop, manufacture, and deliver products with a high level of efficiency (i.e. effort, time and cost).

The widespread dissemination and acceptance of this work have led the same authors to extend their work and go beyond lean production to include the "lean enterprise", where the principles can be applied to the whole value stream or supply chain (Womack and Jones, 1994). This was followed by a book called "lean thinking", in which the authors explain the concept of the lean enterprise in detail (Womack and Jones, 1997). They claim that a lean factory cannot achieve its potential unless its suppliers and subcontractors are lean adopters as well. They also emphasise the importance of building a collaborative and close relationship with suppliers and reducing the supplier base to those with whom they have a long-term relationship. Cox (1999) argues that most SCM practices are just based on a modelling of Toyota's approach toward external resource management, a topic which was extensively discussed by Womack and Jones (1997).

The lean approach has the potential to increase the responsiveness of a supply chain in a variety of aspects. Holweg (2005), for instance, emphasises the need for a lead-time reduction and a focus on customer value to reach the desired level of responsiveness. Indeed, the lean enterprise at its most generic level can be described as a method of lead-time reduction (Hines, 1998).

Lean philosophy also considers the changeover or set-up time as waste that must be eliminated, and which occurs when changing

from producing one set of products to another. The Single-Minute Exchange of Dies (SMED) technique, for instance, was developed by Dillon and Shingo (1985) to reduce changeover time by converting as many set-up tasks as possible to external tasks that can be undertaken while the machine is running. This assists the reduction of production lot sizes (i.e. EPQ), therefore minimising the total inventory cost, as illustrated in Figure 2.12 below. MacDuffie et al. (1996) demonstrated that lean factories are more capable of reacting to greater product variety with far shorter set-up time than non-lean factories. Levy (1994) also described lean production as a philosophy that can be adopted to manage complex systems and allow accurate prediction of supply chain behaviours.

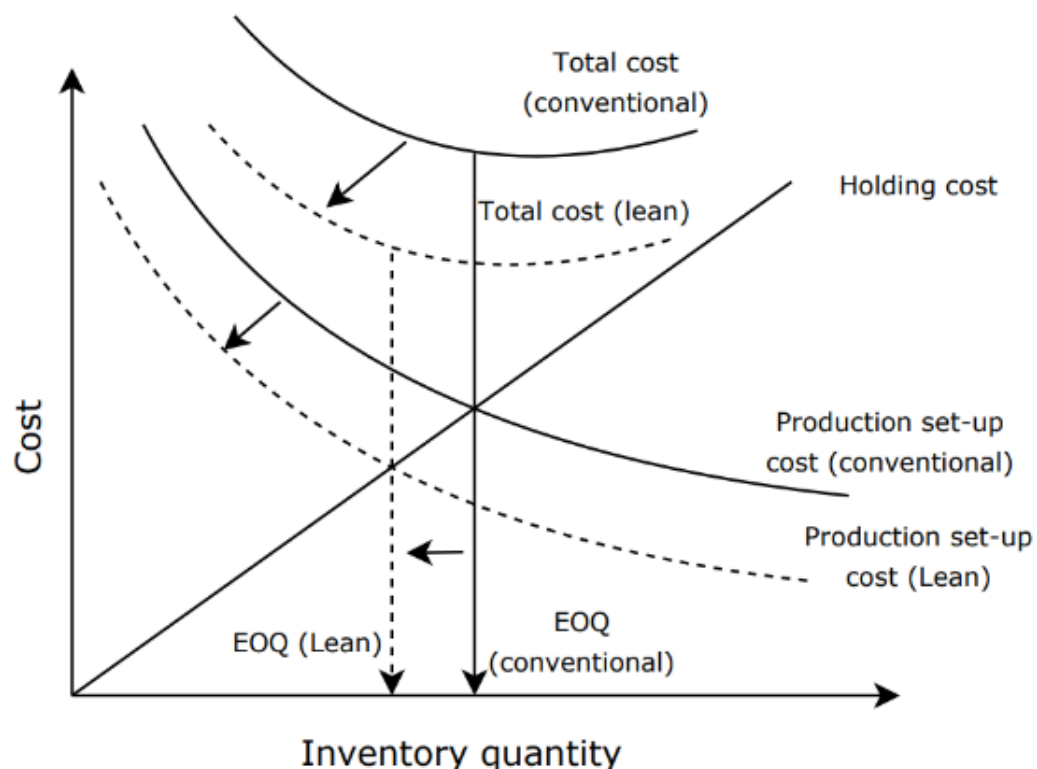


Figure 2.12: Comparing an EOQ using Lean philosophy with a conventional EOQ.

The debate surrounding whether the lean approach can improve supply chain responsiveness has focused around the inflexibility or rigidity of levelled schedule, or the "Heijunka" approach (Katayama

and Bennett, 1996; Goldsby et al., 2006). The term Heijunka refers to Toyota's approach towards eliminating unnecessary inventory that is held because of conventional batch production techniques. If one considers the typical scenario, factories tend to produce one set of products at a time in anticipation of their customer orders. These batches are produced based on forecasting methods which makes it difficult to provide the customer with flexibility in their orders (i.e. different kind of products or changes on volume). Thus, production planners either produce more volumes in the form of finished goods inventory or leave the customer dissatisfied with long lead-time replenishment (Furmans, 2005). This technique of mass production provides a high level of responsiveness to sudden changes in production volumes.

In contrast, Heijunka is a production planning methodology where a mix of families of products are evenly produced to increase the responsiveness of any changes in customer orders. For instance, a company that produces product family A in the morning shift and product family B in the night shift can instead evenly mix them throughout the day and continuously aim at reducing the change-over time. Hence, a system that is more flexible and adaptive will be the product of this approach. Also, this technique will leave production managers relying on rather short forecast periods instead of the long ones utilised by conventional production planning techniques (Rother and Shook, 2003). A prerequisite to this even product mix is the progressive realization of the target of one-piece flow. In lean manufacturing, the lot size is ideally reduced to one piece (i.e as opposed to a batch of units). In this scenario, the part is carried, processed and inspected one piece at a time (Li and Rong, 2009). This in turn allows parts to be pulled smoothly from the customer side through the utilization of what is known as the Kanban system (Kumar and Panneerselvam, 2007).

It should be noted that although lean systems have been known as "pull" systems, where no processes in the supply chain take place until the most downstream customer pulls an order, inventory is still "pushed" or produced in advance. For instance, Goldsby et al. (2006) differentiate between "lean push" and "mass production push" based on two distinct points: lean push is characterised by shorter forecast periods and more flexibility to cope with any changes on the production schedule. According to this, it is the willingness of the customer to wait that determines if that forecast-horizon can fill the gap. An alternative approach that has the potential to deal with such unwillingness is the agile supply chain; a subject that is discussed in the following section.

2.6.2. Agile Supply chain

The concept of agility originated from the Flexible Manufacturing System (FMS), which is characterised by rapid responses to either predicted or unpredicted volatility in demand (Christopher and Towill, 2001). It has subsequently been extended by the Iaccoca Institute to describe the adaptive version of TPS and was conceived from a supply chain perspective (Nagel and Dove, 1991). Naylor et al. (1999, p. 108) define agility as:

"Agility means using market knowledge and a virtual corporation to exploit profitable opportunities in a volatile market place".

Agile manufacturing endorses three main concepts to facilitate a quick response: holding "response" buffers, postponing decisions until the latest possible manufacturing stage and to delay product configuration (Kidd, 1997). Christopher and Towill (2000) defined four unique characteristics that each supply chain should have to be agile, which are:

1. Market sensitive: this implies the ability to instantly receive and respond to demand data. A demand-driven organisation, through capturing real data from the point-of-sale, rather than forecast-driven is needed to achieve this sensitivity,
2. Virtual: the use of IT to share data between different actors in the supply chain creates a virtual supply chain,
3. Process alignment: once the information needed is shared between supply chain partners, they can align their processes with utilising this data and exploiting opportunities (e.g. joint product development), and;
4. Network-based: as companies gradually focus on their core competencies and outsource everything else, greater dependence on suppliers is essential. Thus, a company has to collaborate and build a trust-based relationship with such partners so that a network of partners responds to the market rather than isolated entities.

While a lean supply chain emphasises the minimisation of waste throughout systems and enhances operational efficiency, an agile supply chain focuses on coping with uncertainty in demand and exploits this uncertainty to strategically gain a competitive advantage (Mason-Jones et al., 2000). In a lean supply chain, the customer purchases a particular product whereas in an agile scenario, the customer reserves a capacity that might be needed at very short notice. Moreover, a finished goods inventory might be considered as a waste in lean, yet a valued buffer to quickly respond to demand in agile. Therefore, agile is not synonymous with lean but still can be built upon it (Christopher, 2016). This can apply where demand is characterised by stability upstream and volatility downstream. A combination of lean and agile supply chain strategies has resulted in an emergent paradigm called the leagile supply chain, which is covered in the next section.

2.6.3. Leagile supply chain and the de-coupling point

As mentioned previously, there are two basic types of products described by Fisher (1997): functional and innovative. As these are categorized based on the demand attributes of the products, it is clear that functional products are well-matched with lean practices where the implementation of levelled schedule can be utilised. This contrasts with innovative products which require more agility to mitigate the risk of demand volatility and to exploit opportunities emerging from demand uncertainty (Mason-Jones et al., 2000). However, there are situations where these two elements need to be combined; a strategy coined by Naylor et al. (1999) as leagile.

Christopher and Towill (2001) describe how this hybrid strategy can be manifested in three distinct situations:

1. Pareto model or 80/20 rule: based on the assumption that the top 20% of products by volume are presumably more predictable than the other 80% of products, hence, lean should be the supply chain strategy for these high-volume products. Figure 2.13 below illustrates this match based on the Pareto model.

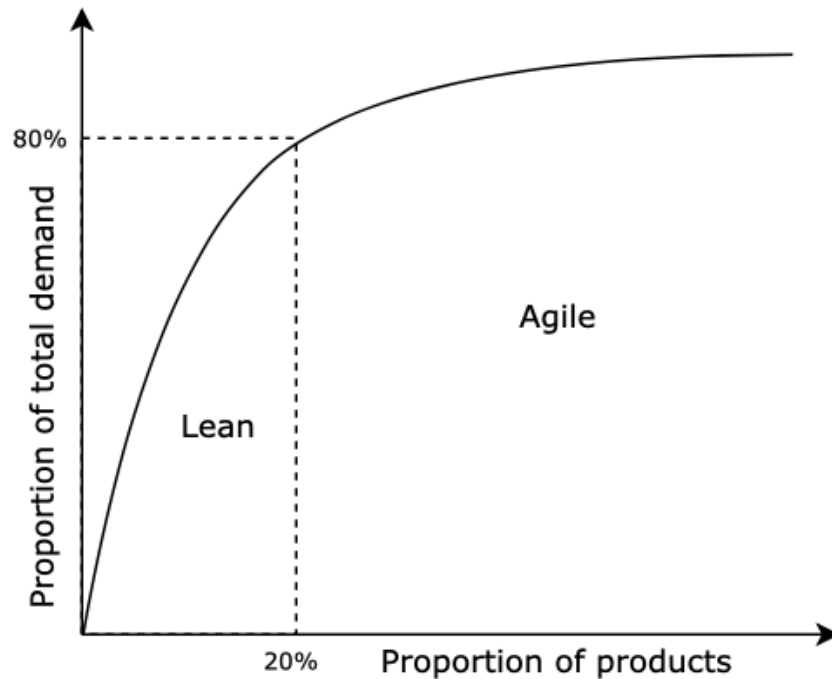


Figure 2.13: Pareto model for leagile (adapted from Christopher and Towill (2001)).

2. Base and surge demand separation: most companies experience stable demand for most of the year and it is only at a certain season where demand spikes and is heightened. Therefore, lean is a valid strategy during the period where demand is predictable and agile can be used during the peak periods or heavy promotions (i.e. outside capacity can be procured to fulfil required orders).
3. De-coupling point: another way of combining lean and agile is by creating a de-coupling point in the supply chain and placing what is known as "generic" or "strategic" inventory at this point. This means producing in advance all different components that have predictable demand and delay the final assembly or configuration to the last possible moment so that a rapid response to unique customer needs can be achieved. This approach is also referred to as "postponement" and has been used with the "customer decoupling point" interchangeably in the literature when it comes to late

customisation. Figure 2.14 provides further clarification of this process.

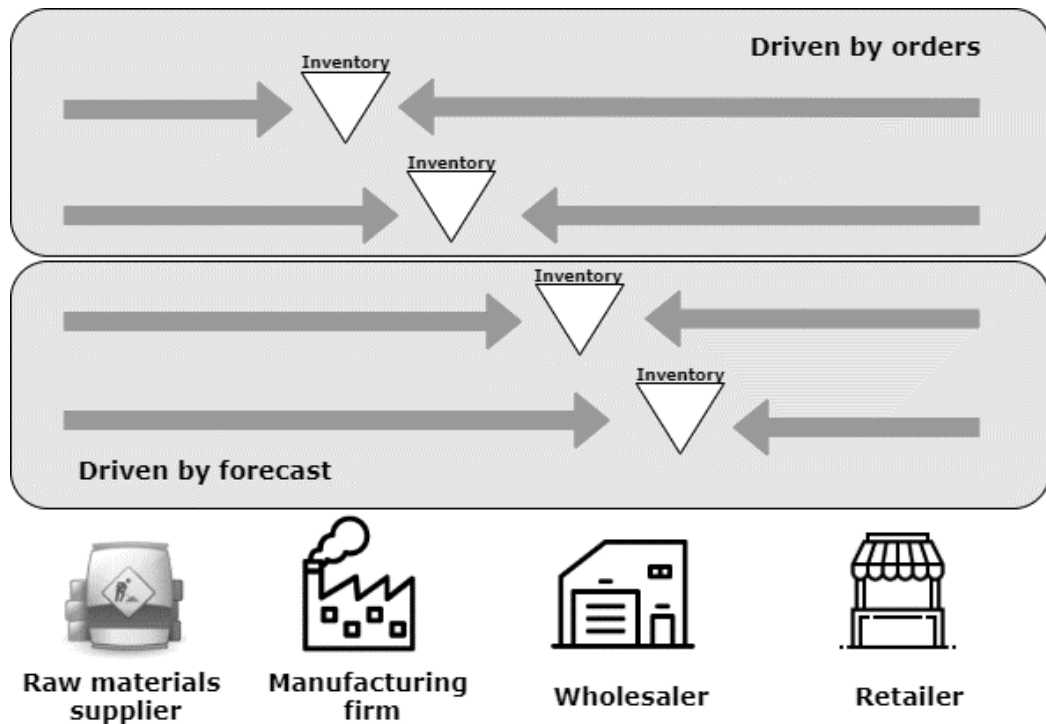


Figure 2.14: Different possibilities for locating the de-coupling point (adapted from Mason-Jones and Towill (1999)).

However, it should be noted that Figure 2.14 represents a simplistic view of a supply chain. In most real-world manufacturing supply chains, a particular part might be assembled from different components, each of which is either produced in-house or outsourced to an external supplier. This has led to an evolution from a supply chain to supply network (Cousins et al., 2008). Furthermore, a product passes through different stages of production and so therefore might alternate from the lean stage to agile stage due to the nature of the demand for each stage.

Having reviewed and discussed these responsive strategies (i.e. lean, agile, leagile), it would be useful to review the literature on a competitive priority concept that has been repeatedly discussed in relation to the responsive supply chain; namely that of flexibility.

2.7. Flexibility in SCM

There has been an increasing interest in flexible manufacturing of late (ElMaraghy et al., 2013). A large body of research has emerged which has focused on distinct aspects of flexibility in manufacturing including its definition and classifications (Shewchuk and Moodie, 1998), dimensions (D'Souza and Williams, 2000), measurements (Gupta and Somers, 1992; Tsourveloudis and Phillis, 1998) and its wider context in the supply chain (Stevenson and Spring, 2007). Despite these efforts, comprehending the importance of flexibility in manufacturing and SCM is still quite challenging; a point aptly highlighted by Sethi and Sethi (1990) who referred to flexibility as quite an elusive, difficult-to-capture concept.

This is why it is difficult to summarise flexibility in manufacturing systems, particularly with such a large volume of literature (De Toni and Tonchia, 1998). Most of the work in this field to date has been published and built upon the seminal works of Slack (1987), Gerwin (1993) and Upton (1994).

Slack (1987) classifies flexibility into four distinct kinds of products with two dimensions being identified for each type. The first is product flexibility, which implies the ability to introduce new products or improve existing products. The second refers to volume flexibility which describes the ability to make changes in production output. The third type is mix flexibility, which is defined as the ability to change the existing mix of products. The fourth component is delivery flexibility, which refers to the ability to change delivery agreements either by shortening the lead-time or changing the targeted location.

Swamidass and Newell (1987) empirically developed a theory of manufacturing strategy, where Gerwin (1993) later built on his conceptual framework of flexibility as a manufacturing strategy.

Gerwin identifies the relationship between manufacturing strategy, flexibility, environmental uncertainty, methods for delivering flexibility and performance measurement, as shown in Figure 2.15. The key element in this framework that plays a critical role in framing the context is manufacturing strategy, which is defined by Swamidass and Newell (1987, p. 509) as follows:

"the effective use of manufacturing strengths as a competitive weapon for the achievement of business and corporate goals".

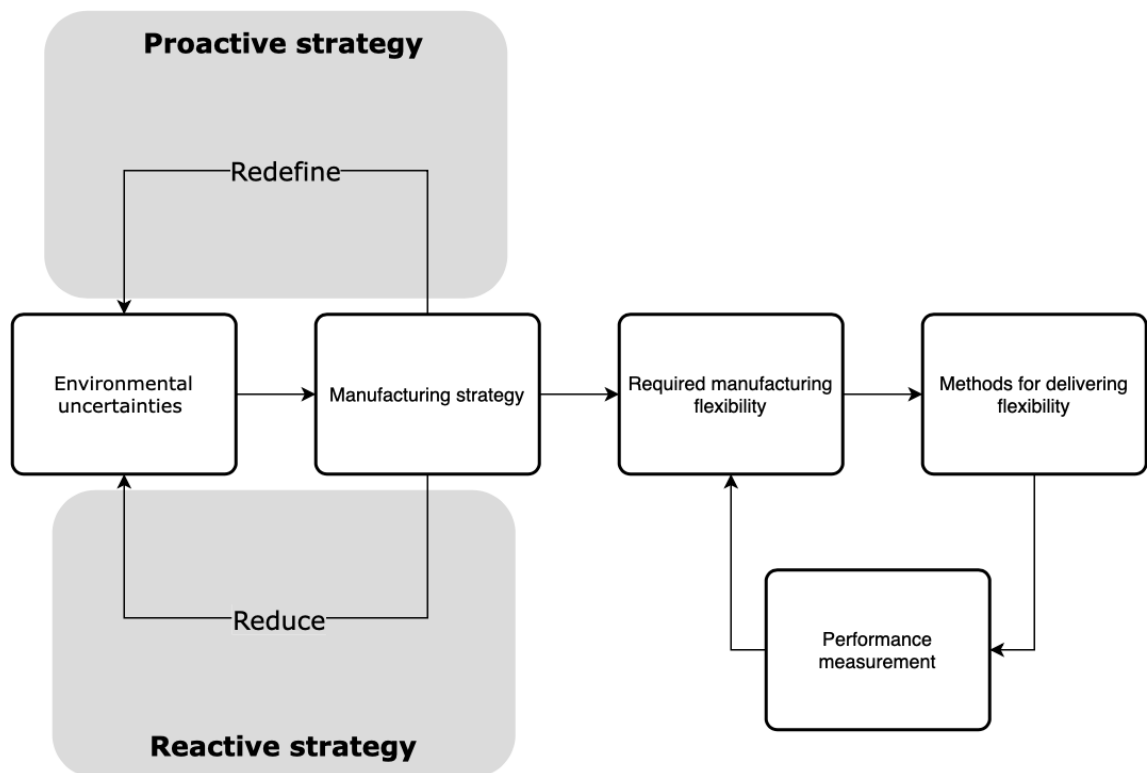


Figure 2.15: The interdependencies between environmental uncertainty, manufacturing strategy and manufacturing flexibility (adapted from Gerwin (1993)).

According to Gerwin's conceptual framework, a manufacturing strategy can be established in three clear ways. The first involves a reactive change in flexibility whereby the development of internal flexible capabilities is triggered by perceived environmental

uncertainties. The manufacturing system in this scenario is purely adaptive to the environment or market. The second strategy is of a proactive nature where utilisation of internal flexible competencies are directed towards redefining the uncertainties in the market. This can be approached, for instance, by faster and more frequent introduction of new products to the market. The last of the three strategies implies reducing the need to deliver flexibility through the reduction of environmental uncertainties. This could involve, for example, adopting long-term contracts with suppliers and customers.

Upton (1994) acknowledged the ambiguity of the use of flexibility in manufacturing and identified 15 different categories of flexibility which include routing, product, mix, action, state, volume, program, long-term, short-term, expansion, machine, labour, decision-change, operation and process flexibility. To formalise this into an appropriate framework and remove the ambiguity surrounding flexibility, he focused on identifying the nature of flexibility and its different contexts. Upton elaborates on the concept of flexibility and describes it as a quality that can be perceived either internally or externally. Internal flexibility reflects what the manufacturing firm is capable of while external flexibility is determined by what the customer perceives as flexible. Therefore, internal forms of flexibility are not relevant to the external unless their impacts constitute customer flexibility requirements. He also referred to the definition of the manufacturing boundary as a source of confusion in the appropriate use of flexibility. Manufacturing systems can be viewed from different levels based on the target time horizon. While long-term adaptation requires perceiving the manufacturing system from a strategic level, short-term adaptation involves operational or even tactical level.

Both Slack (1987) and Upton (1994) identified two different dimensions for each flexibility type: range and response. Range means the number of different outcomes a resource with the corresponding flexibility type can reach (i.e. the number of product variants a certain machine can produce). The response dimension represents the time and cost needed to achieve different range values (i.e. products changeover cost and time). Upton, however, added a third dimension: uniformity. By this dimension he meant the consistency of performance a certain resource could maintain during its range. Upton also distinguished between flexibility types that are 'internal' and others that are 'external'. While external flexibility types describe those that are seen by customers (i.e. delivery flexibility), internal types can be realised by developing internal competencies (i.e. adopting flexible machines) that enable any of the external ones.

As has been previously highlighted, manufacturing flexibility can have a significant impact upon supply chain responsiveness, and so understanding the relationship between these two elements is critical. This is discussed in the next section.

2.8. Responsiveness and flexibility in SCM

Responsiveness is a term that has been used interchangeably with flexibility both from a manufacturing system level (Slack, 1987; Gindy et al., 1999) and a supply chain level (Handfield and Bechtel, 2002; Lummus et al., 2003). Responsiveness has been consistently defined in several works as the ability to rapidly adapt to market disturbances (Matson and McFarlane, 1999; Catalan and Kotzab, 2003; Holweg, 2005). McCutcheon et al. (1994), however, link it exclusively to the lead-time of a specific product; hence, a shorter lead-time means higher responsiveness. Hines (1998) compared Toyota's supply in the UK with Toyota's supply in Japan, and

concluded that the less inventory a supply system has through its different supply tiers, this can lead to shorter lead-times, which in turn means the achievement of greater/enhanced responsiveness. This is a view that more or less represents the "lean" perspective towards supply chain responsiveness, as demonstrated in Section 2.6.1.

The common themes that supply chain responsiveness definitions share in the literature are i) it is the market that causes uncertainty and; ii) consistent emphasis on fast response. These definitions, however, still lack a unified delineation that distinguishes responsiveness from flexibility or shows how they may or may not be interrelated to one another. To this end, Reichhart and Holweg (2007, p. 1149) have defined responsiveness as follows:

"The responsiveness of a manufacturing or supply chain system is defined by the speed with which the system can adjust its output within the available range of the four external flexibility types: product, mix, volume and delivery, in response to an external stimulus, e.g. a customer order."

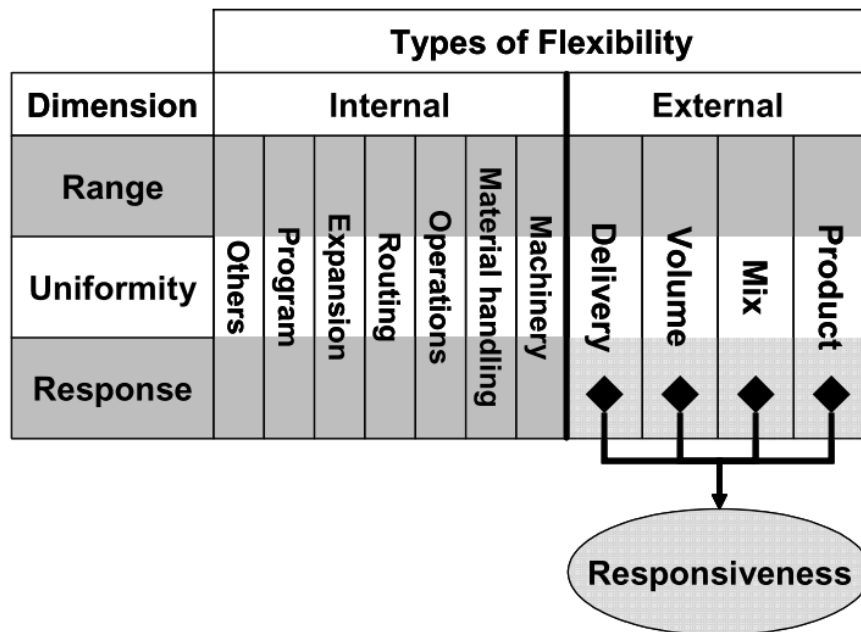


Figure 2.16: The link between flexibility and responsiveness (Reichhart and Holweg, 2007).

Responsiveness can therefore be approached by developing external flexibility types as competitive capabilities. These competitive capabilities allow firms to gain a competitive advantage in volatile markets. Another important element to enhance supply chain responsiveness in turbulent markets can be perceived using dynamic capability theory, which is considered below.

2.9. Organizational learning and supply chain responsiveness

Inherent in the conceptualisation of supply chain responsiveness is the firm's ability to rapidly and effectively reorganize strategic resources to gain a competitive advantage. This is a subject that has been widely discussed and seen through the RBV lens of the firm, which was introduced in Section 2.1.1.1.

In this context, the capability of a firm to accumulate knowledge pertaining to consumers, processes and suppliers in its supply chain

has emerged as a crucial subject (Willis et al., 2016) as learning among supply chain entities is considered a strategic action (Yang, 2016). In fact, Butner (2010) linked the concept of the smarter supply chain of the future to the firms' capability to learn. This organizational learning capability represents an intangible strategic resource (Biotto et al., 2012). In the domain of SCM, scholars have indicated that learning constitutes an internal competence as well as a connecting element that is profoundly rooted in supply chain collaboration (Hult et al., 2003). Defee and Fugate (2010) also consider learning in supply chains as a dynamic supply chain capability.

One important factor that contributes to the organizational learning capability is labour learning curves. The learning curve, or the experience curve, is a phenomenon that was observed in the 2nd World War. Researchers observed that workers become more predictably productive with each repetition of a process. This phenomenon was later abstracted into a mathematical model that reflects the rate by which unit cost decreases with repetition of cumulative outputs (Wright, 1936; Badiru, 1991). In order to realise this phenomenon, if work is planned in such a way so as to ensure that it is uninterrupted and repeated, this would give manufacturing firms a cost advantage in the market.

Thus far, various theories that describe the approach towards gaining competitive advantage under demand volatility have been discussed. From a supply chain perspective, it has been illustrated in this chapter that uncertainty in demand hinders the effective management of supply chains. Inventory management, as an important element of SCM, also becomes challenging with the presence of demand uncertainty. To mitigate the effect of such uncertainty, responsive supply chain strategy should be designed. For such a strategy, flexibility as a competitive capability is of key

importance, and the exhibiting learning effect can form an internal competence in the process of gaining competitive advantage. Having discussed and considered the major theories and practices in terms of their impact and contribution to SCM, the next section reviews the extant literature on AM as a form of manufacturing technology by evaluating those studies that have dealt with this technology in the context of the supply chain.

2.10. AM in the supply chain context

2.10.1. AM

AM, widely known as 3D printing, fabricates objects in layers directly from a digital sliced file that is derived from a 3-Dimensional Computerized Aided Design (3D CAD) file (Gardan, 2016). AM uses a computer design file, known as Standard Triangle Language (STL), to generate successive layers of the desired material. Rather than cutting away raw material or using moulds, as with conventional manufacturing, its manufacturing process follows an additive rather than subtractive or formative approach. AM can be described as being rooted in the ink-jet printing technology that was developed in the late 1970s (Dimitrov et al., 2006). Similar to ink-jet printing, a printer head forms a layer, and once it has solidified, another layer is built upon it to create the third dimension. While there are a wide variety of quite specific technologies used in AM, the main or underlying principle broadly remains the same.

The key principle of AM is that parts are created by adding layers upon layers where each layer is a thin cross-section of the 3D CAD design. Since thickness is limited, the created part will always approximate its counterpart 3D CAD design, where the thinner the layer the similar the created part to the 3D CAD design. All AM technologies utilise a layer-upon-layer method of fabricating parts. However, they differ in the materials that can be utilised, the

mechanism of creating layers and how layers are fused together. These differences make the build time, the postprocessing activities and the cost vary from one technology to another. These differences also establish the accuracy level needed for the target part and its corresponding material and mechanical properties.

Most AM variants, however, follow the generic process shown in Figure 2.17. The first step involves the creation of the part design or model via any available CAD software. The second step is to convert this CAD model into an STL file for the AM machine to identify it. The STL file then is transferred in the third step to the AM machine taking into account any adjustments needed in terms of size, position or orientation. The fourth step involves the machine set up where build parameters such as layer thickness and cool down time are calibrated. This followed by the build process as the fifth step where the deposition of layers takes place. The sixth step includes the removal of the printed part from the AM machine. Certain post processing activities then take place in the seventh step. Finally, the part is ready for use.

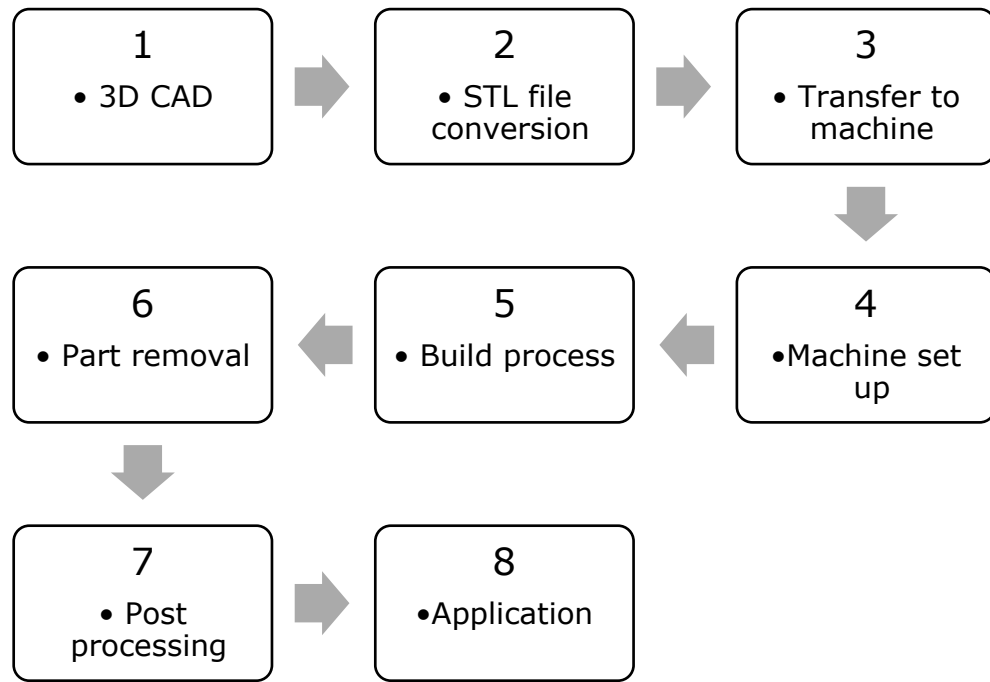


Figure 2.17: AM generic process (adapted from Gibson et al. (2014)).

For its relevance to this research, a brief description of Laser Sintering (LS) as a key polymeric AM variant is presented here. Figure 2.18 shows the schematic diagram of LS (Reiff et al., 2014). In this technology, polymer powder is first heated to a below-melting point inside a building chamber. The chamber is typically filled with inert gas to reduce powder oxidation. Once preheated to the target level required, the powder is then spread in layers to a bed contained in the building chamber. Then, a laser which is focused by optics and deflected by a scanner system (i.e. generally utilizing mirrors) fuses each layer according to its corresponding cross-section of the part. Following this, the bed is dropped by the layer height and a recoater blade adds a new layer. The unused powder is removed to an overflow tank for potential reuse. The laser then fuses the next layer, and the same procedures take place repeatedly until the final part is completed.

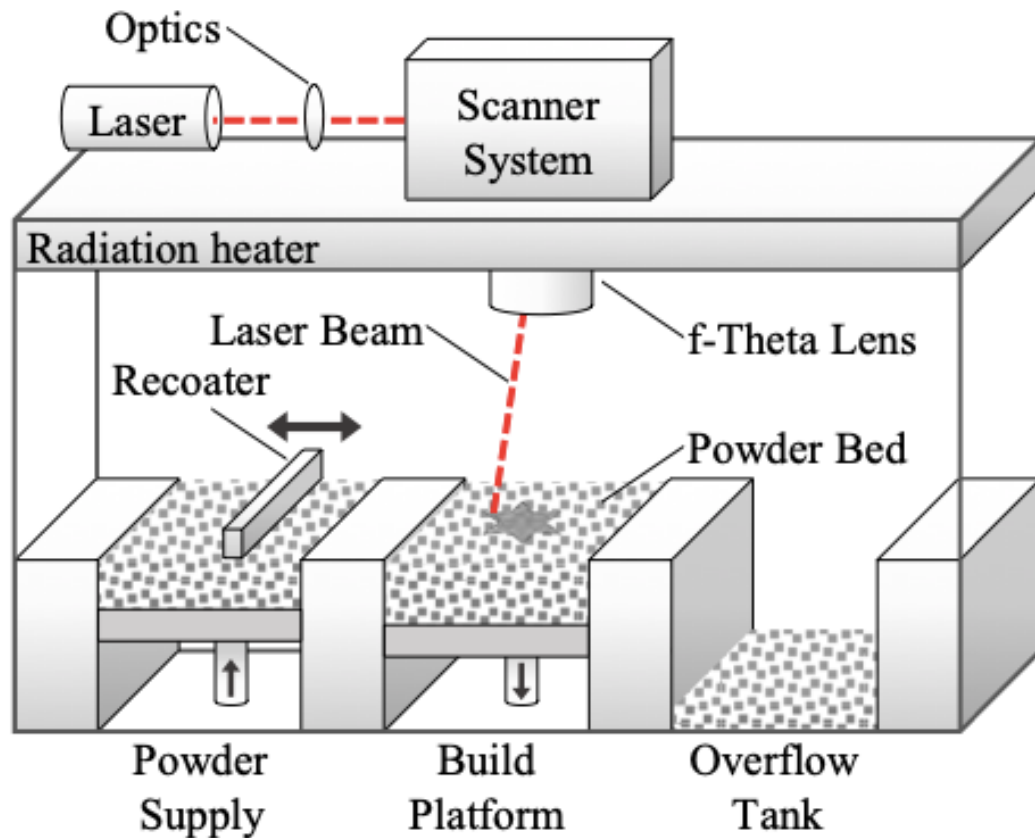


Figure 2.18: Schematic diagram of LS (Reiff et al., 2014).

The layer-upon-layer approach allows parts to be manufactured without the need for moulds or tooling. The absence of moulds in this technology makes it unique in its ability to produce a variety of parts in one build and empower designers to have higher levels of freedom of geometry (Yang et al., 2015). Since the 1980s, the employment of AM has evolved from being used as a rapid prototyping technology to a rapid tooling and manufacturing technology (Huang et al., 2015). This has led to its use in a variety of industries such as automotive, aerospace, jewellery and pharmacy (Ben-Ner and Siemsen, 2017).

This technology has several advantages which stem from its lack of tooling and its additive as opposed to subtractive approach. For instance, highly complex products can be produced, with far less waste and without the need for assembly (Bak, 2003; Petrovic et al., 2011; Berman, 2012). Moreover, the absence of tooling leads to fast

set-up and mass customization is realized (Tuck et al., 2007). This element, accompanied by the relatively small size of the machine and ease of distributing design files enables distributed manufacturing, where production is in close proximity to the customer (Nyman and Sarlin, 2014).

The technology does, however, have some limitations and challenges that need to be overcome. One of these is linked to the time taken by an AM machine to produce an object (Campbell et al., 2011). Also, the raw material for AM can be significantly more expensive than other options (Hague et al., 2003). Furthermore, the low precision of the printed objects and the limited choice of materials act as barriers in attaining the desired properties of the printed objects (Campbell et al., 2011; Berman, 2012). Next section reviews and highlights the common themes found in the literature that deals with this technology in the context of SCM.

2.10.2. AM in the context of SCM

To identify quality articles of this rather important part of the literature, the subjects of AM and SCM were reviewed in combination. Due to the nature of these two subjects, various interdisciplinary journal sources were surveyed using Google Scholar. The keywords utilised for picking the relevant articles were "additive manufacturing supply chain", "3D printing supply chain", "additive manufacturing demand uncertainty", "3D printing demand uncertainty", "additive manufacturing value chain" and "3D printing value chain". These keywords were chosen based on the author prior review of the AM and SCM fields and particularly informed by Oettmeier and Hofmann (2016); Durach et al. (2017); Verboeket and Krikke (2019). Since the AM was first utilised for toolmaking and rapid prototyping and then its applications extended to direct manufacturing, the scope of the reviewed articles was restricted to

the period from 2000, where articles that focus on the application of AM in direct manufacturing from SCM perspective started to populate, to 2021. Articles that focus on AM for production settings that involve toolmaking, prototyping or mass customization were excluded from this literature review, as the scope of this research includes only production settings where AM is utilised for low to high production volumes.

AM is not a new technology, yet there is little research that has been devoted to exploring its impact on supply chains. Recently, however, an increasing number of scholars have been examining its technical and business implications. Oettmeier and Hofmann (2016) have classified the literature in this area into six different categories: studies that focus on the advances in AM, studies focused on improving existing materials and technologies, studies examining the cost of AM, studies that concentrate on the adoption of AM, researchers analyzing the implementation of AM and make-or-buy decisions and research that discusses AM in the context of SCM.

A major part of the research that studied AM in the context of SCM has been devoted to understanding the impact of AM on spare parts supply chains. Walter et al. (2004), for instance, discussed how applying both a centralized and decentralized AM strategy has the potential to reduce inventory turnover in the spare parts supply chain. The authors provide an example case from the aerospace industry where the applications and benefits of AM were discussed. Holmström et al. (2010) concluded that a centralized deployment of AM by Original Equipment Manufacturers (OEMs) is more feasible than a decentralized strategy. Khajavi et al. (2014) and Mellor et al. (2014), however, described how AM could enable distributed manufacturing (i.e. decentralized) of spare parts so that customers could enjoy higher service levels. den Boer et al. (2020) also discussed the impact of AM on the spare parts supply chain of the

military and noted how AM has the potential to reduce lead-times, waste, energy use and spare parts inventories. Knofius et al. (2020) also showed how the effectiveness of some spare parts supply chains have been improved by using AM as a dual sourcing option. While research in the aerospace industry continues to expand, practical, actual examples of AM use are limited due to quality assurance concerns and the lack of certification guidelines (Frandsen et al., 2020).

Other researchers broadly discussed the opportunities and challenges of AM in the context of SCM. For example, Tuck et al. (2007) showed how different concepts of different supply chain strategies such as lean, agile, leagile and mass customization, could be achieved by the use of AM technologies. They also provided examples of cases that show the application and impact of AM in three different industries. Moreover, Nyman and Sarlin (2014) indicated how certain promises of lean, agile and leagile as supply chain strategies can be attained through the adoption of AM. They suggested four foundations on which researchers and practitioners could link between different supply chain strategies and AM. These included green operations, distributed manufacturing, unit cost, and redefinition of supply chain concepts. In terms of considering the unit cost context, Oettmeier and Hofmann (2016) described the role AM could play in diminishing the common dilemma between product variety and unit cost, thus, affecting supply chain strategies. In the redefinition of supply chain concepts, Attaran (2017) discussed how the potential benefits of adopting AM not only eliminates some traditional manufacturing limitations, but also alters global supply chain models. In a similar vein, Luomaranta and Martinsuo (2019) showed that employing AM requires supply chain innovations, involving innovations in enterprise processes, technology and

structure. Jimo et al. (2019) also analysed the potential impacts of AM processes on conventional supply chain structures.

Some other researchers have been specific in their studies and systematically analyzed the effect of AM on certain aspects of supply chain performance. Based on a simulation model, Chiu and Lin (2016) revealed that using AM as a supplementary capacity under three different fluctuating demand levels, improves supply chain performance both in lead-time and total cost. Interestingly, Sasson and Johnson (2016) have argued that these types of performance measures are not the only drivers of effective SCM that should be investigated. They showed how low volume products such as spare parts that usually disrupt production lines could be separately produced using AM. This manufacturing variability, in a mass production environment, caused by low volume orders is another driver to the adoption of AM that has been discussed in this study. Minguella-Canela et al. (2017) have also supported this view using a different methodology. Using a stochastic mathematical model, the authors estimated the total cost and lead-time to manufacture a specific product (either via injection moulding and AM or via AM only) in different postponement strategies. They concluded that AM can be best used for low volume products with a low degree of customization or, in other words, functional products that have low demand. Strong et al. (2018) also examined the incorporation of AM with traditional manufacturing technology and found that the cost element of transportation was not a significant factor in this hybrid supply chain configuration. Braziotis et al. (2019) discussed the potential impact of AM on performance objectives from an operational level. Ghadge et al. (2018) studied the impact of AM on aircraft supply chain performance and found out that AM increases supply chain efficiency through balancing the inventory levels. While Singamneni et al. (2019) also emphasized that the appropriate

employment of AM in the aircraft industry can achieve a higher level of inventory balance, they observed how the absence of quality assurance and certification for this technology hinders wide adoption. Table 2.1 summarizes the literature that dealt with the AM in the context of SCM.

While these studies are attentive to the understanding of the effect AM on distinct supply chain aspects, nevertheless there remains to be a gap in systematically examining the impact of adopting AM on supply chains operating under demand volatility. As discussed throughout this chapter, such supply chains require the development of capabilities that enable higher levels of responsiveness to the market. The literature reviewed in this chapter reveals three key capabilities that offer higher levels of responsiveness. The first one is the learning organization capability, which is underlined through the lens of the dynamic capability perspective. A key contributor to the development of the learning organization is whether labour exhibits learning effects. The second key capability for such supply chains to be responsive is through the effective balance of the inventory in a manner that provides the optimal trade-offs between stockout cost in one side and the inventory holding and order costs from another side, as discussed in Section 2.5. The third competitive capability required for such supply chains, as reviewed in Section 2.7 and Section 2.8, is flexibility which, based on the trade-offs theory discussed in Section 2.1.1.3, can be in conflict with other competitive capabilities such as cost. Therefore, it is imperative for these three aspects to undergo a sufficient, rigorous investigation so as to yield a more realistic assessment of the costs and benefits of AM from a supply chain perspective. The following three sections review these capabilities in the context of AM.

Table 2.1: Summary of the reviewed literature on AM in the supply chain

Spare parts supply chain		Opportunities and challenges		Impact on supply chain performance	
Research	Factor	Research	Factor	Research	Factor
Walter et al. (2004)	Inventory turnover	Tuck et al. (2007)	Lean, agile, leagile and mass customization	Chiu and Lin (2016)	Supplementary capacity based on lead-time and total cost
Holmström et al. (2010)	Centralization feasibility	Nyman and Sarlin (2014)	Lean, agile and leagile	Sasson and Johnson (2016)	Variability isolation in mass environments
Khajavi et al. (2014); Mellor et al. (2014)	Distributed manufacturing feasibility	Oettmeier and Hofmann (2016)	Engineer-To-Order environment	Minguella-Canela et al. (2017)	Functional products with low demand based on total cost and lead-time
den Boer et al. (2020)	Lead-times, waste, energy use and inventories	Attaran (2017), Luomaranta and Martinsuo (2019)	Global supply chain model alteration	Braziotis et al. (2019)	Performance objectives from an operational level
Knofius et al. (2020)	Improve effectiveness by using AM as a dual sourcing option	Rogers et al. (2016), Jimo et al. (2019)	Impact of AM services/AM only on manufacturing supply chain	Ghadge et al. (2018)	Supply chain efficiency through balancing inventory levels

2.10.3. Learning in AM

As discussed in Section 2.9, learning curves exhibited by workers represents an important element in the development of the learning organization. From the dynamic capability perspective, this capability (i.e. the learning organization) contributes to the attainment of a competitive advantage in markets characterized by volatility in demand. Furthermore, learning curves exhibited by workers directly affect the unit cost of parts produced by AM. Therefore, it is useful to perceive this effect from the literature that deals with the relationship between cost and quantity in AM.

Broadly, the available literature relating to AM can be divided into two main fields: the first area of literature covers engineering topics and technical aspects of AM, including analyses of applications (e.g. Bak, 2003; Berman, 2012), materials (e.g. Vasquez et al., 2011; Gu et al., 2012; Huang et al., 2015; Ning et al., 2015; Wang et al., 2017) and processes (e.g. Ram et al., 2006; Murr et al., 2012). The second area explores AM from the commercial, economic and business viewpoints. Within this field, a further subdivision can be made into three focal areas: studies of the implementation of AM (e.g. Mellor et al., 2014), impact of AM on supply chain practices, as discussed in the previous section, and the monetary cost of AM (e.g. Baumers et al., 2017; Baumers and Tuck, 2019). While providing important empirical results and valuable data, these different perspectives have not succeeded in articulating a unified perspective on the overall relationship between unit cost and the cumulative output of AM as production volumes approach the levels associated with conventional manufacturing activity, ranging into millions of units per year. The lack of knowledge regarding the cost-quantity relationship in AM is worrying considering the currently high rates of AM technology adoption (Baumers and Holweg, 2019).

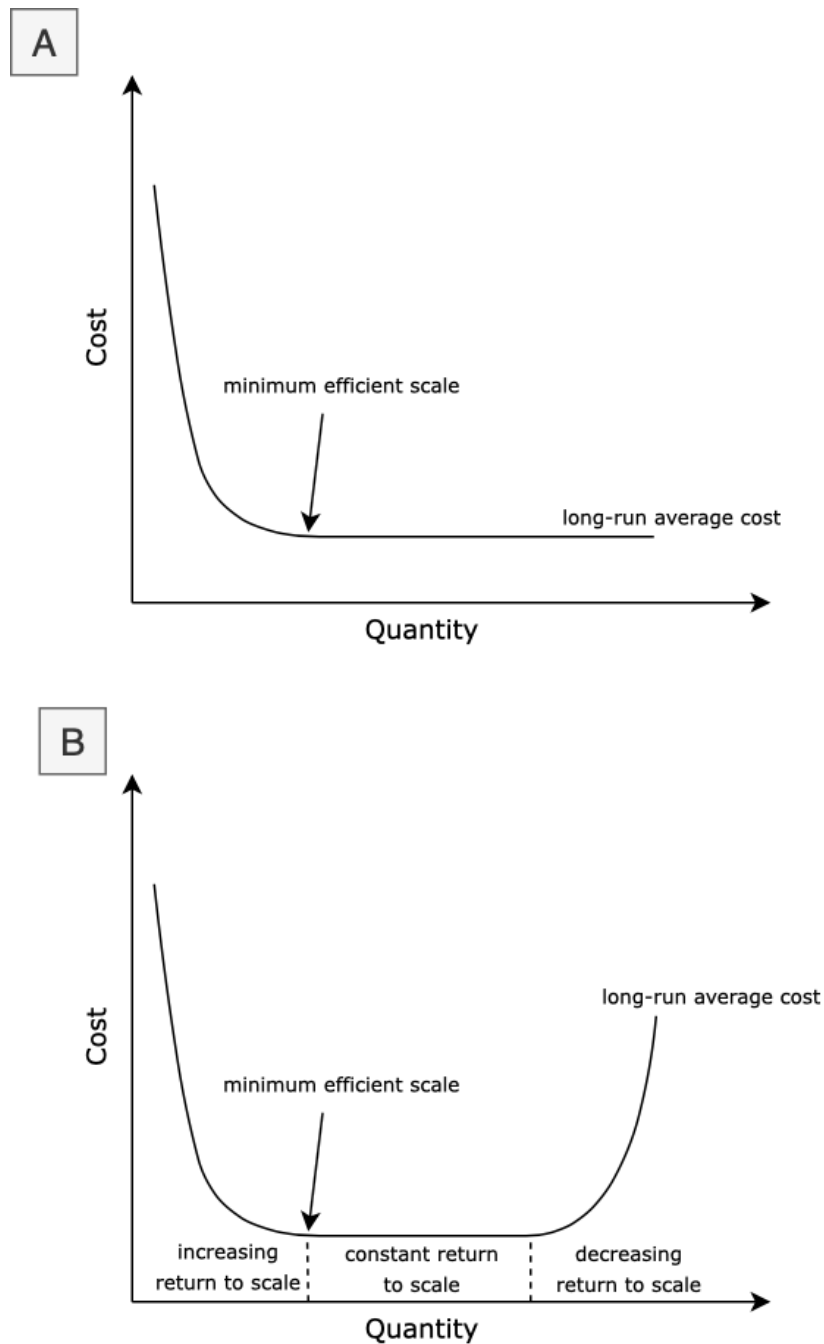


Figure 2.19: Long-run average cost curves. (a) L-shaped curve (b) U-shaped curve displaying increasing, constant and decreasing returns to scale (adapted from Tholkes and Sederberg (1990)).

Formally, the relationship between cost and quantity in manufacturing is encapsulated in the concept of economies of scale (Carlino, 2012) which occur if unit costs drop as production quantities increase. This results in a characteristic L-shaped unit cost function show in Figure 2.19A that is associated with many conventional manufacturing technologies in the engineering

literature and with the downward sloping part of the U-shaped long-run average cost function (Figure 2.19B) known in microeconomics. Discussing the sources of economies of scale, Haldi and Whitcomb (1967) provide a classification of three different types:

1. The first is reflected by static cost curves, which mainly derive from lumpy initial investments and can arise from indivisibilities of machinery and increases in throughput through the scaling-up of production assets and physical spaces.
2. The second type is the result of certain dynamic relationships such as the labour learning curve that occurs when workers become productive as they gain experience.
3. The third kind derives from stochastic processes and can arise as a result of random variation that does not increase proportionally to the increase in related equipment and processes.

The AM literature is in conflict with respect to the availability of economies of scale. While some authors identify a relationship between unit cost and quantity (Ruffo et al., 2006; Ruffo and Hague, 2007; Baumers et al., 2017) other investigations appear to suggest that economies of scale are non-existent in AM (Hopkinson and Dickens, 2003; Atzeni and Salmi, 2012; Berman, 2012; Weller et al., 2015; Ben-Ner and Siemsen, 2017). Emphasizing the perceived absence of a cost-quantity relationship in AM, Petrick and Simpson (2013) coined the term “economies of one” as a way of describing the suitability of AM for markets characterized by low volume and highly customizable needs. Similarly, Weller et al. (2015) argued that decreased product changeover cost is an inherent characteristic of AM, suggesting the availability of economies of scope as opposed to economies of scale, denoting a pattern of decreasing unit costs as the variety of products generated by an organisational unit

increases. In contrast, Baumanns et al. (2016) argued that only process-borne economies of scale associated with dedicated tooling, such as cutting implements, moulds or dies, are absent in AM, with other aspects of the technology resulting in a negative relationship between cost and quantity, for example through the degree of capacity utilization, as identified by Ruffo et al. (2006). Additionally, Baumanns et al. (2016) demonstrated that traditional economies of scale are available through increased machine throughput and larger build volume capacity.

As some research into the cost structure of AM (Ruffo et al., 2006; Baumanns et al., 2017) documents, significant labour inputs are required in the AM process. To that end, Afshari et al. (2019) investigated the impact of learning and forgetting on AM time and proposed a model to evaluate the effect of interruptions on the feasibility of adopting AM in supply chains. However, what has not been discussed systematically is how operator learning can result in economies of scale of the dynamic type described by Haldi and Whitcomb (1967). Common forms of capturing this type of progress in a consistent manner include the learning rate, progress rate or experience curve (Elshurafa et al., 2018; Glock et al., 2019). This allows the determination of a progress ratio expressing unit cost reductions associated with output quantity increases.

2.10.4. Impact of AM on inventory-related costs

Another important advantage concerning AM unit cost that has been suggested in the literature is relates to the impact of AM on reducing inventory-related costs (Thomas and Gilbert, 2014). This section reviews the relevant literature, highlights the significance of these costs and identifies the gap that needs to be addressed.

By systemizing workloads and machines, automation requires the drawing of clear distinctions between fixed costs (i.e. machines,

salaries, and rent) and variable costs (i.e. labour and materials) (Desmet et al., 2019). To minimise unit cost, it is usually assumed that maximum possible volumes must be pursued in one batch, permitting fixed costs to be amortized over the largest possible production run (Silberston, 1972). Established manufacturing methods such as Injection Moulding (IM) therefore have been utilised for mass production benefiting from the amortization of their moulds over high production volumes. Volatility in demand however leads to periods with unexpected low demand volumes (Gunasekaran et al., 2007). Utilizing such established manufacturing methods during these times of low demand volumes deemed unviable due to the restrictions imposed by the EPQ formula discussed in Section 2.5.

To fill this gap, AM has been proposed as a technology that allows for economic production of small lot sizes (Mellor et al., 2014; Weller et al., 2015). The absence of moulds, tools or dies in this technology makes it unique in its ability to produce a variety of parts in one build (Yang et al., 2015). However, the cost characteristics of AM still make an assessment of its adoption feasibility difficult. Several studies therefore have been devoted to realizing its different cost elements. For the purpose of this section, these studies can be categorised into two groups. The first group of studies focuses on estimating the resources consumption at each stage in the AM process (Baumers et al., 2010; Baumers et al., 2013; Thomas, 2016) while the second group examined the different conditions whereby AM can be cost effective (Hopkinson and Dickens, 2003; Ruffo et al., 2006; Atzeni et al., 2010).

This second group of these studies usually evaluates the unit cost of a specific part produced by a conventional manufacturing technology and compares it to the unit cost of the same part produced by AM. In these studies, such comparisons are frequently constructed as

break-even analyses contrasting the unit cost functions of AM and conventional manufacturing. This has allowed researchers to identify quantity-thresholds beyond which conventional tooled processes are more cost effective than AM for a given product (Ruffo et al., 2006). In comparisons of the cost performance of AM against IM, which is one of the most widely adopted technologies in mass manufacturing of polymer components, two broad scenarios have been proposed to establish the commercial viability of AM. First, Mellor et al. (2014) have shown that where production runs are limited to small quantities, AM adoption might be beneficial from a unit cost perspective due to the absence of sunk tooling costs. Second, Sasson and Johnson (2016) proposed that AM forms a cost-effective approach in applications in which demand is volatile and infrequent. In such cases, AM and conventional manufacturing systems can be run alongside each other, with conventional technologies used to serve predictable and regular order flows and AM being used to cater for volatile demand elements resulting in irregular orders. The spare parts industry, for instance, has been suggested as a production environment in which AM can be cost effective (Liu et al., 2014) due to demand uncertainty and disruptive low order quantities.

While these studies succeeded in articulating the cost effectiveness of AM considering key cost elements (i.e. material and machine), they have neglected to address this cost effectiveness considering other cost elements. For instance, the costing literature traditionally distinguishes between two types of manufacturing costs (Son, 1991): well-structured costs incurred through predictable aspects such as material purchases, machines and operators, and ill-structured costs which are hard-to-predict costs arising from aspects such as quality, process failure and inventory. Although a considerable body of literature investigates the performance of AM in terms of well-structured cost models (e.g. (Ruffo et al., 2006)),

few AM cost models include ill-structured cost variables (e.g. (Baumers and Holweg, 2016)). The impact of AM on inventory-related costs, however, is still overlooked and can be well-understood from a supply chain perspective.

In order to characterize this in a greater depth, these inventory-related costs will be briefly discussed. One important aspect in the managing of supply chains is the matching of supply and demand (Wagner et al., 2012). As recent research has shown, the costs of both holding large amounts of inventory and not being able to fulfil orders due to insufficient inventory, referred to as a 'stockout', must be carefully traded off (Christopher, 2016). Demonstrated by Desport et al. (2017) for instance, this trade off can be managed with a strategy of optimisation in environments where demand is accurately forecasted and deterministic inventory management policies are employed. The contrasting situation occurs if demand is uncertain: in this case, it is likely that excess inventory and stockouts lead to high costs. Such costs are effectively the result of a binary decision to either produce in batches or not to produce at all, driven by the logic of economies of scale discussed earlier in which average unit costs decrease as the produced quantity increases by spreading fixed costs across higher production volumes (Nahmias and Cheng, 2009).

Baumers and Holweg (2016) nonetheless have argued that realistic cost models should be used as a basis for the statement of cost-quantity relationships in AM and should reflect ill-structured elements. Therefore, evaluating AM from a supply chain perspective raises the necessity to include inventory-related costs as an ill-structured part of the AM cost model. To date, no studies have addressed the cost effectiveness of AM in mass production environments while accounting for inventory-related costs and the opportunity costs resulting from stockouts.

2.10.5. Impact of AM on supply chain flexibility

This section provides a review on the impact of AM on developing the competitive capability of flexibility from a supply chain perspective. It discusses the relevance of AM in the context of supply chain flexibility, elaborates on the trade-offs among different flexibility aspects and reviews the AM potential effect on penalty cost incurred by increasing the flexibility of a supply chain. This section ends with an identified gap concerns the AM impact on supply chain flexibility.

The importance of managing supply chains manifests itself when there is fluctuation in demand that tends to disrupt production schedules and efficiencies (Chopra and Sodhi, 2014). Such fluctuation in demand arises from the growing movement in recent years towards product customisation, rendering products life cycle short (Brettel et al., 2014). Fluctuation in demand also arises from competitive forces caused by the rise of globalisation in recent decades. These factors have promoted the necessity of developing flexibility as a critical competitive capability (Olhager, 1993). By developing flexibility, manufacturing firms can respond to changes in customer requests that come in the form of increasing, decreasing, cancelling, or changing the timing of customer orders (Sreedevi and Saranga, 2017). Since meeting these changes has become more challenging without collaborating with other companies, flexibility recently has been evolved to be seen from a supply chain perspective (e.g. Duclos et al., 2003; Sánchez and Pérez, 2005).

In pursuit of developing such capability, firms are considering AM as a technology that is capable of fabricating products directly from digital files without the need of tooling or moulds (Mellor et al., 2014; Brettel et al., 2016). Unique characteristics of this technology such

as lack of tooling, on-demand production, freedom of geometry and parts consolidation have led recent studies to suggest AM as a technology that could improve flexibility (e.g. Cotteleer and Joyce, 2014; Weller et al., 2015; Brettel et al., 2016). In the past years, research has also drawn the attention to the potential of AM to extend the qualities of established FMS (Berman, 2012; Mellor et al., 2014). While AM adoption may increase supply chain flexibility in some respects, it can, at the same time, lead to a decrease in other competing aspects such as cost. This potential trade-off is critical because, in reality, manufacturing firms operate in different environments and under different market conditions. Some of these companies may prioritise efficiency over flexibility (Selldin and Olhager, 2007). Thus, relying on dedicated manufacturing technologies (i.e. to manufacture core products with high volumes), as opposed to flexible ones, is more appropriate to these manufacturing firms. For instance, standard products with predictable demands, such as water bottles, would not require as much supply chain flexibility as products in the fashion industry. This distinction cannot be overlooked because adopting AM for industries that do not require many product variants or do not confront uncertain demand might unnecessarily lead to a higher unit cost. Such fatal mistake was discussed by Pujawan (2004), who stressed that firms must carefully assess the target flexibility level to avoid unnecessary costs. In fact, enhancing supply chain flexibility can be counterproductive in certain contexts (Chan et al., 2006; Kim et al., 2013; Tipu and Fantasy, 2014).

Another critical issue is that flexibility is not a standardised capability; but rather a capability with multi-aspects that must be customised for its motive (Sethi and Sethi, 1990). Responding to different changes in demand volumes, for instance, requires a flexibility aspect known as volume flexibility while responding to

different choices of customer preferences requires different flexibility types such as mix or process flexibility. Trade-offs exist between these different flexibility aspects where an increase in one of them can lead to a decrease in another. Vokurka and O'Leary-Kelly (2000) emphasised the need to examine the inter-relationships between these flexibility aspects for the successful development of flexibility. Therefore, adopting AM as a capability to increase supply chain flexibility without realising these inter-relationships can result in investment failures.

The important issue of examining the impact of AM on supply chain flexibility has recently begun to attract the attention of AM and supply chain researchers. For instance, Evers and Potter (2017) showed how AM improved flexibility through the dynamic allocation of labour. Evers et al. (2018) also provided a detailed study examining different flexibility aspects that can be achieved through AM. By conducting a structured literature review, Verboeket and Krikke (2019) suggested that AM can improve supply chain flexibility in terms of both volume and variety of products. Delic and Evers (2020) investigated the relationships among AM adoption, supply chain flexibility and supply chain performance in the automotive industry; they found out that AM can positively impact flexibility and, hence, performance. These studies are valuable in studying distinct flexibility aspects in AM, yet their varying perspectives reflect the remaining gap of understanding whether AM can increase supply chain flexibility considering its unit cost in comparison with other dedicated manufacturing technologies.

2.11. Summary of the literature review

This chapter provided a review of the literature that supports the contextualization of AM's impact on responsive supply chain performance. The key theme highlighted in the reviewed literature

is the constant quest for a competitive advantage by manufacturing firms. While the dynamic capability perspective describes the characteristics of internal competencies such as organizational learning associated with the attainment of competitive advantage, other theories underlined the development of competitive capabilities such as cost and flexibility as a way to gain a competitive advantage. A conflict in describing the relationship among these competitive capabilities also is highlighted in this chapter, which is then resolved through reviewing the performance frontiers theory. These theories together formed a theoretical framework through which the AM effect on responsive supply chain performance can be realized.

From a supply chain perspective, uncertainty in demand is identified in the literature as detrimental efficiency, which hinders the attainment of competitive advantage. For this reason, theories and practices on the effective management of inventory and the appropriate development of flexibility are discussed and reviewed. The generic responsive supply chain strategies have been reviewed, and their overlaps and contradictions are detailed.

This theoretical understanding is then contextualized in terms of AM, where the research gaps that justify the research objectives posed in this study have been demonstrated through the structured review and up-to-date synthesis of current research concerning learning curves in AM, the impact of AM on inventory-related costs and supply chain flexibility. These three aspects increase the scope of the costs and benefits of AM from a supply chain perspective, hence allowing more realistic assessment to be made for this technology. Table 2.2 presents the research objectives in relation to the identified gaps in the literature.

Table 2.2: Summary of the literature gaps addressed by the research objectives.

Factor	Key references	Identified literature gap	Research objective
Dynamic type of economies of scale in AM	Haldi and Whitcomb (1967) identified learning as one type of scale economies.	Labour learning curve represents a key element of the development of the organizational learning capability. However, there has not been a systematic examination of the existence of operator learning in AM and how this can result in economies of scale of the dynamic type described by Haldi and Whitcomb (1967).	1. To examine whether AM exhibits a learning effect for both expert and novice operators.
	Petrack and Simpson (2013) and Weller et al. (2015) suggest AM does not exhibit economies of scale.		
	Ruffo et al. (2006) and Baumers et al. (2016) argued that economies of scale is shown in AM through the capacity utilization.		
	Afshari et al. (2019) investigated the impact of learning and forgetting on AM time and proposed a model to evaluate the effect of interruptions on the feasibility of adopting AM in supply chains.		
Impact of AM on supply chain inventory-related costs	Mellor et al. (2014) suggest that AM adoption might be beneficial for low volume production.	Baumers and Holweg (2016) have argued that realistic cost models should be used as a basis for the statement of cost-quantity relationships in AM and should reflect ill-structured elements such those related to inventory. No study has examined the impact of AM on inventory-related costs for a responsive supply chain.	2. To evaluate the total cost of a supply chain employing AM including inventory-related costs under demand volatility.
	Sasson and Johnson (2016) proposed that AM forms a cost-effective approach in applications in which demand is volatile and infrequent.		
	Son (1991) identified inventory cost as ill-structured cost element		
	Thomas (2016) suggests that AM can be cost effective when inventory cost is considered as one ill-structured element.		

Factor	Key references	Identified literature gap	Research objective
Impact of AM on supply chain flexibility	Cotteleer and Joyce (2014); Weller et al. (2015); Brettel et al. (2016) suggest AM as a technology that could improve supply chain flexibility.	No studies exist that attempt to understand whether AM can increase responsive supply chain flexibility considering its unit cost in comparison with other dedicated manufacturing technologies.	3. To examine whether the adoption of AM increases the supply chain flexibility under demand volatility.
	Berman (2012); Mellor et al. (2014) has drawn the attention to the potential of AM to extend the qualities of established FMS.		
	Sethi and Sethi (1990) and Pujawan (2004) stressed that firms must carefully assess the target flexibility level to avoid unnecessary costs.		
	Vokurka and O'Leary-Kelly (2000) emphasised the need to examine the inter-relationships between the different flexibility aspects.		
	Eyers and Potter (2017) showed how AM improved flexibility through the dynamic allocation of labour.		
	Eyers et al. (2018) examined the different flexibility aspects that can be achieved through AM.		
	Verboeket and Krikke (2019) suggested that AM can improve volume and mix flexibility.		
	Delic and Eyers (2020) investigated the relationships among AM adoption, supply chain flexibility and supply chain performance.		

3. Methodology

The chapter describes the materials and methods utilised in this project. The primary goal of this doctoral project is to investigate the effect of adopting AM on the performance of responsive supply chains. This overall goal is further divided in Section 1.3 into three research objectives as follows:

1. To examine whether AM exhibits a learning effect for both expert and novice operators.
2. To evaluate the total cost of a responsive supply chain employing AM, including inventory-related costs.
3. To examine whether the adoption of AM increases the flexibility of responsive supply chain.

The examination of these three aspects increases the movement towards a more realistic assessment of the costs and benefits of this technology. To examine the existence of learning effect in AM, a distinct approach is chosen where a repetition of build experiments that were performed by an expert operator is repeated by a novice operator with no previous experience. The author conducted this role since he has not previously worked on any AM machine before these experiments. These build experiments were performed at the AM lab of CFAM at the University of Nottingham, UK.

Since examining the impact of AM on supply chain cost and flexibility requires broader exploration in terms of operational scale, a different methodology was executed for these two aspects. For both aspects, conceptual models are developed first. Then, an inter-process comparison is built using a case study in a plastics manufacturing firm. While inventory-related costs (i.e. second aspect) is examined using a simulation approach, supply chain flexibility (i.e. third aspect) is investigated using flexibility metrics.

To logically progress in describing the methodology of this thesis, this chapter is divided into three main sections. Section 3.1 discusses the materials and methods employed for the 1st research objective concerning learning in AM. The second Section 3.2 discusses the developed conceptual models for the 2nd and 3rd aspects of this thesis. The following section, Section 3.3, reviews the case study utilised to obtain in-depth contextual insight into the developed conceptual models.

3.1. Experimental work for learning in AM

This part forms a continuation of the experimental work reported by Baumers and Holweg (2016) towards establishing a total cost model for AM. This work was based on the manufacture of a test specimen in repeated identical build experiments carried out by an expert operator. In this doctoral project, an additional 14 build experiments were performed by the author (representing the novice operator) followed by an analysis of the experimental data to systematically probe for evidence of operator learning and by applying the learning curve equation to specify the progress ratio on the basis of an experimental method, as described by van Sark (2008). It thus involves a detailed assessment of various process elements involving LS as a polymeric variant of AM technology. As a major AM technology type, LS builds up objects by selectively melting layers of powder material with the use of a laser (Yap et al., 2015). The system investigated in this research is an EOS P100 (see Figure 3.1), which is a relatively small industrial AM machine; it has been run at factory settings to build parts using the standard Polyamide 12 type (PA2200) build material.



Figure 3.1: The laser sintering system used for this study EOS P100 (Image source: www.3dprint-uk.co.uk).

One important early insight from the AM literature (Thompson et al., 2016) is that AM processes are not single-step operations but require a host of surrounding pre-and post-processing operations, which often rely heavily on labour inputs. Establishing appropriate models of resource consumption, such as cost models, therefore relies on drawing the correct boundaries of the investigation. Figure 3.2 summarises the process elements surveyed in this study in the form of a process map.

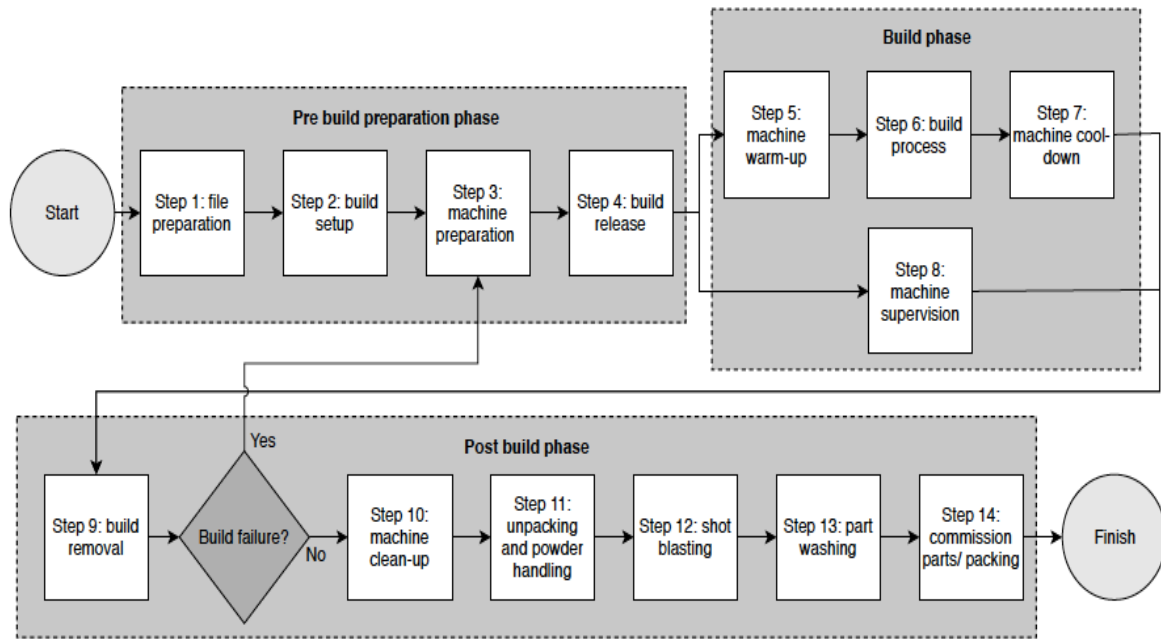


Figure 3.2. Process map for manufacturing part using LS process (adapted from Baumann and Holweg (2016)).

For more efficient indexing of the various activities summarised in Figure 3.2, this investigation assigns each step to a phase in the LS process. The first phase is the Pre build phase, including steps 1, 2, 3 and 4. It captures tasks required to initiate and prepare the build process. Initially, the operator receives the product geometry in a digital file interchange format and checks the file for quality, applying corrections if necessary. Subsequently, the operator configures the build by adding multiple parts to the available build volume, divides the build into slices and transfers the build data to the LS system. In the following step, Step 3, the operator carries out Pre build checks and fills up the machine's internal powder container if required. When ready, the build operation is initiated in Step 4.

The second phase of the LS process is the actual build, consisting of steps 5, 6, 7 and 8. This phase includes the main processes of machine operation, consisting of warm-up, material deposition (including the initial deposition of blank layers and tensile test parts) and machine cool-down after the material deposition has been completed. During the Build phase, the machine is intermittently supervised by an operator, entering the process map as Step 8.

The final stage is the Post build phase which consists of Steps 9 to 14. Once the machine has cooled down, the operator removes the build container to the powder handling table. Should the build operation suffer from a failure event, symbolized in Figure 3.2 as a decision node, the operator cleans and resets the machine and goes back to Step 3 where the system is prepared again. If the build has been executed successfully, a sequence of five additional post-processing steps is undertaken, including cleaning the machine up, unpacking the powder container and powder handling, shot blasting to remove excess powder, washing and drying of the parts and finally packing and commissioning.

3.1.1.Experimental set-up and data collection

This investigation expands on original results reported by Baumers and Holweg (2016), who carried out 14 build experiments through an expert machine operator. The instructions provided to the expert and novice operators were identical, in addition to this the novice received technical training to complete the build process shown in Figure 3.2 and a safety induction. Figure 3.3A shows the test specimen used in the original experiment and this work; Figure 3.3B represents the full build configuration used in the build experiments, featuring five identical test specimens. In these experiments, the overall available build space was limited to a vertical band of build space with a height of 30 mm. This was done to limit the length and expense associated with each build in order to permit a sufficient number of repetitions. In total, ten build arrangements were planned at full capacity, as shown in Figure 3.3B, and four further ramp-up experiments were carried out with partially filled build volumes. Table 3.1 summarises the schedule of build experiments executed in this research. As reported by Baumers and Holweg (2016), the completion times of all steps shown in Figure 3.2 were recorded using a timer, except Step 8 (cool-down time), for which the time data were extracted from the machine operating system.

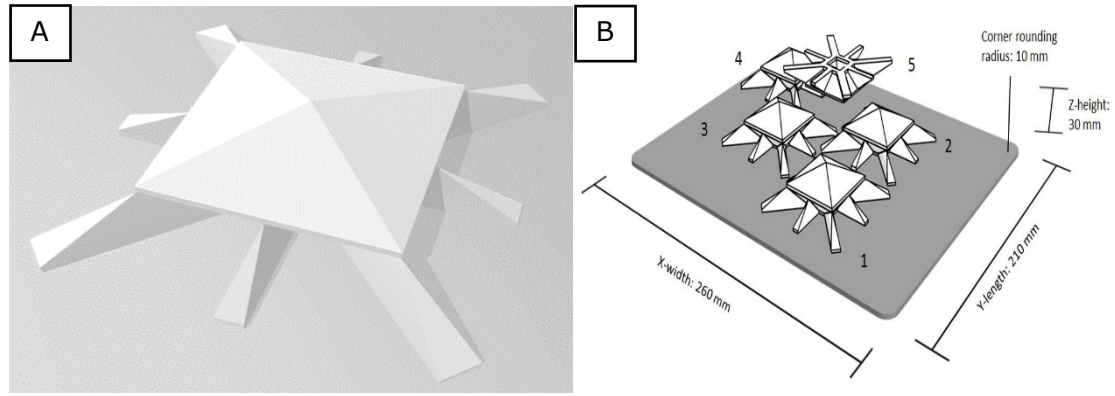


Figure 3.3. Test specimen (A) and the full build configuration (B) (adapted from Baumann et al. (2016)).

Table 3.1: The planned build experiments with different configurations.

Number of the experiment	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Number of test parts included	5	1	2	3	4	5	5	5	5	5	5	5	5	5

3.1.2. Learning curve equation and progress ratio

This section presents the metrics used for the assessment of operator learning as part of production progress in AM. The conventional power function forms a traditional model for learning curves and can be described in the following general form (van Sark, 2008):

$$y = aq^{-b} \quad 3.1$$

where y is the duration reflecting direct involvement of the operator to generate an accumulated quantity of units, a is the duration required by the operator to make the first unit, q is the cumulative number of units produced and b is a parameter measuring the rate by which operator time is reduced as cumulative output increases. As learning can progress at different speeds in the phases involving operator activity shown in Figure 3.2 (i.e. Pre build and Post build), the original model is split into two sub-models, denoted by additional subscripts:

$$y_{pre} = a_{pre}q^{-b_{pre}} \quad 3.2$$

$$y_{Post} = a_{Post}q^{-b_{Post}} \quad 3.3$$

This division into subprocesses was inspired by Peltokorpi and Jaber (2020) and has been demonstrated to improve the accuracy of such models. To compare different model specifications, y_{Pre} and y_{Post} are also presented in an aggregated model.

Additionally, learning curve phenomena are often characterized by the progress ratio, p (van Sark, 2008). To estimate the progress ratio, the constant parameter b in Equation 3.1 is used to approximate the slope of the model curve as a percentage (Kim and Lee, 2018). Thus, p represents the reduction in operator time as a result of doubling cumulative output. For $q_2 = 2q_1$, p can thus be expressed as follows:

$$p = \frac{y_2}{y_1} = \frac{aq_2^{-b}}{aq_1^{-b}} = \frac{a(2q_1)^{-b}}{aq_1^{-b}} = 2^{-b} \quad 3.4$$

For example, if the doubling of cumulative output is associated with a 20% reduction in process time, then $p = 80\%$. A minor variation of this progress ratio can result in a major effect on, for instance, predicted output quantities. To further evaluate this model, the error in the resulting progress ratio (σ_p) must be assessed. One way of estimating this error is by applying the error propagation theory (van Sark, 2008):

$$\sigma_p = \ln 2 \times p \times \sigma_{-b} \quad 3.5$$

where σ_{-b} denotes the standard errors in the rate of the reduction parameter b described above, which arises from the model fitting process.

To evaluate the goodness of fit, the R^2 value which is a measure of how well the function represents the data was estimated using the following equation:

$$R^2 = 1 - \frac{\sum_{i=0}^N [y_n - yfit_n]^2}{\sum_{i=0}^N [y_n - \bar{y}]^2} \quad 3.6$$

where y_n represents the n th data point in a series of N observations, y_{fit} refers to the value of the fitting function at n and $\bar{y}$ is the mean of y . The estimation of R^2 was approached using a nonlinear regression method known as iterative nonlinear squares fitting. This is based on the estimates of parameters b and a in Equation 3.1 above. For this study, b was estimated initially at 0.32 based on the typical 80% learning rate cited in the literature (Wright, 1936), whereas a was estimated initially as the observed time spent by each operator for the first experiment. Following this, the first iteration is conducted by computing R^2 given the initial values of b and a . Then, a second iteration with recalculation of R^2 is implemented by slightly changing the initial parameter values. This iterative process is continued until the optimal value of b and a relative to the maximum R^2 is found (see Lasdon et al. (1978) for further explanation). This curve-fitting was conducted following the procedures shown by Brown (2001) using the SOLVER function contained in Microsoft Excel 2019 (version 16.33), utilizing an iteration procedure based on the Generalized Reduced Gradient (GRG) method.

Since this study investigates the relationship between operator experience and process time, total time spent by each operator was used to estimate the progress ratio. Therefore, any steps that did not feature labour content were omitted from this calculation (Steps 5, 6 and 7 in Figure 3.2). Moreover, the ramp-up experiments were also excluded from the calculation, due to their sub-maximal use of build volume capacity.

Following the estimation of progress ratios, a labour cost model is proposed and utilised for further insights into the cost impact of learning in AM. This model was adapted from Badiru (1991) and further revised to allow the incorporation of the distinct estimations of learning in the pre and Post build phases.

This section described the experimental work applied to address the 1st research objective. Next section describes the logic behind the

development of the conceptual models to represent the connection between the different variables needed to address the 2nd and 3rd research objectives.

3.2. Development of conceptual models of supply chain costs and flexibility in AM

Conceptual frameworks are developed in this research to identify the relevant variables for the 2nd and 3rd research objectives and map out how they might link to each other. Next subsections briefly describe the logic behind constructing each one of these two conceptual models.

3.2.1. Development of a conceptual model of inventory-related costs in AM

In articulating the costs and benefits of adopting AM in market environments that are characterized by demand uncertainty, various production configurations are possible. AM can be utilised to replace a conventional manufacturing technology or it can be utilised in combination with it (e.g. Minguella-Canela et al., 2017; Ramón-Lumbierres et al., 2020). Three key production configurations, therefore, are possible: AM alone, a conventional manufacturing technology alone, or a combination of the two. The costs and benefits analysis of each one of these configurations is affected by the demand volume level. This is because high demand levels can result in a preference towards dedicated manufacturing technologies whereas low demand levels make AM a more favourable option (Mellor et al., 2014; Weller et al., 2015). In terms of the inventory-related costs under demand uncertainty, both the inventory holding costs and the order costs are not as decisive factors as the stockout costs. This is because if demand is known then certain statistical formulas can be applied to set optimal production parameters, as discussed in Section 2.5. Whereas if demand is uncertain, stockout events become inevitable. The severity of the stockout penalty (i.e. the number of future lost orders with each stock out event) therefore becomes a key factor that affects the costs and benefits of each

one of the configurations described above. The first conceptual model thus matches the possible production configurations in relation to the two discussed variables: demand volume level and stockout cost.

3.2.2. Development of a conceptual model of supply chain flexibility in AM

Responsive supply chains need to be flexible in different ways to successfully respond to the nowadays market volatility, as elucidated in Section 2.10.5. Previous research has recognised several types of flexibilities and perceived flexibility as an enabler to a higher level of firm responsiveness that lines up supply competencies with demand fluctuations (Koste and Malhotra, 1999; Holweg, 2005; Reichhart and Holweg, 2007; Stevenson and Spring, 2007; Malhotra and Mackelprang, 2012). While researchers are not in agreement as to what flexibility types are correlated with an overall higher level of supply chain responsiveness, researchers like Reichhart and Holweg (2007) and Stevenson and Spring (2007) agreed on four external flexibilities: new product (i.e. launch) flexibility, mix flexibility, volume flexibility, and delivery (i.e. distribution) flexibility. In favour of consistency, this research also perceives supply chain flexibility as a mix of external flexibility types derived from these publications. The need for these external flexibility aspects is triggered by external market requirements. The key external market requirements are demand uncertainty, demand variability, product variety and lead-time compression (Reichhart and Holweg, 2007). Figure 3.4 shows how these external market conditions such as demand uncertainty or demand variability trigger the need for external flexibility (i.e. perceived by the customer viewpoint) which in turn requires the development of internal competencies by the firm.

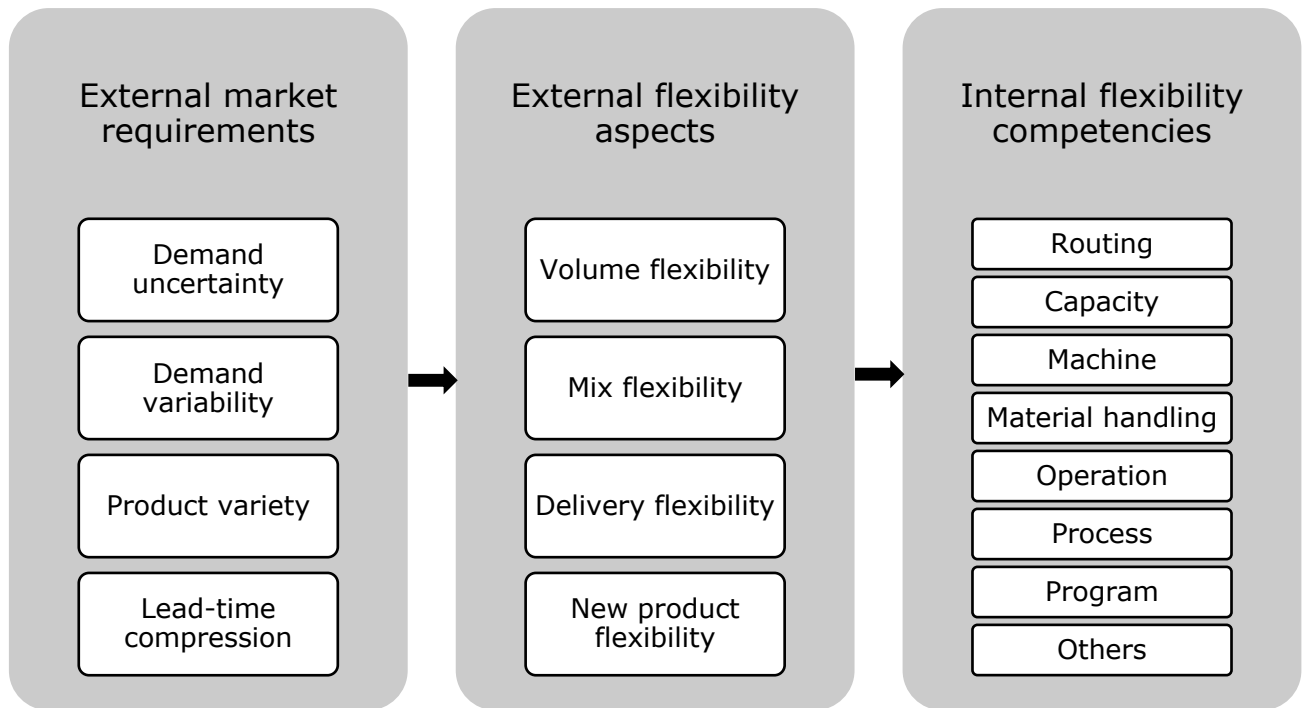


Figure 3.4: The link between external market requirements, external flexibility and internal flexibility (inspired by Reichhart and Holweg (2007)).

AM, on the other side, exhibits various characteristics that can affect certain aspects of flexibility. The first of these characteristics is freedom of geometry, which explains the freedom by which product designers have when designing complex AM products (Ngo et al., 2018). The second of these AM characteristics is part consolidation, which describes the AM capability to produce multiple discrete components fabricated as one final part (Gibson et al., 2014). The third AM characteristic relevant to flexibility is the absence of tooling (i.e. moulds) in this technology. The last of these AM characteristics is on-demand production, where products can be produced when and as needed (Mani et al., 2014; Chen et al., 2015). A conceptual model that maps these characteristics relevant to flexibility to the key market requirements is developed accordingly.

3.3. Case study on the impact of AM adoption on supply chain costs and flexibility

This section reviews the case study undertaken to obtain further insights into the developed conceptual models discussed in Section 3.2 to address

the 2nd and 3rd research objectives concerning the impact of adopting AM on inventory-related costs and supply chain flexibility. This section first provides a detailed description of the case study and then illustrates the conceptual and simulation models built, representing the supply chain under study. This section ends with a description of the cost parameters and flexibility metrics used for these two research objectives. Figure 3.5 represents an overview of the process executed for this part of the research.

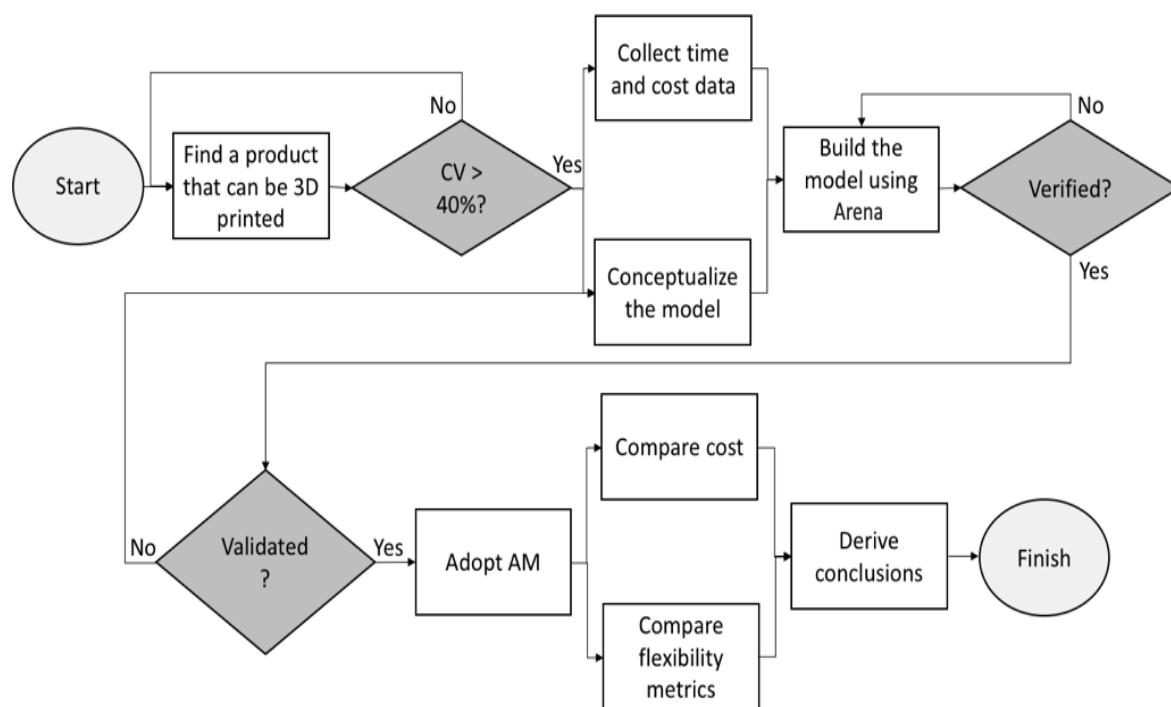


Figure 3.5: Overview of the process followed to address the 2nd and 3rd research objectives. CV stands for the Coefficient of Variation.

Since this research is exploratory, the chosen research design is a case study (Yin, 1994; Ellram, 1996) undertaken in stages of retrospective data collection to perform a thorough exploration of the impact of adopting AM on supply chain performance in comparison with the current manufacturing technology. This case study, in turn, assists in gaining practical insights and laying the foundation for future work to be undertaken accordingly (Eisenhardt, 1989; Gerring, 2004). An observational case study (Wieringa, 2014), therefore, was carried out in this research for a production line that

utilizes a conventional manufacturing technology and followed by the construction of an inter-process comparison with AM. While other methods such as interviews and questionnaires can be used, an observational case study avoids problems related to self-reported accounts and offers insights that are not accessible through interviews and questionnaires (Morgan et al., 2017).

Following conducting the observational case study, interventions are made through constructing an inter-process comparison between AM and IM (Injection Moulding) and simulating a supply chain based on the data collected from a plastic products manufacturing company that produces pipe fittings in Jeddah, Saudi Arabia. This manufacturing company was chosen for its fitness to the scope needed. Three key criteria were needed before choosing the manufacturing company, as follows:

1. the company should be an OEM of polymer processing technology manufacturing relatively small size parts (i.e. can be 3D Printed); hence, they would be a realistic adopter of AM, and
2. The company should also be a stockiest, which means they need to address volatility in demand and reduce inventory-related costs.

This is because the scope of this research is to investigate the impact of AM on responsive supply chain performance for products that are produced in volumes (i.e. low to high).

Table 3.2: Key Facts about the chosen manufacturing company.

KEY FACTS	
Business description	Manufacture of packaging products including containers, bottles, trays bowls, plastic injected moulded products, tables, chairs, films, aluminium foil, sheets, solid masterbatches, paper cups, pipes and fittings.
Country of Incorporation	Saudi Arabia
Primary Sector	Industrial manufacturing
Industries served	• Civil Construction Industry • Sewage and Water Treatment Industry • Water Irrigation • Electricity, Telephone & Water Department for underground piping. • Chemical Industry • Consumer Goods • Water Purification Industry • Dairy Industry • Food and Beverage Industry • Confectionary Industry • Restaurants • Departmental Stores and Retail outlets
Establishment year	1965
Number of Employees	1100+
Area	90,000 square meters
Number of warehouses	9

This manufacturing company was established in 1965 and now has grown to more than 90,000 square meters of facilities and 1,100+ employees. The company is equipped with advanced extrusion systems enabling them to supply a wide range of uPVC & cPVC pipes ranging from ½" diameter to 8". The company has five warehouses adjacent to the manufacturing site and four warehouses in different regions around Saudi Arabia. Additionally, the company stocks and monitors pre-determined quantities of products to ensure JIT delivery to customers.

Taking into account the three levels of supply chain management, namely: operational (i.e. specific function unit), tactical (i.e. plant), and strategic (i.e. network) (Muñoz et al., 2012), this case study considers a tactical perspective so that an appropriate reflection of the external flexibility aspects is achieved.

In a preliminary step, the products manufactured by the company were surveyed and data on demand for each product were collected. The demand volatility level, known as the Coefficient of Variation (CV), was estimated using the method proposed by Olhager (2003) to establish the level of volatility in demand faced by each product. Following this assessment, one product with a CV value in excess of 40% (based on the threshold value identified by Halawa et al. (2017)), was chosen for the study. Pertaining to this product, additional process time and cost data were collected, including changeover durations and lead-times. The specified cost model is based on the structure proposed by Atzeni et al. (2010) for the comparison of polymeric AM versus IM. Additionally, a set of historical sales data have been collected from the host company for a period of 48 months, which were used to specify an inter-arrival time and quantity distribution. A detailed description of the steps and procedures undertaken for these activities is discussed in the next sections.

3.3.1.Data collection and input analysis

Input data are a critical component of the constructed simulation models. These data are utilised to construct models of the stochastic demand nature in this investigated study. Two required distribution models have been identified based on the scope of this research. The first describes the pattern of the inter-arrival period between customer orders, whereas the second one describes the distribution of the quantity of each order received. The process by which these two distribution models were developed is discussed in this section.

The process of modelling random component of any system under study is known as Input Analysis (Kelton, 2002; Altiook and Melamed, 2010; Rossetti, 2015). This process of modelling can be split into three sequential phases, although iterations between these phases might be required at some points (Altiook and Melamed, 2010):

1. Data collection and analysis
2. Time series data modelling
3. Goodness-of-fit testing

The following subsections discuss each one of these phases.

3.3.1.1. Data collection and analysis

Altiook and Melamed (2010) stressed out the importance of collecting data that only serve the project objectives. Since this research focuses on markets characterized by demand volatility, the first step in collecting the necessary data was to choose a product that is characterized by high demand volatility. The host company manufactures numerous products and a major obstacle to the successful collection of these data was the difficulty in fetching them all. To further illustrate this point, the sales and marketing team has two types of stored data. The first type can be easily obtained and consists of historical demand data that were aggregated on a monthly basis for their reference in their monthly meetings. The second type of the

stored data represented the historical daily orders, and these data were harder to obtain. This is because these data required the collection of all invoices from different sources as printed ones obtained from the accounting and finance department and as electronic ones found on the cloud or their emails. Therefore, the host company advised the author to go through three phases to obtain the required data, as seen in Figure 3.6.

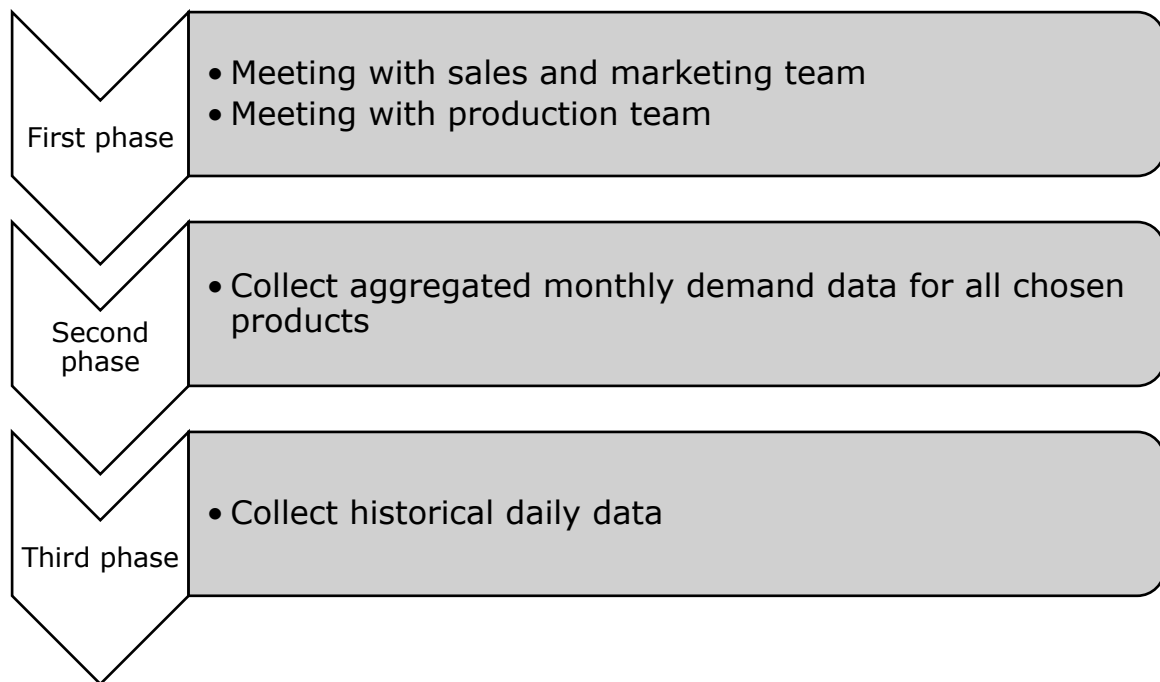


Figure 3.6: The three phases to collect the necessary data.

The first phase involved conducting meetings with the sales and marketing team and the production team to choose based on their prior experience the most disrupting orders (i.e. product orders that are characterized by demand volatility). Four main products were chosen to be of high disruption nature based on their feedback. They all were Un-plasticised Poly Vinyl Chloride (UPVC) pipe tee joints, but they differ in their sizes.

The second phase involved the collection of the historical aggregated monthly demand data and the estimation of the CV (Coefficient of Variation) of each one of these four chosen products. Table 3.3 shows the data obtained for this phase and the corresponding CV level for each one of these products. Among these products, UPVC pipe tee joint size $\frac{3}{4}$ " was chosen due to its higher CV level (i.e. 233%) compared to the others. All

products nonetheless showed high CV levels, indicating the accuracy of the feedback obtained from the company experts in the first phase. The selected product is shown in Figure 3.7.

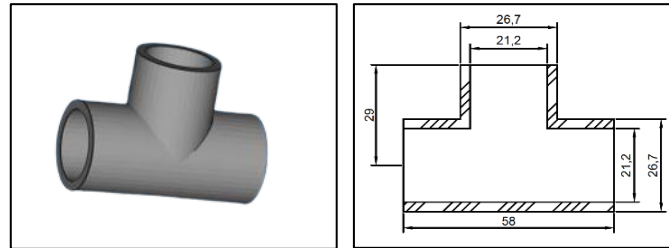


Figure 3.7: CAD drawing of the part selected as a case study: Pipe tee joint $\frac{3}{4}$ " (dimensions in mm).

Table 3.3: The historical sales orders for the four products with the most volatile demand.

Month	Order quantity			
	UPVC tee joint 1"	UPVC tee joint ¾"	UPVC tee joint 6"	UPVC tee joint 8"
1	0	0	0	0
2	35,900	0	6,872	514
3	44,800	1,000	1,056	224
4	5,600	0	0	122
5	0	0	3,486	336
6	0	0	1,684	176
7	22,400	0	1,999	196
8	12,200	0	0	77
9	6,600	0	1,680	35
10	13,300	200	3,168	0
11	13,300	12,100	5,936	2,016
12	100	0	672	56
13	5,600	1,000	320	280
14	27,300	23,400	8,744	5
15	0	18,200	1,384	107
16	0	0	0	56
17	19,600	0	6,384	0
18	39,200	0	0	0
19	95,900	0	2,352	1,512
20	43,000	0	6,212	0
21	39,200	0	1,568	0
22	0	0	5,040	840
23	0	0	7,032	266
24	24,400	0	7,544	112
25	47,600	30,400	4,032	173
26	63,400	0	0	112
27	0	22,400	2,128	331
28	0	11,400	2,964	56
29	0	21,400	1,120	280
30	0	0	468	509
31	12,200	0	3,472	0
32	13,200	0	4,684	100
33	500	0	1,708	319
34	4,100	0	2,872	504
35	0	0	224	0
36	0	0	3,248	224
37	0	11,200	4,704	0
38	0	0	2,128	840
39	0	0	1,904	63
40	16,800	0	2,700	10
41	17,700	0	628	168
42	0	1,600	764	0

43	1,700	400	2,284	112
44	200	0	3,488	95
45	8,000	600	3,024	0
46	0	0	4,320	28
47	0	0	0	0
48	0	0	0	0
CV	153%	233%	88%	170%

The third phase involved the collection of the historical daily demand data of UPVC pipe tee joint size $\frac{3}{4}$ ". After collecting all relevant invoices of the investigated period, historical daily demand data pertaining to the chosen product were merged and reconciled, as shown in Table 3.4. Since the collected data in this phase is different from the aggregated data collected in phase two, CV was reestimated to validate the volatility of the demand of this product (the revised CV level is also shown in Table 3.4). Despite the drop in the CV level compared to the aggregated monthly data, the chosen product still shows a high level of demand volatility (i.e. 98%) exceeding the 40% minimum level set in this research. Of critical importance to the input analysis of this project, inter-arrival time (i.e. the time between orders in days) is also shown in Table 3.4. These inter-arrival time data are also utilised to identify the appropriate theoretical distribution candidate to be used in certain modules in the simulation model, as will be seen in the following section.

Table 3.4: The historical daily demand data for UPVC pipe tee joint 3/4".

Month	Inter-arrival period (in Days)	Order quantity
3	65	600
3	23	400
10	187	200
11	37	12,100
13	53	200
13	24	800
14	15	12,200
14	7	11,200
15	10	3,600
15	12	11,200
15	11	3,400
25	310	1,200
25	10	11,200
25	12	6,800
25	3	11,200
27	38	11,200
27	22	11,200
28	28	200
28	2	11,200
29	12	10,000
29	15	200
29	5	11,200
37	215	11,200
42	153	1,000
42	11	600
43	30	400
45	48	200
45	10	200
45	5	200
CV		98%

3.3.1.2. Time series data modelling

This phase forms a key component of the successful application of the input analysis process. In this phase, a probabilistic model (i.e. description of the stochastic demand nature) is fitted to the empirically collected data in Phase 1 described in Section 3.3.1.1. This fitting is approached through the stochastic process, which is widely utilised to model random phenomenon throughout a time period (Pinsky and Karlin, 2010). The appropriate way to perform the stochastic process is dictated by the type of data obtained.

If the collected data points indexed by its time set are mutually independent, (i.e. do not have time dependence), data then can be assumed to have the Independent Identically Distributed (IID) property. In this study, the sales and marketing team were not able to identify any seasonal pattern to the author, which could have indicated time dependence. Therefore, it is assumed in this study that the data obtained represent independent observations that are modelled as a sequence of random variables with IID property.

The initial step in choosing a distinct input distribution is to determine the possible general distribution(s) (e.g. Normal, Gamma, Exponential, Weibull, Beta and others) that seem to be suitable based on their shapes. There are various fitting software programs that identify the distribution that best fits the collected data (e.g. ExpertFit by FlexSim, BestFit by Palisade and Input Analyzer by Arena). These software tools rank the distributions based on their corresponding square errors with the use of algorithms that iteratively conduct square error fitting procedures. The parameters of these distributions are initially estimated using Method of Moments (MoM) or Maximum Likelihood Estimation (MLE) and then iterate upon the results using algorithms such as the Levenberg-Marquardt method (Jankauskas and McLafferty, 1996).

In this research, hypothesising the class of distribution is undertaken first based on the descriptive statistics and histogram of the collected data. These hypotheses are then discussed in comparison with the ranking outcome obtained from the Input Analyzer tool, which fits and ranks the distributions based on their least square errors. This tool is contained in the simulation software used in this research, the Arena software package (version 15.1). The Arena simulation software from Systems Modelling Corporation is a flexible and well-established tool that provides a graphical user interface to permit experts to construct simulated representations that can accurately model almost any system.

There are distinct formulas to estimate simple sample statistics from the IID data, known as summary or descriptive statistics. The first descriptive statistic of these is the sample mean ($\bar{X}$) and it is indicative of the central tendency of the data. It is estimated as follows:

$$\bar{X}(n) = \frac{\sum_{i=1}^n X_i}{n} \quad 3.7$$

The second descriptive statistic and an alternative measure to the central tendency is the sample median ($x_{0.5}$), which excludes the outliers in the data that might skew the Mean of the IID values. If n represents the size of the dataset in which values are arranged from smallest to largest, the the sample median can be estimated as follows:

$$x_{0.5}(n) = \begin{cases} X_{(\frac{n+1}{2})} & \text{If } n \text{ is odd} \\ \frac{X_{\frac{n}{2}} + X_{(\frac{n}{2})+1}}{2} & \text{If } n \text{ is even} \end{cases} \quad 3.8$$

The third sample statistic is the sample variance (s^2) and it is indicative of the variability of the collected data. The variance can be estimated as follows:

$$s^2(n) = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n - 1} \quad 3.9$$

The fourth sample statistic is the Coefficient of Variation (CV), described earlier in this section, and it is an alternative measure of the variability in data. The CV can be estimated as follows:

$$CV(n) = \frac{\sqrt{s^2(n)}}{\bar{X}(n)} \quad 3.10$$

The skewness (v) is the last sample statistic, and it measures the symmetry of the collected data. The skewness can be estimated as follows:

$$\hat{v}(n) = \frac{\sum_{i=1}^n (X_i - \bar{X})^3 / n}{(s^2(n))^{3/2}} \quad 3.11$$

These descriptive statistics can be utilised to indicate, albeit tentatively, the appropriate distribution that represents the data. For instance, for a collected data if the estimate $\bar{X}$ has a value that approximately equates to $x_{0.5}$, an underlying symmetric distribution then is expected. Also, it is expected that the underlying density function has a longer right tail than left tail if $\bar{X}$ has a higher value than $x_{0.5}$. The CV value occasionally offers a helpful indication of the shape of the distribution. For instance, exponential distribution implies a CV value that approximately equals 1. The skewness $\hat{v}$ also indicates the underlying density function.

Table 3.5: Descriptive statistics for the inter-arrival times and order quantity.

Functions	Inter-arrival time (in days)	Order quantity
$\bar{X}$	47	5,355
$x_{0.5}$	15	3,400
s^2	5,452	27,418,276
CV	1.56	0.98
v	2.46	0.23

Table 3.5 presents the summary statistics related to the historical demand data of the pipe tee joint $\frac{3}{4}$ ". The inter-arrival data indicates a higher mean value compared to the median, which suggests asymmetric distribution. The CV value also suggests a curve that resembles an exponential distribution since its value is close to 1. The appropriateness of the exponential distribution also can be dictated by observing the histogram shown in Figure 3.8.

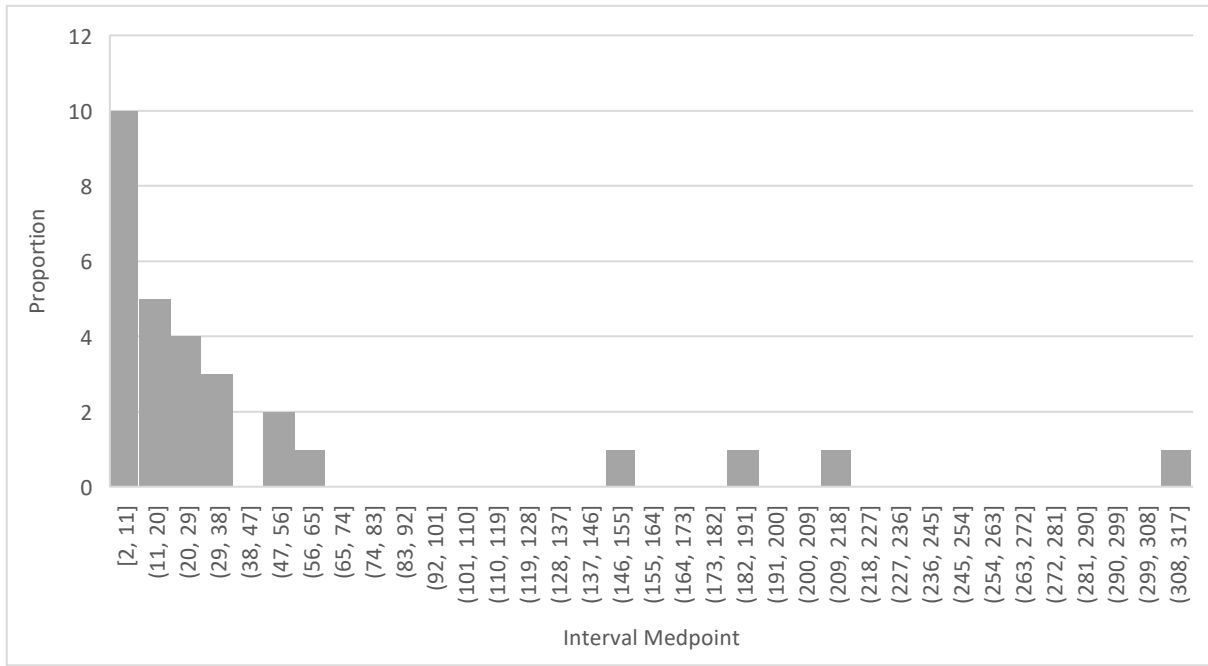


Figure 3.8: Histogram of 29 inter-arrival periods of the pipe tee joint fitting 3/4" with an interval width of 9.

The exponential random variables are commonly used to model stochastic (i.e. random) inter-arrival times for collected IID observations and its distribution (depicted in Figure 3.9) can be symbolized with $\text{Exponential}(\lambda)$, where λ is the rate parameter (Johnson et al., 2005). The Probability Density Function (PDF), which describes the probability that the variable takes the value x , of the exponential distribution is defined as follows:

$$f(x) = \lambda e^{-\lambda x}, \quad x \geq 0 \quad 3.12$$

whereas its Cumulative Distribution Function (CDF), which describes the probability that the variable takes a value less than or equal to x , is:

$$F(x) = 1 - e^{-\lambda x}, \quad x \geq 0 \quad 3.13$$

Thus, it is suggested that customers come to the host company to purchase pipe tee joint 3/4" at a rate (i.e. inter-arrival time) that follows an exponential pattern. This suggestion is supported by the wide application of this distribution to simulate inter-arrival times in various contexts (Kelton, 2002).

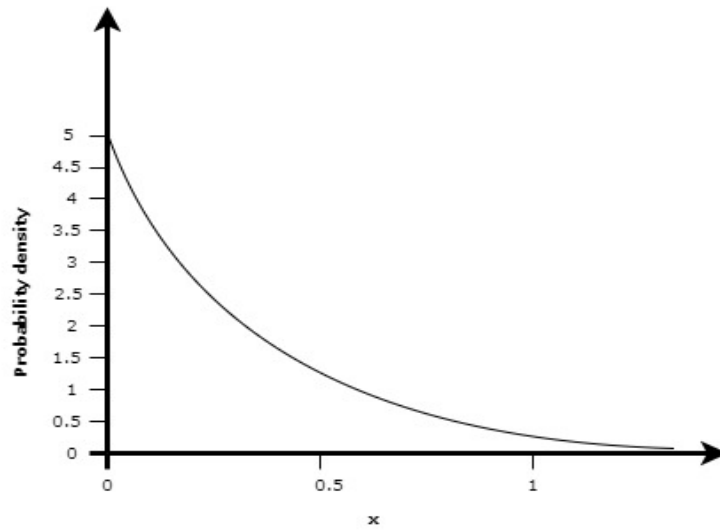


Figure 3.9: Density function of the exponential distribution with λ value of 5.

On the other hand, the descriptive statistics of the order quantity indicate different distribution family. While the CV almost equates one here, the mean of these quantities is almost equal to the median suggesting symmetric curve, which excludes exponential distribution as a possibility. By observing the order quantity histogram shown in Figure 3.10, a pattern that resembles beta distribution can be deduced (see a depiction of Beta distribution in Figure 3.11). A beta random variable is usually employed in statistics to represent an unknown probability, considered as a random variable, and can be symbolized with $\text{Beta}(\alpha, \beta)$, where α and β are two shape parameters (Johnson et al., 2005). The PDF for $\text{Beta}(\alpha, \beta)$ is:

$$f(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{\text{Beta}(\alpha, \beta)}, \quad 0 \leq x < 1. \quad 3.14$$

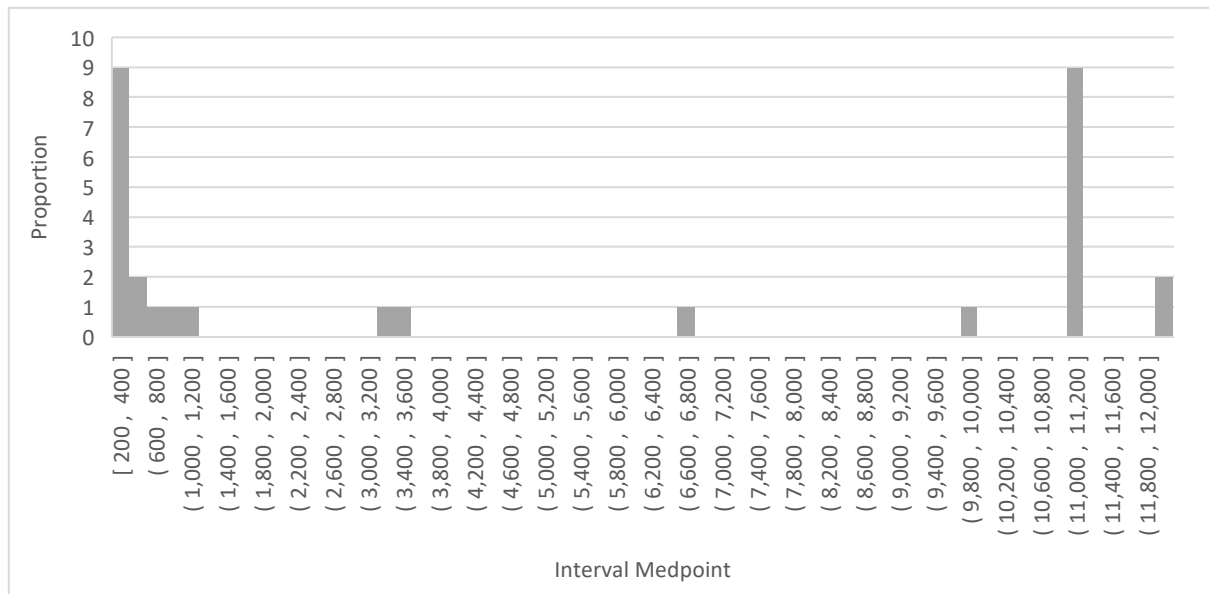


Figure 3.10: Histogram of the 29 orders and their quantities of the pipe tee joint fitting 3/4" with an interval width of 200.

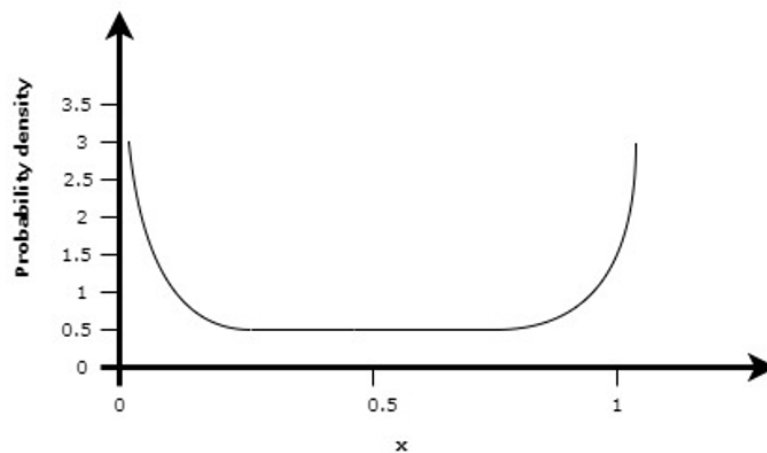


Figure 3.11: Density function of the beta distribution with equal values of 0.5 for both α and β value of 5.

Now that the collected data are characterized, although hypothetically, by a pattern that resembles an exponential distribution for the inter-arrival times and a beta distribution for the order quantities, it is useful to compare these hypotheses with the outcomes obtained from Arena Input Analyzer, which computes the square error of all distribution classes that are supported by Arena (shown in Table 3.6) and ranks them based on the least square error values. The collected data first were pasted in a plain

text file and uploaded to Arena Input Analyzer. Following this, the user had two options, either fitting a prespecified class of distribution or fitting all distribution families in Arena to the uploaded data. The latter was utilised for the collected data. Arena Input Analyzer supports general and widely used distributions. Each one of these distributions has a specific syntax that must be used when attempting to use the distribution as an input to any Arena Module. Table 3.6 summarizes these distributions and their expressions in Arena.

Table 3.6: The distribution families supported by Arena Input Analyzer and their corresponding expressions and parameter values (adapted from Rockwell (2010)).

Distribution	Expression in Arena	Parameter values
Beta	BETA	Beta, Alpha
Continuous	CONT	CumP1 ,Val1 , . . . CumPn ,Valn
Discrete	DISC	CumP1 ,Val1 , . . . CumPn ,Valn
Erlang	ERLA	ExpoMean, k
Exponential	EXPO	Mean
Gamma	GAMM	Beta, Alpha
Lognormal	LOGN	LogMean, LogStd
Normal	NORM	Mean, StdDev
Triangular	TRIA	Min, Mode, Max
Uniform	UNIF	Min, Max
Weibull	WEIB	Beta, Alpha

The collected data related to the inter-arrival time were first analysed using the Input Analyzer tool. All distributions in were fitted into the inter-arrival time data, and they were compared with each other based on the

corresponding square errors. Table 3.7 shows the results of this comparison.

Table 3.7: Comparison of the different distribution fits the inter-arrival data based on the least square error.

Distribution	Square error
Exponential	0.0328
Erlang	0.0328
Gamma	0.0338
Weibull	0.041
Beta	0.053
Lognormal	0.0599
Normal	0.103
Triangular	0.121
Uniform	0.152

As evident in Table 3.7, Exponential and Erlang are the distributions with the best fit for the collected inter-arrival data based on the least square error values. Since the exponential distribution is widely used as a model for inter-arrival times, it was chosen as the appropriate model for this study. The Exponential parameter (see Table 3.6) estimated by Arena Input Analyzer is 23.5 day. The Exponential parameter in Arena represents $1/\lambda$ and not the rate λ (Altioek and Melamed, 2010). Therefore, λ in this research equates to $1/23.5$ days. The final expression to be used (i.e. as a syntax in Arena) as an inter-arrival time input is $2 + \text{Expo}(23.5)$ days. The value 2 in this expression is known as the offset or location parameter where every candidate distribution can be added with this parameter, and it is estimated

by the Input Analyzer algorithm to account for shifted distributions (Rossetti, 2015).

Table 3.8 also shows the square error values for each distribution fitting to order quantity data, suggesting beta distribution as the best representative theoretical candidate to the collected order quantity data. The Beta parameters α and β (see Table 3.6) estimated by Arena Input Analyzer is 0.147 and 0.253. The final expression to be used (i.e. as a syntax in Arena) as an input representing the order quantity distribution is $200 + 11000 * \text{BETA}(0.147, 0.253)$. To further ensure the representativeness of these theoretical distributions, two goodness-of-fit tests were performed. Each one of these tests is reviewed next.

Table 3.8: Comparison of the different distribution fits the order quantity data based on the least square error.

Distribution	Square error
Beta	0.102
Gamma	0.111
Lognormal	0.115
Weibull	0.137
Exponential	0.178
Erlang	0.178
Uniform	0.188
Triangular	0.196
Normal	0.198

3.3.1.3. Goodness-of-fit testing

The goodness-of-fit of a distribution class to empirical data is usually assessed by various statistical tests. In these types of tests, the null

hypothesis is that the fitted distribution is sufficient to fit the data, whereas the alternate hypothesis states that it is not. There are many tests that examine the goodness-of-fit of a distribution class to data. This research utilizes Chi-squared goodness-of-fit test (Snedecor and Cochran, 1989), which one of the widely used tests. The other test performed in this research is the Kolmogorov-Smirnov (K-S) test (Chakravarty et al., 1967), which is another well-established test for this purpose.

The chi-square test operates by comparing empirical histogram density built from collected data to a theoretical density counterpart. For instance, for a sample $\{x_1, \dots, x_N\}$ which is a set of N IID observations from an underlying random variable X . This sample is subsequently utilised to create an empirical histogram with J bins, where bin j relates to the interval $[l_j, r_j)$. So, if N_j is the number of observations in bin j , then the relative frequency of observations in bin j is computed as follows:

$$\hat{p}_j = \frac{N_j}{N}, \quad j = 1, \dots, J. \quad 3.15$$

Considering $FX(x)$ to be a candidate theoretical distribution that needs to be assessed for its goodness-of-fit, the theoretical probabilities then can be estimated as follows:

$$p_j = Pr\{l_j \leq X < r_j\}, \quad j = 1, \dots, J. \quad 3.16$$

Finally, the chi-square (X^2) test is defined as follows:

$$X^2 = \sum_{j=1}^J \frac{(N_j - Np_j)^2}{Np_j} \quad 3.17$$

where N_j represents the j th data point in a series of N observations, Np_j refers to the value of the fitting function at j . Thus, the j th term on Equation 3.16 estimates the relative deviation of the empirical observations in bin j

from the theoretical fitted number in the same bin. Smaller observed value of the chi-square statistic indicates a better fit and vice versa. The chi-square statistic is compared against a critical value c based on the significance level α of the test. A value of X^2 that is smaller than c indicates that the null hypothesis is accepted (i.e. the theoretical distribution is sufficiently a good fit). The null hypothesis otherwise should be rejected. The chi-square critical values are found in Appendix A. These values are organized by significance level, α , and the degrees of freedom, d , which can be estimated as follows:

$$d = J - E - 1 \quad 3.18$$

where E is the number of parameters in the candidate theoretical distribution. One disadvantage of this test is that while the chi-square test allows the parameters that have been fitted to be considered in the test method, the grouping of data into ranges or intervals requires subjective judgment. The chi-square test could not be used for both the inter-arrival data and the order quantities data because there are some Np_j values (i.e. the denominator in Equation 3.17) that were equal to zero.

While the chi-square test contrasts the collected (i.e. observed) histogram PDF to that of its theoretical counterpart, the K-S test contrasts the observed CDF to the theoretical one. The K-S test process requires first sorting the collected data in an ascending order and then creates the empirical CDF function as follows:

$$\hat{F}_X(x) = \frac{\max\{j: x_j \leq x\}}{N} \quad 3.19$$

Therefore, $\hat{F}_X(x)$ is the relative frequency of collected observations less than or equal to x . Once a theoretical distribution $F_X(x)$ is chosen, a realistic approach to measure the goodness-of-fit is the largest absolute

discrepancy between $\hat{F}X(x)$ and $FX(x)$. Hence, the K-S test can be computed as follows:

$$KS = \max_x \{|\hat{F}X(x) - FX(x)|\} \quad 3.20$$

Smaller observed value of the K-S statistic indicates a better fit and vice versa. The relevant statistics of the above two goodness-of-fit tests were computed and presented in Appendix C for the inter-arrival time and in Appendix D for the order quantities. The K-S test statistics KS , then, was computed for the inter-arrival time and resulted in a value of 0.136. The K-S table (shown in Appendix B) shows that for significance level of $\alpha = 0.1$ and $d = 35 - 1 - 1 = 33$ (i.e. exponential distribution has one parameter), the critical value is 0.201. Since the test statistic computed above is 0.136, which is less than the critical value 0.201, the null hypothesis that the inter-arrival rate follows an exponential distribution with $\lambda = 1/23.5$ days is an acceptably good fit to the collected data is accepted.

The K-S test statistics KS also was estimated for the candidate theoretical distribution for order quantities and resulted in a value of 0.151. The K-S table shown in Appendix B indicates that for a $d = 61$ with a significance level of $\alpha = 0.1$, the critical value is 0.156. Since the test statistic computed above is $0.151 < 0.156$, the null hypothesis that the order quantity follows a beta distribution with parameters $\alpha = 0.147$ and $\beta = 0.253$ is a sufficiently good fit to the collected data is accepted.

A note should be made on the use of these statistical distributions in Arena. Arena simulation encompasses randomness by sampling random values from these theoretical distributions through utilizing algorithms with specific code related to Random Number Generators (RNG). This RNG code generates uniformly distributed values, (i.e. values that are equally likely) between 0 and 1. These values are then altered to correspond to the theoretical distributions obtained above (Altiok and Melamed, 2010). It should be illustrated that the produced values can be replicated

algorithmically, but they are still random in a statistical sense (Rossetti, 2015). This RNG sampling process is generally known as Monte Carlo sampling as a reference to the famous casino at Monte Carlo and the relation between random number generation and casino gambling (Hammersley, 2013).

3.3.2. The representation models

In order to examine the impact of AM on inventory-related costs, three distinct configurations with three representation models were specified in this research. These configurations are referred to as pathways throughout this thesis, as listed below:

1. The current supply chain configuration is referred to as the 1st pathway.
2. The AM only supply chain configuration is referred to as the 2nd pathway.
3. The combined approach of IM and AM supply chain configuration is referred to as the 3rd pathway.

Based on the information provided by the company, a representation process model for the current production line (the 1st pathway) using IM was specified, as summarized in Figure 3.12. In this pathway, the company initially receives orders from customers who are either rejected or accepted based on the availability of sufficient stock in the inventory. If accepted, an order is processed and shipped. If the order is declined, the process ends with no additional action taken.

In order to set the boundaries of the simulation model, the manufacturing line of this product was isolated from other production lines with a newly revised inventory management policy appropriate for a single-product single-location inventory type. Therefore, new production activity is initiated on the basis of inventory data using a continuous review inventory model (Tersine, 1988), as discussed in Section 2.5. For such a policy,

inventory is reviewed continuously, and a decision is made about whether and how much to order. First, in collaborating with experts from the host company, subjective assessment of the service level was set at 0.46. Then, following a practical approach by Tersine (1988), a safety stock of 273 parts was determined with a reorder point at 11,600 parts and a target stock of 13,800 parts.

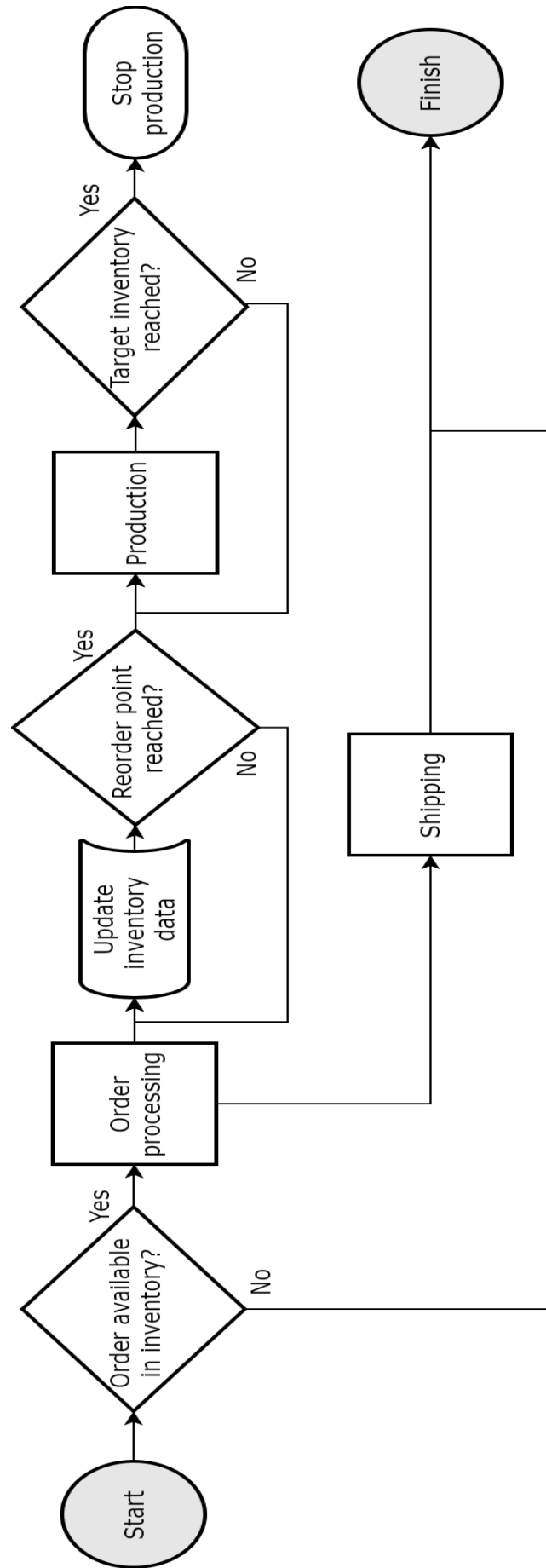


Figure 3.12: Flowchart of the current supply chain configuration of the manufacturing company (1st pathway).

Through this continuous review inventory model, the host company implicitly takes into account demand and market characteristics. Where a quantity in excess of the currently available inventory level is requested by the customer, and hence cannot be served out of existing stock, the customer will usually contact competing companies motivated by the long lead-time needed to fulfil the order. Due to a normal level of capacity utilisation of the available IM equipment, resulting from the manufacture of products featuring predictable and continuous demand, the lead-time for the production for other products exceeds two weeks in most cases, which is deemed too long for a reactive pull approach. Figure 3.13 shows a picture of a production line in the host company.



Figure 3.13: The pipes production line in the hosted company (Image source: provided by the sales and marketing team of the host company).

The AM system selected for this simulation is the EOS P770 system (see Figure 3.14), which is a polymeric laser sintering system featuring a relatively large nominal of build volume of 700 mm x 580 mm x 380 mm (EOS, 2019). This machine was chosen because of its industrial size that can occupy a large build volume. A raster-type model of build volume

packing was used to estimate that each AM build could accommodate a quantity of 1,584 units of the tee joint at full capacity considering a clearance of 5 mm from every dimension for each part, as seen in Figure 3.15. The volume of the minimum box that could accommodate the parts, also known as the bounding box (Ruffo et al., 2006), was 149,787.2 cm³, which gives a ratio of 0.97 between this volume and the volume of its bed.

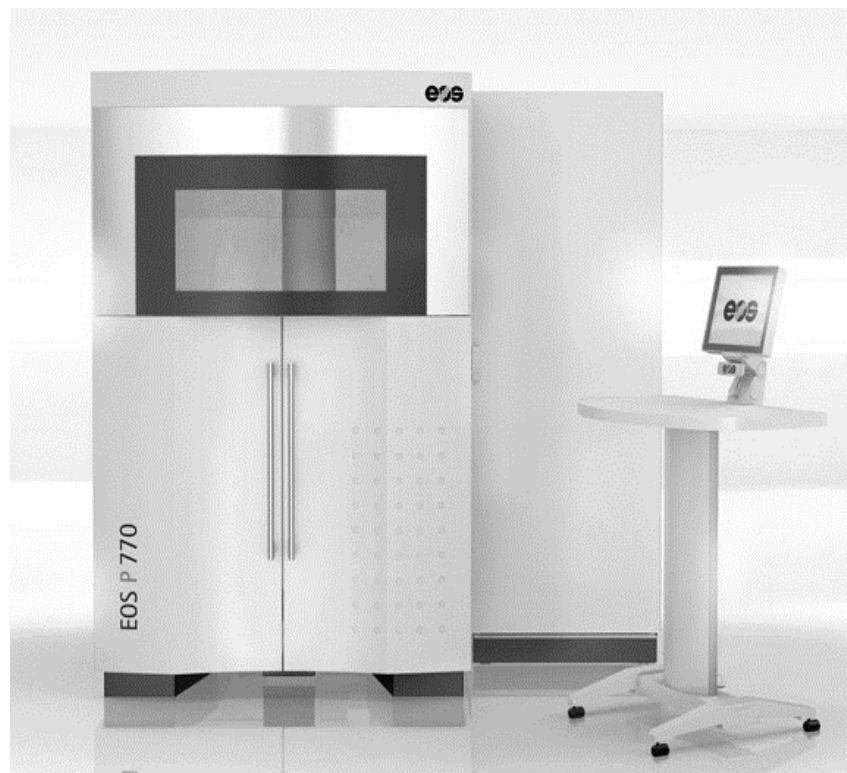


Figure 3.14: The AM system used for the comparison with IM for the 2nd and 3rd research objectives (image source: www.eos.info/systems_solutions/eos-p-770).

The total time to produce each build with the above quantity is estimated using the typical building rate of 32 mm/hr for a layer thickness of 0.12 mm given by the supplier (EOS, 2019). This estimation resulted in a total build time of 51.35 hrs. The part volume of the product shown in Figure 3.7 is 14.83 cm³. As the volume of the bounding box for these parts overestimates the total volume of the parts contained in the box, a revised total time of 23.87 hrs was obtained using a parameter that was derived experimentally by Ruffo et al. (2006) to estimate the reduction in time based on the real volume of the parts. Based on the data obtained following

the application of the methodology described in Section 3.1, additional 59 hrs of warm-up, pre and post-processing and cool down times were also needed before parts were ready to be shipped. A final total process time of 82.87 hrs for AM was used in this model.

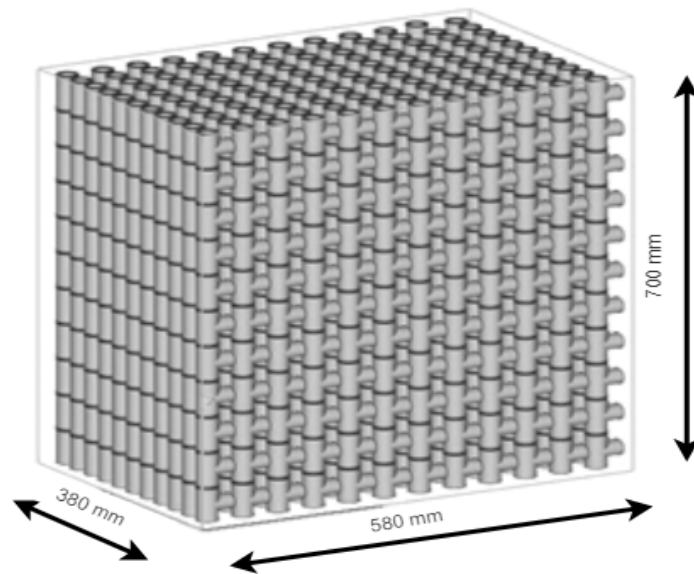


Figure 3.15. The build configuration of the target part using AM at full capacity utilization with a clearance of 5 mm between parts.

The following step in the investigation was to construct a corresponding process model for AM, referred to as the 2nd pathway in this study. As shown in Figure 3.16, the replacement of the conventional IM process by AM technology significantly altered the structure of the model. Based on the maximum expected demand, five AM machines were allocated in the simulation to ensure the availability of sufficient machine capacity to cover the investigated demand levels.

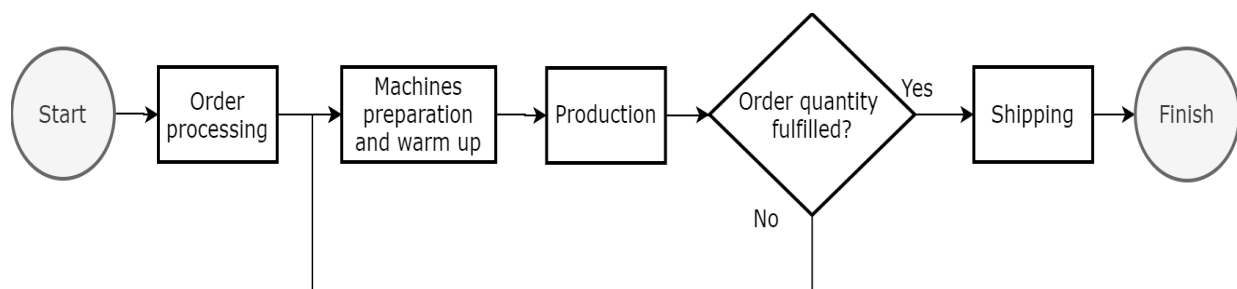


Figure 3.16: Flowchart of the supply chain configuration with AM only (2nd pathway).

A third model, from now on referred to as the 3rd pathway, is also constructed to investigate the suitability of adopting AM as a means to respond to orders that cannot be otherwise met by the available inventory produced via IM in the 1st pathway. In this pathway, if there is not enough inventory to satisfy an order and it could have otherwise resulted in a stockout event, the AM is initiated instantly to fulfil the quantity difference between the available inventory and the order. In other words, the order will be fulfilled by i) the amount of remaining inventory and ii) the quantity produced instantly by AM. Figure 3.17 represents this pathway in more details.

Since activity-based cost models of this type require the statement of a depreciation period for the AM system, it was possible to simplify the overall modelling approach by setting the simulation time span and the depreciation periods for both the IM and AM processes to 5 years (as done by Atzeni et al. (2010)). Furthermore, to better understand the performance of the three supply chains constructed in the simulation software, which will be described next section, the models were executed for a pre-specified period (five years) and an extended period (ten years).

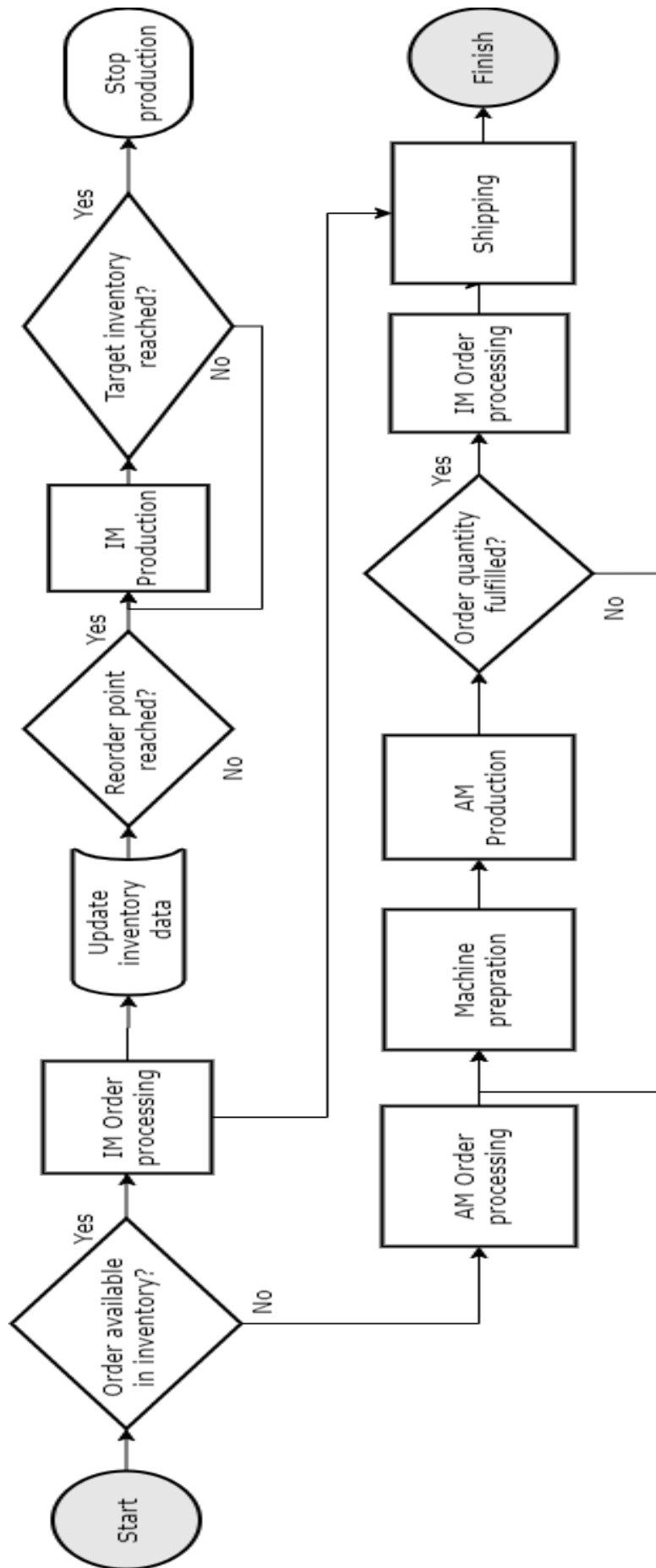


Figure 3.17: Flowchart of the supply chain configuration utilizing AM in combination with IM (3rd pathway).

3.3.3.Arena simulation models

In the following step of the investigation, the system behaviour of the supply chain of the studied product was simulated to ensure adequate examination of the 2nd objective of this thesis. This simulation software used in this thesis was the Arena software package (version 15.1). The Arena simulation software is built on the SIMAN simulation language and utilizes an object-oriented design for completely graphical model development.

In Arena, simulation experts locate graphical objects called modules on a blueprint to characterize real system parameters such as operators, machines, and material handling devices. These built-in modules are provided for experts as a part of its template. They can be customized and programmed to feature different types of applications such as queueing, processing, inspection and resource allocation. In addition to these features, Arena provides modules that represent certain aspects of manufacturing, such as machine downtime and production planning and scheduling (Kelton, 2002).

3.3.3.1. Arena software review and selection

Two simulation software tools were assessed thoroughly before embarking on the construction of the simulation models; these are: Arena (by Rockwell Automation) and AnyLogic (by XJ Technologies). Three main criteria were chosen during the assessment process, as follow:

1. ease of building a simulation model
2. possibility of integration with other standard programs (e.g. Microsoft Excel), and
3. acquisition cost

In terms of ease of use, both Arena and AnyLogic were evaluated as relatively easy to use and accessible in terms of building the simulation models. Arena software, however, is a well-established simulation software and had been used for a relatively long time before the introduction of AnyLogic software to the market. Therefore, the Arena community and resources, including books, articles, videos were superior to those of AnyLogic.

One critical element to the appropriate development of the three simulation models was the connectivity with other essential tools in Microsoft. Arena software connects well to Microsoft office database, Excel and Access using built-in features or thorough other Microsoft integration technologies. This ease of integration either did not exist in AnyLogic or its demonstration was not found by the author.

In AnyLogic software, specific advance components (e.g. Key-Value Table, Update, Text file) and specialised model features that need to be used for troubleshooting (e.g. Cut-off points, tracing model variables, and others) were only accessible on the professional AnyLogic, which could not be purchased due to its high price compared to the free version of the Arena software.

3.3.3.2. The simulation building process

The building process of any simulation model should follow the flowchart shown in Figure 3.18. First, project objectives and data collection plan are decided based on the formulated problem. Then, data are collected, and the desired model is conceptualized accordingly. A simulation model then is constructed based on the final conceptualized model. Verification should be undertaken following the building of the simulation model to ensure that the model behaves as intended and that it is debugged. Following this, validation is undertaken by ensuring that the system behaves like the real system. If the model is verified and validated, new experiments (i.e.

scenarios) are designed and performed. Finally, the obtained findings can be documented and reported.

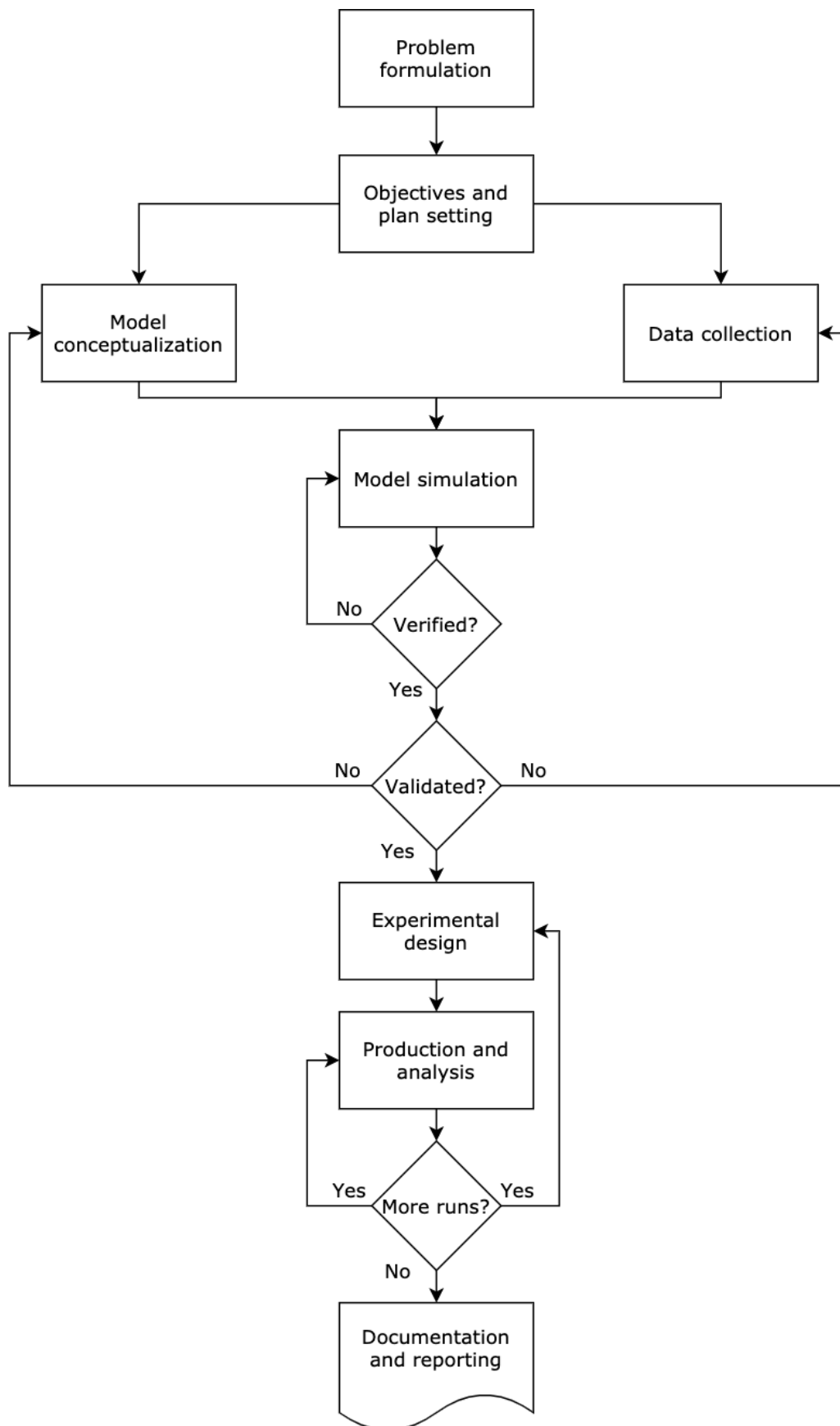


Figure 3.18: Flowchart of the simulation building process (adapted from Banks (2005)).

3.3.3.3. Assumptions for building the model

Several assumptions have been made to simplify the building of the models of the investigated manufacturing supply chains, as follow:

1. Simplification of all working areas into two departments (i.e. production management and demand management) is made in developing the simulation model.
2. First-Come First-Served (FCFS) is assumed as a processing priority rule.
3. High-level modelling is applied to simulate the processes in the manufacturing system.
4. Each order is processed by the same processing machines. Any shared manufacturing machine can process only one mould at a time.
5. Breakdowns to the machines or any other supply processes are not permitted in the built models.
6. Raw materials are always available. Therefore, a shortage of raw material is not permitted in the model.
7. The initial inventory is set at the target level of 13,800; thus, the production process is idle in the beginning.

3.3.3.4. The 1st pathway simulated model

As this study takes a supply chain perspective, it was useful to divide the simulated model into two main functions. The first function, as shown in the lower part of Figure 3.19, characterizes the demand management procedures of the host company, where customer orders are received, processed and either fulfilled or rejected. The second function represents the production management process of the host company, where production is initiated, based on the continuous review data of the inventory level, to fill the inventory back to its target level.

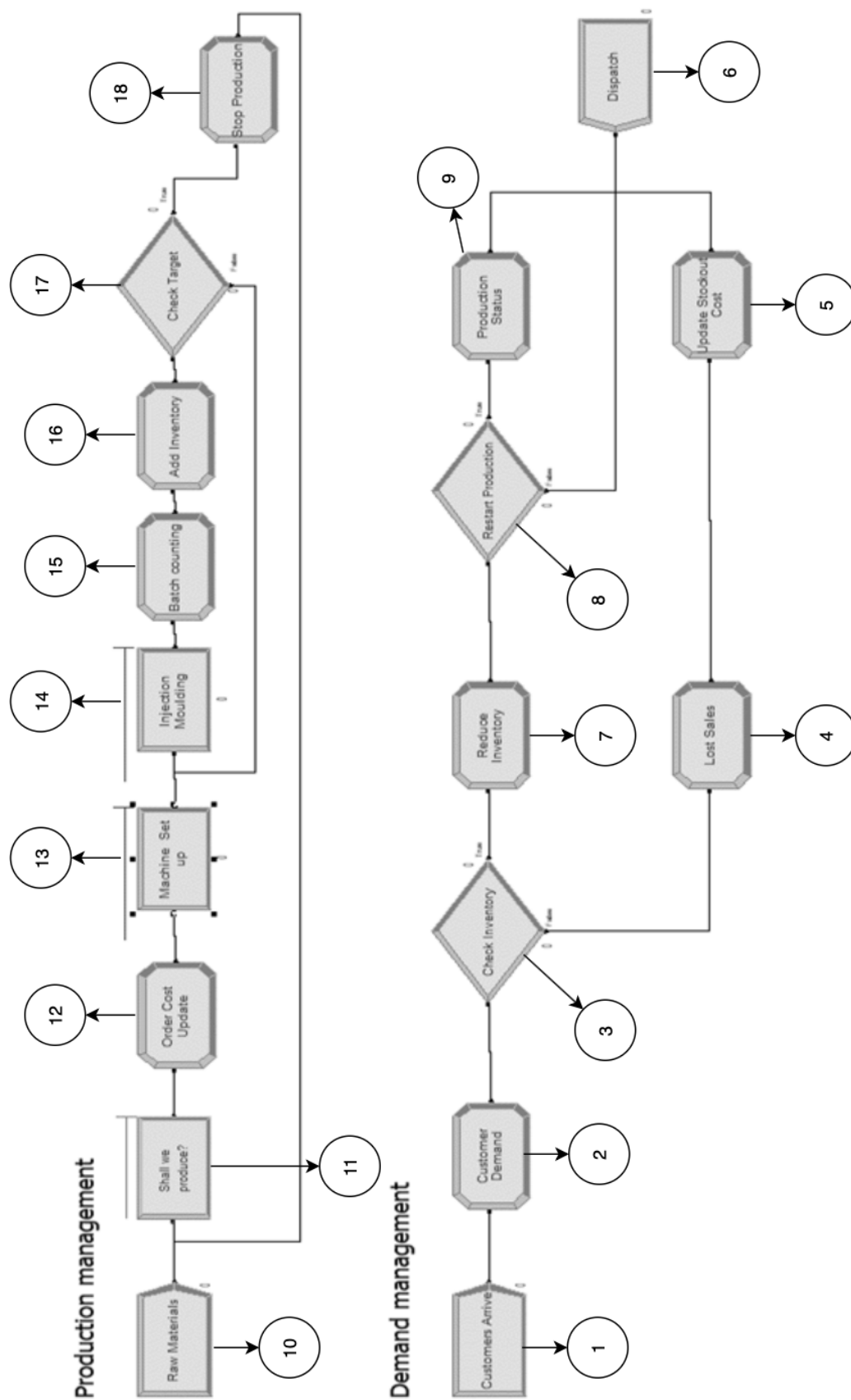


Figure 3.19: The supply chain of the 1st pathway simulated by Arena (numbers in circles and the arrows pointing to these circles were added by the author, the remaining are components of the graphical user interface of Arena).

For more efficient indexing of the various modules shown in Figure 3.19, a number is assigned to each one of them. Each one of these modules contains programming inputs that have been configured accordingly by the author. Screenshots of these inputs are shown in Appendix E where each module with its assigned index number is presented.

For the demand management path, the first step is to model the nature of the demand for the investigated part. This modelling was successfully achieved using the first two modules (Modules 1 and 2 in Figure 3.19). Module 1 generates entities into the system using a prespecified input in the form of a constant number or expressed distribution every specific period (day, month, etc.), representing the inter-arrival time of customers. As discussed in Section 3.3.1, this has resulted in an Exponential distribution expressed as $2+\text{Expo}(23.5)$ (i.e. as a syntax in Arena), where 2 represents the location parameter reflecting the shifted distribution.

Following this module, Module 2 in Figure 3.19 is an Assign module which assigns an attribute or number to the entities generated by the Create module described above. This module was utilised here to assign orders for each coming customer (i.e. generated entity in the language of Arena) following a stochastic demand distribution as well. As presented in Section 3.3.1, this has resulted in a beta distribution expressed as $200+11000*\text{BETA}(0.147, 0.253)$ (i.e. as a syntax in Arena) in this module.

Next, on the basis of the current inventory level, the generated customer orders are held and either accepted or rejected as shown in the "Decision" node (Module 3) within the Demand management section shown in Figure 3.19. The Decision module was programmed to initially checks the current inventory level, as identified by the variable "Inventory" that increases or decreases according to the simulation inputs, and the customer order will be released to either way based on the inventory capacity. If rejected, the customer order will go through another two Assign modules (Modules 4 and 5) to record it as a lost customer, record the quantity lost, and cumulatively

update the stockout cost. If accepted, however, the customer order first will go through an Assign module (Module 7) to update the inventory level (i.e. to subtract the order quantity from the current inventory level). Then, another Decision module (Module 8) takes place to decide whether the production of this specific part needs to be restarted on the basis of the current inventory level in relation to the reordering point, as discussed on Section 3.3.2. If the reorder point reached, the customer order will be released to the following Assign module (Module 9), which will change the production status from Off to On using binary labelling of 0 to 1. Customer orders then are dispatched from the system from Module 6, which is a normal Dispatch module in Arena to depart entities from the system.

For the Production management section on the upper part of Figure 3.19, this path is activated based on the signal that is received from Module 9. The first module in this path is a Create module (Module 10) labelled with Raw Materials in Figure 3.19. In this module, entities are generated to denote the receiving of the raw material. These entities are held just before the next module, which is a Hold module (Module 11) that holds the incoming entities until a condition is met. That was achieved using Module 9 in the Demand Management section. Once the binary variable in Module 9 changes from 0 to 1, Module 11 releases the entity to the next module. The next module (Module 12) updates the order cost by cumulatively adding €44.22 to the Order cost variable, which was set to 0 before running the simulation.

Now the order cost is updated, two subsequent processes take place where the first represents the machine set-up time (Module 13) and followed by the second one that represents the IM process (Module 14). Both utilise the logic action of Seize-Delay-Release where the entity is held and delayed for a pre-specified period before it is released to the next module. The delay time for the machine set-up was 4.91 hrs, while it is delayed for 74 seconds in the IM process, reflecting the production cycle time of the investigated IM. Following Module 14, two consecutive Assign modules (Modules 15 and

16) are placed to count the accumulated batch and add them to the inventory. A Decision module (Module 17) then checks whether the updated inventory level reaches the Target stock variable, representing the desired inventory level for the next period. Once this target level is achieved, production stops using an Assign module (Module 18), shown as Stop Production in Figure 3.19, by resetting the production status to 0. Table 3.9 presents the generated inter-arrival times and their corresponding order quantities in the pathway. These generated values were used for the 2nd and 3rd pathways as will be discussed in the following sections.

Table 3.9: The inter-arrival time and order quantities data generated from the 1st pathway simulation model.

Entity no.	Inter-arrival period (days)	Order quantity	Entity no.	Inter-arrival period (days)	Order quantity
1	11	3,786	40	5	4,361
2	3	1,708	41	24	3,976
3	21	11,113	42	28	674
4	2	10,245	43	44	307
5	14	254	44	9	7,111
6	50	214	45	6	10,828
7	23	7,660	46	6	4,671
8	36	524	47	25	200
9	12	200	48	6	715
10	37	8,629	49	28	10,581
11	105	4,430	50	55	10,404
12	17	9,088	51	11	9,554
13	5	10,870	52	6	201
14	31	974	53	19	363
15	58	2,635	54	54	8,362
16	33	3,998	55	8	10,816
17	2	6,061	56	12	5,878
18	13	10,250	57	26	4,551
19	15	2,302	58	90	983
20	37	11,123	59	15	249
21	7	5,256	60	18	515
22	11	10,241	61	32	2,878
23	10	5,537	62	56	720
24	23	225	63	37	376
25	36	967	64	43	9,129
26	12	3,770	65	14	11,181
27	4	209	66	3	1,830
28	6	467	67	3	11,193

29	3	363	68	26	9,527
30	34	10,949	69	20	476
31	21	11,198	70	27	786
32	12	8,133	71	2	11,166
33	23	2,302	72	12	414
34	20	1,261	73	6	5,912
35	50	10,451	74	4	227
36	48	250	75	18	11,189
37	42	590	76	23	1,378
38	29	839	77	48	7,498
39	15	10,623			

3.3.3.5. The 2nd pathway simulated model

In the 2nd pathway simulation model, shown in Figure 3.20, an alteration was made to the 1st pathway where IM was replaced entirely with AM taking into account a range of adjustments needed. Initially, the model was constructed and run, but the software has generated different customer inter-arrival and quantity data even though the same inputs (i.e. statistical distributions) were used. This discrepancy in the generation is due to the RNG process, described in Section 3.3.1.2, that Arena utilizes. Therefore, new modules (i.e. Modules 1, 2, 3 and 4 in Figure 3.20) were constructed in place of the first two modules in the 1st pathway simulation shown in Figure 3.19. These six modules read from an external file, a Microsoft Excel one, to generate the same data to the system. This file content was extracted from the simulation generated customer inter-arrival time and order quantity data generated by the 1st pathway simulation model. Table 3.9 shows the generated inter-arrival time and the order quantities that were extracted from the 1st pathway simulation run. These new modules, therefore, were designed and constructed to replicate the same inputs that have been generated by the 1st pathway simulation. Figure 7.2 in Appendix F shows the distinct two modules utilised in the 2nd simulation pathway, which are Modules 6 and 7. Module 6 represents the AM process, whereas Module 7 cumulatively count the order produced by AM.

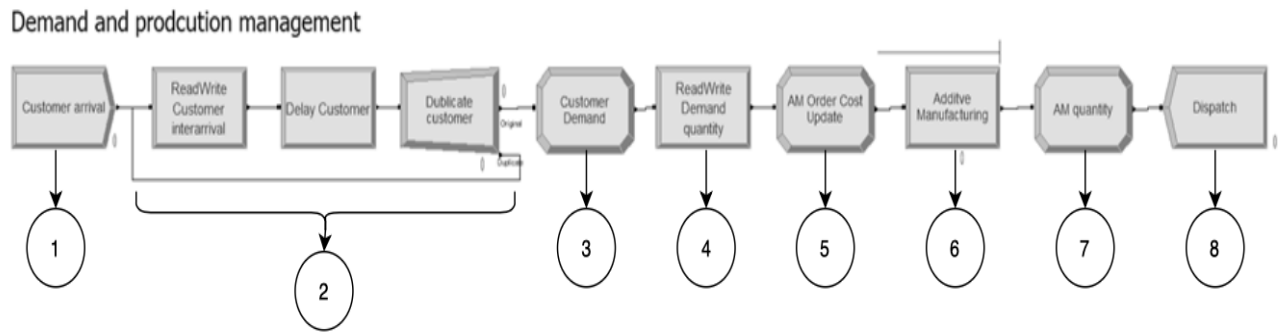


Figure 3.20: The supply chain of the 2nd pathway simulated by Arena (numbers in circles and the arrows pointing to these circles were added by the author, the remaining are components of the graphical user interface of Arena).

3.3.3.6. The 3rd pathway simulated model

A 3rd simulation model also was constructed using Arena based on the conceptual model shown in Figure 3.17. In this simulation model, a combination of the previous two simulation models shown in Figure 3.19 and Figure 3.20 resulted in the construction of this pathway model taking into account a variety of alterations needed. The purpose of this pathway is to examine the effect of utilizing AM as a complementary manufacturing technology to avoid stockout events from happening. To achieve this, customer orders that are lost in the 1st pathway, are now redirected to be served via AM. Customer orders, therefore, can be fulfilled mainly by the IM inventory if available or by instant production of these orders using AM if the IM inventory can not serve the whole order. Figure 3.21 shows the Arena simulation model of this 3rd pathway.

In this simulation model, orders that are not entirely fulfilled by the current inventory level are completed by the instant production of the remaining quantity using AM, following the same simulation process described in the 2nd pathway and shown in Figure 3.20. Furthermore, if the order quantity is not available in the inventory, customer orders are fulfilled partially from the remaining inventory and update of the stock level is undertaken to determine if the reorder point is reached. Once the reorder point reached

the IM production is initiated until the target stock level is reached, as described in the 1st pathway and shown in Figure 3.19.

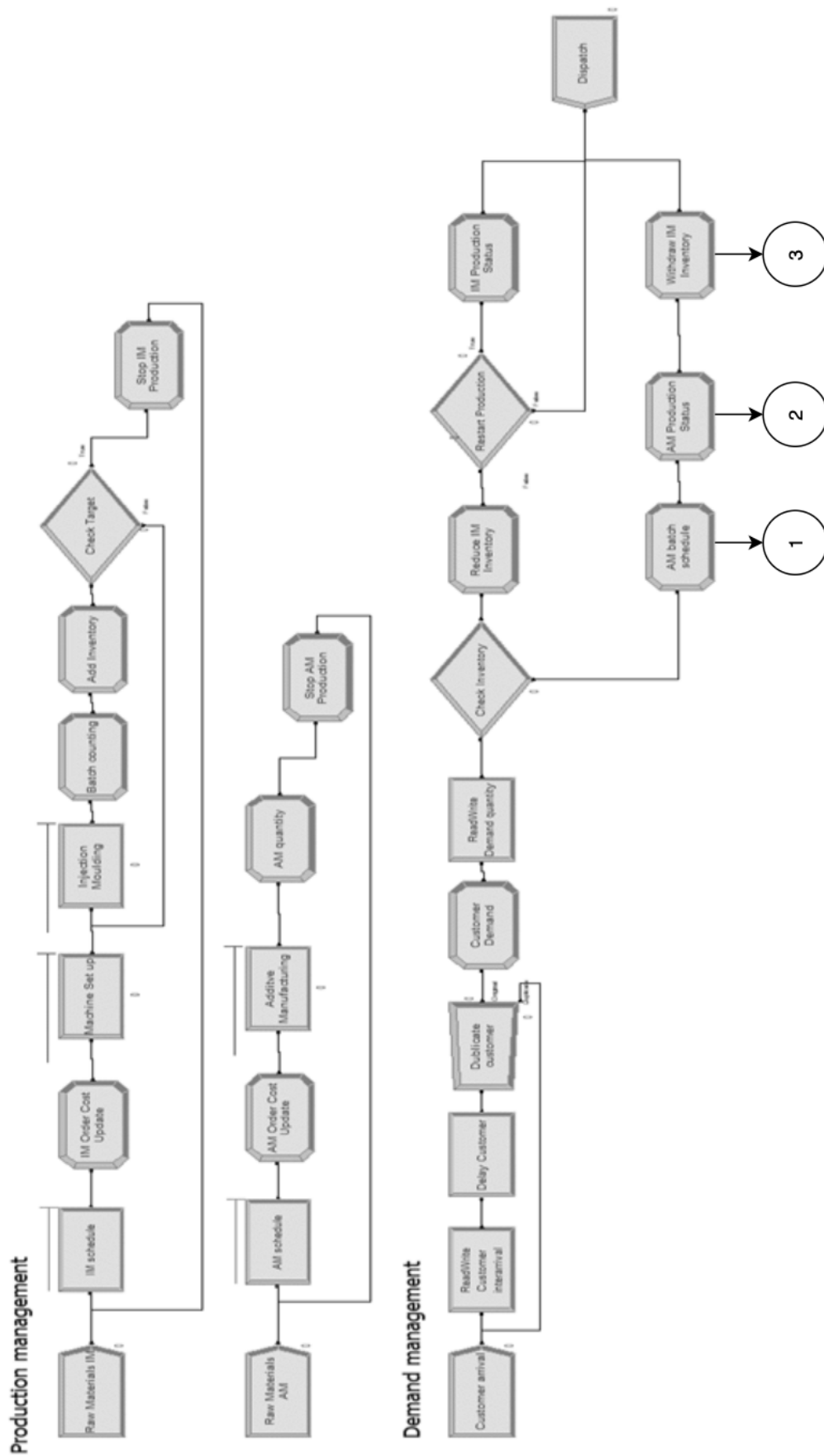


Figure 3.21: The supply chain of the 3rd pathway simulated by Arena (numbers in circles and the arrows pointing to these circles were added by the author, the remaining are components of the graphical user interface of Arena).

3.3.4. Model verification and validation

The method by which the accuracy of the simulation model is assured usually involves the execution of two activities: verification and validation (Kelton, 2002). Verification and validation procedures are performed continuously throughout the simulation building period. Caughlin (2000) states that while verification ensures that the simulation model behaves as expected and intended, validation ensures that the simulation model behaviour represents the investigated real-world system. Both activities comprise specific tests to establish various characteristics of representation accuracy.

This section focuses on the verification and the validation procedures undertaken to ensure that the simulation model built for the 1st pathway behaves as expected and intended. It also validates that the model behaviour represents the real-world system. As commonly performed, the verification is undertaken first, and then the validation steps are discussed.

3.3.4.1. Simulation model verification

Verification concerns with ensuring, through measurable facts and reproducible test data, that the simulation model and its inputs, the simulation model processes and the simulation model outputs are essentially and numerically accurate and free from bugs and errors (Reagan, 2014). Various approaches can be used to verify a simulation model, among them: system debugging, visual scrutiny, model-logic, outputs assessment. All of these were utilised in this project and are discussed here.

During building the 1st pathway simulation model, several bugs and errors have emerged while attempting to run the simulation models. One valuable feature exists in Arena is its ability to locate and describe the error. Whenever an error occurred, the author conducts a full investigation of the error and corrects it accordingly. Most

errors were related to the excess entities that were delayed at the Process modules, incompatibility of time units between different stations, and improper connection from one module to another. The simulation model of the 1st pathway also was replicated several times to verify that the built model accommodates various quantities generated by the distribution expression inserted in the Create and Assign modules. In all of the replications, the simulation models behaved as expected. The data generated by the final simulation run were chosen for the 2nd and 3rd pathways. For these two pathways, an additional verification step has been performed by comparing the resultant processed quantities and the ones obtained from the 1st pathway, which were found to be identical.

A visual inspection was also performed during the running of the simulation models. This inspection was approached by slowing down the animation speed, which is another useful feature in Arena for error and performance traceability. The animation was slowed down to a level where entities can be observed as they transition from one module to another. This inspection process allowed a comparison between the simulation model and the conceptual one. Entities, therefore, were traced to ensure that they move as expected and along their appropriate route. At some points where entities were stuck in an unexpected module (i.e. not leaving an Assign module), the simulation model and its parameters underwent reviews until entities were back again and visually observed following their appropriate route.

Another verification step that was undertaken is the comparison between the total entities left the system and orders that were processed. Since the entity in the simulation model enters as a customer but then transformed using the Assign module into an order quantity, this order must exit the simulation model in the form of multiple entities (i.e. order quantity). Each order can be either

rejected or accepted. Once the order is rejected, the order quantity is recorded in the results as a lost quantity using an Assign module. Once the order is accepted, it is recorded as fulfilled quantity. Therefore, it is expected that the sum of these two types of recorded orders (i.e. lost quantity and fulfilled quantity) equates to the entities left the simulation system (i.e. total sales orders). This verification step has been performed several times throughout the build process and for all simulation models the results always verified the accuracy of the simulation models. Next section discusses the validation techniques utilised for this study to ensure the representativeness of the simulation models to the real-world system under study.

3.3.4.2. Simulation model validation

Validation is the method of confirming that the simulation model is accurate enough to represent the real-world system (Reagan, 2014). It should be noted here that validation does not ensure that the built model is identical to the real-world one, but rather a model that represents the real-world one "enough". In the words of Kleijnen (1995, p.145):

"Validation cannot be assumed to result in a perfect model, since the perfect model would be the real system itself (by definition, any model is a simplification of reality). The model should be 'good enough', which depends on the goal of the model".

Brooks and Robinson (2001) suggested that it is practically impossible to claim a complete validity of the simulation model since it is not conceivable to validate all elements of the simulation model. This is particularly true as there will always be insufficient accurate data from the real-world system to be used for comparison with the constructed simulation model. Not to mention that most simulation models are proposed ones (e.g. the 2nd and 3rd pathways in this

project) rendering comparison to a counterpart real-world system unattainable.

There is a plethora of literature on various ways to validate a simulation model (e.g. Kleijnen, 1995; Kelton, 2002; Sargent, 2010; Reagan, 2014; Roungas et al., 2018). Some of these techniques were utilised in this research, as follow:

- Conceptual model validation: the purpose of this validation technique is to establish whether the scope and level of details of the simulation model fulfil the objectives required. This technique was performed by assessing whether the built simulation models achieved the objectives aimed at in this doctoral project. The generation of sales orders, the processing of each order through a chain of modules, and the outcomes related to fulfilled and lost quantities and their corresponding production quantities all behaved within the scope of this research project and in fulfilment of its objective.
- Black-box validation: the purpose of this approach is to, from a macro-level, establish whether the complete simulation model represents the real-world system with enough accuracy. The conceptual model of the current supply chain configuration was reviewed and validated with the experts from the host company, and they agreed to its merit to represent a tactical view of the investigated supply chain.
- White-box validation: unlike the Black-box approach, this is a micro-level approach with the purpose of validating whether the essential components of the computer model represent their corresponding real-world ones with sufficient accuracy. In all simulation models, the performance of the Process module for the investigated manufacturing technologies (i.e.

IM and AM) were compared to their counterpart in reality. Each Process module is first assigned with a machine as a Resource in the language of Arena simulation. This resource records all its activities as value-added time. The processing time of the two technologies in the simulation models was similar to their performance in reality. The logarithm of the Decision module for whether an order should be accepted or rejected was reviewed with the sales and marketing director of the host company and was confirmed and validated. Inventory policy in the simulation model was confirmed with the logistics and supply chain department. However, although they follow the same continuous review policy utilised in this simulation model, they incorporate all products in their inventory models.

- Dynamic validation technique: this is a functional validation technique which is performed to evaluate the accuracy of the simulation model based on the outputs obtained given specific inputs. In this approach, the historical sales data were used as an input to the system (i.e. using constant creation of entities from a provided Excel sheet in the Create module) to represent incoming orders from customers. The simulation model was then executed for 48 months, and it was found that the sum total of the lost orders and the fulfilled orders equates to the historical sales data for 48 months.

The next section offers a detailed description of the cost model utilised in this research project.

3.3.5. Manufacturing cost parameters

The unit cost models developed for all pathways are based on the general model structure for inter-process comparisons proposed by Atzeni et al. (2010). The cost model of parts produced by IM consists

of four elements. The first element is the material cost, MC , and is estimated as follows:

$$MC_{IM} = W \times M_{IM} \quad 3.21$$

where W denotes the part weight and M_{IM} represents the material cost per kg. The material used to produce the part using IM is PVC procured as a feedstock at a price of €16/kg. The second element of the IM cost model is the machine cost per part IC_{IM} , which is estimated as follows:

$$IC_{IM} = CH_{IM} \times T_{IM}/N_{IM} \quad 3.22$$

where CH_{IM} denotes the IM machine cost per hour which is estimated based on the machine price and the depreciation technique, T_{IM} refers to the cycle time and N_{IM} represents the number of cavities in each mould. The IM machine (Haitian MA 5300) price is estimated at €110,000 with an assumed service life of five years. This results in a depreciation cost of €22,000 per year. The tooling features four mould cavities, allowing the concurrent processing of four units in the moulding cycle, with each moulding cycle taking 74 seconds to complete. The third element is the mould cost per part KC_{IM} , and it is estimated as follows:

$$KC_{IM} = K/V_{IM} \quad 3.23$$

where K is the mould cost and V is the production volume. The tooling expense represented the most significant cost element and was estimated by the host company at €30,000; this cost was amortised over the manufactured quantity. The fourth element of the IM cost model is the operator cost per part OC_{IM} , which is computed as follows:

$$OC_{IM} = O_{IM} \times T_{IM}/N_{IM} \quad 3.24$$

where O_{IM} is the operator cost per hour. This resulted in a OC_{IM} of €0.009/part for all parts produced by IM. Finally, these four elements are added together to form the unit cost of parts produced by IM, UC_{IM} , as follows:

$$UC_{IM} = MC_{IM} + IC_{IM} + KC_{IM} + OC_{IM} \quad 3.25$$

On the other side, the cost model of parts produced by AM consists of three cost elements. The first one is the material cost per part, MC_{AM} , and it is computed as follows:

$$MC_{AM} = \frac{0.5 \times M_{AM} \times V_{AM}}{N_{AM}} \quad 3.26$$

where M_{AM} denotes the AM material cost per kg, V_{AM} represents the build volume in cm³ of the selected AM machine and N_{AM} represents the number of parts produced in one job. Since PVC cannot be processed with the investigated variant of AM technology, laser sintering, the corresponding material employed in the AM supply chain is a Nylon 12 type material (PA2200) procured at a cost of €54/kg. Due to the characteristics of proposed AM technology, sacrificial support structures are not needed in the AM route and degraded raw material is the only form of waste. The second element is machine cost per part, AC_{AM} , and it is estimated using the following equation:

$$AC_{AM} = CH_{AM} \times \frac{T_{AM}}{N_{AM}} \quad 3.27$$

where CH_{AM} denotes the AM machine cost per hour which is estimated based on the machine price and the depreciation

technique, T_{AM} represents the build time in hours. The purchase price for each AM system (EOS P770) is estimated at €668,475, based on Hasan (2017), with assumed useful life of five years (as stated above). A depreciation cost of €133,695 per year, therefore, has been estimated in this study following a straight-line depreciation technique. The third and last element is the operator cost per part, OC_{AM} , and it is computed as follows:

$$OC_{AM} = \frac{O_{AM} \times A}{N_{AM}} \quad 3.28$$

where O_{AM} represents the machine operator hourly rate (i.e. €0.23/hr for this case study) whereas A denotes the pre and post-processing hours needed for each build. The unit cost of parts produced by AM, UC_{AM} , then is estimated as follows:

$$UC_{AM} = MC_{AM} + IC_{AM} + OC_{AM} \quad 3.29$$

Once these cost elements are computed for each pathway, they are added to a broader total supply chain cost model that incorporates other inventory-related costs. These costs are discussed next.

3.3.6. Inventory holding, order and stockout costs

The total supply chain cost model was obtained by combining the manufacturing cost estimate, described in the previous section, with three additional elements: inventory costs, order costs and stockout costs. An order cost estimate of €44.22 per order was obtained from the host company data. It is assumed that the order cost is identical for all three pathways. An inventory holding cost estimate was obtained by applying an inventory carrying cost factor of 0.25 reported in the literature (Brolin, 2015) to the manufacturing cost estimate of the annual average inventory.

Finally, the stockout cost incurred by the company is modelled as an opportunity cost incurred via profit loss resulting from unmet orders. In addition to this short-run opportunity cost, and as approached by Koulamas (2008), it is assumed that in the event of a stockout, future demand is expected to be reduced by an amount equal to the recent stockout quantity. This is to conservatively account for the observed phenomena known as brand substitution, where customer responds to shortages in inventory by switching to another supplier (Mishra and Raghunathan, 2004). While this study considers one future lost sale only for every stockout event, other studies have concluded that some customers indeed switched permanently to another supplier (Emmelhainz et al., 1991; Anderson et al., 2006). It should also be noted that such assumption does not account for the indirect effect of stockout events on increasing the probability of a customer cancelling other items in the order (Sloot et al., 2005) since this is beyond the scope of this study.

Thus, the total supply chain cost was established using the following model:

$$\text{Total supply chain cost} = HC + OC + SC + MC \quad 3.30$$

where HC refers to the inventory holding cost, OC refers to the inventory order cost, SC represents the stockout cost, and MC represents the manufacturing cost.

Since the chosen inventory-related costs are critical to the outcome of this research study, the following section introduces a process by which the sensitivity of these costs to changes is analyzed.

3.3.7. Parametric analysis

Parametric analysis describes sensitivity analysis activities undertaken by running a simulation model several times, each of which with different input parameters. The obtained findings on the

performance measures are then compared and analysed. Parametric analysis helps in the understanding of the effect of specific changes in parameters on system behaviour (Kelton, 2002). This analysis is usually undertaken in search of the ideal arrangement with respect to certain performance measures. It is also used to understand if certain input parameters are critical to system performance measures (Altiok and Melamed, 2010).

In Arena's language, an input parameter is known as a control, whereas the performance measure is known as a response. A set of controls and responses for specific simulation runs is known as a scenario, and a set of scenarios is referred to as an Arena project (Rossetti, 2015). The Arena Process Analyzer is a tool that assists in the parametric analysis of the constructed Arena models (Altiok and Melamed, 2010). This tool allows the modeller to create distinct scenarios to examine the effect of changing certain input parameters on prescribed performance measures.

Generally, simulation models of inventory-related systems cover four uncontrollable parameters (Packer, 1967):

1. demand,
2. the order cost,
3. the holding cost, and
4. the stockout cost.

In this study, demand input parameters are analysed and chosen in Section 3.3.1.2. These input parameters satisfy the demand volatility condition needed for this research, and a parametric analysis therefore is not needed for demand. The remaining uncontrollable parameters, however, will be parametrically analysed to detect the criticality of each one of them to the simulation pathway under study.

This section ends the methodology applied to address the 2nd research objective. Next section describes the flexibility metrics utilised to address the 3rd research objective concerning the examination of the AM impact on supply chain flexibility.

3.3.8. Flexibility metrics

As discussed in Section 3.2.2, supply chain flexibility can be examined from four key angles: i) volume flexibility, ii) mix flexibility, iii) delivery flexibility, and iv) new product flexibility. Next subsections briefly discuss the metric used in this case study for each one of these aspects.

3.3.8.1. Volume flexibility

Volume flexibility can be defined as the range of possible manufacturing volumes a company can produce in response to demand. Based on this, Beamon (1999) characterises volume flexibility, F_v , as the probability of the quantity demanded being within a certain interval:

$$F_v = P\left(\frac{O_{min} - \bar{D}}{\sigma} \leq D \leq \frac{O_{max} - \bar{D}}{\sigma}\right) \quad 3.31$$

where D represents the instantaneous market demand as a random variable with an approximately normal distribution with mean $\bar{D}$. O_{min} denotes the minimum profitable production volume a company can produce in a specific period of time, and O_{max} refers to the maximum profitable production volume within the same period. For both supply chain models, it is assumed that profitability is constrained by the maximum time a customer can wait, which is estimated at two weeks based on the information provided by the host company. Using this metric, a high value for F_v represents a high degree of volume flexibility and vice versa. In both supply chain scenarios, $\bar{D}$ was set to 3,240 parts with a standard deviation of 7,530 parts, based on the collected historical sales data.

Additionally, O_{max} for IM was estimated at 134,400 parts and at 78,400 parts for AM. O_{min} was estimated at 200 parts for the IM route (based on the minimum possible quantity a customer can order from the inventory) while a quantity of 1584 parts was assumed to be the minimum order for the AM route to ensure adequate capacity utilisation.

3.3.8.2. Mix flexibility

The concept of mix flexibility represents the range of different product types that can be produced throughout a specific period of time. This aspect can be captured by considering the changeover time as a metric. The mix flexibility, hence, was calculated for each supply chain model by linking it to the changeover time T_{ij} from product family i to product family j , which represents the set-up time in this study. Mix flexibility therefore is estimated as follows (Beamon, 1999):

$$F_m = T_{ij} \quad 3.32$$

3.3.8.3. Delivery flexibility

The primary purpose of the delivery flexibility metric is to reflect the ability to shorten a production lead-time to accommodate rush orders. Therefore, delivery flexibility, F_D , is expressed as the share of slack time in lead-time. The delivery flexibility metric proposed by Beamon (1999) is based on the assumption that the supply chain produces more than one product, which is not the case in the model presented in this work. Therefore, an adapted delivery flexibility equation is used:

$$F_D = \frac{L - E}{L} \quad 3.33$$

where L is the due time (or last possible time to deliver the product) and E is the earliest time the product can be delivered. As specified

in Section 3.3.2, a two-week maximum lead-time window is assumed.

3.3.8.4. New product flexibility

The flexibility of new product introduction, F_n , measures the ability to add new products to the current manufacturing processes. This can be reflected using Beamon's (1999) model, in which C refers to the cost required to add a new product to the system:

$$F_n = C \quad 3.34$$

3.4. Summary of methods

The overall aim of this thesis is to examine the impact of adopting AM on responsive supply chain performance. The second chapter of this thesis has identified three major aspects that need to be studied for such impact to be understood. In this doctoral project, the examination of each one of these aspects required distinct methodological approach.

The first aspect relates to is the existence of learning effect in AM. In this chapter, Section 3.1 described the methodology undertaken for the examination of the existence of this effect in AM. This method involved the performing of 14 repeated build experiments at the AM lab of CFAM at the University of Nottingham to probe for evidence of the learning effect for both novice and expert operators. Learning curve fitting procedures, along with the progress ratio equation, is described accordingly and discussed. A proposed labour cost model is also constructed, with the gathered empirical observations from the lab are the used in this model.

Section 3.2 and 3.3, on the other hand, describes the methodology utilised for the fulfilment of the 2nd and 3rd objectives. Section 3.2 shows the logic behind the construction of conceptual frameworks to

identify the relevant variables and map out how they relate to each other. This section was then followed by a detailed description of the case study in Section 3.3, which was conducted to obtain further validation into the developed conceptual models. This section is further divided into two main sections corresponding to the 2nd and 3rd research objectives. The case study, which was undertaken in a plastic manufacturing company in Saudi Arabia, is utilised for both research objectives. What distinguishes the methodology applied for the 2nd research objective is the construction of simulation models using Arena simulation. This construction required necessary elements such as input analysis and modelling, model verification and validation, and parametric analysis. The 3rd research objective, however, required a distinct method of exploration involving the estimation of supply chain flexibility metrics.

Next chapter presents the findings obtained following the execution of these methods.

4. Results

The previous chapter discussed the methodology executed to achieve the overall aim of this doctoral project, which is to examine the impact of adopting AM on responsive supply chain performance. This overall aim is divided into three research objectives, which are:

1. To examine whether AM exhibits a learning effect for both expert and novice operators.
2. To evaluate the total cost of a responsive supply chain employing AM, including inventory-related costs.
3. To examine whether the adoption of AM increases the flexibility of responsive supply chain.

This chapter presents the results obtained following the execution of the methodology to address each of these research objectives. In this chapter, Section 4.1 first shows the findings of investigating the learning effect in AM following the repetition of 14 build experiments at the AM lab of CFAM at the University of Nottingham. This section first shows the results for each phase (i.e. Pre build phase, Build phase and Post build phase). It then presents the estimations of the progress ratios for each phase separately and in an aggregated manner for all operator steps. It ends with the application of the obtained progress ratios in a proposed labour cost model.

Section 4.2 reveals the developed conceptual model concerns the impact of AM on inventory-related costs. This section also contains the findings acquired by performing a case study and executing the simulation models for the three pathways described in Section 3.3 (i.e. IM only, AM only and IM combined with AM). It also shows the estimations of the total supply chain cost for each one of these pathways and presents the results of the parametric analysis conducted for these simulations.

Section 4.3 finally shows the developed conceptual model that maps out certain AM characteristics relevant to flexibility to key market requirements. This is followed by a presentation of the results pertaining to the effect of AM on the supply chain flexibility aspects in comparison with IM. It also presents findings that reveal the cost penalty incurred with the various levels of volume flexibility for both manufacturing technologies.

4.1. Results on learning in AM

This section presents the findings obtained after carrying out the methods described in Section 3.1 to probe for evidence of the existence of learning effect in AM for both the novice and the expert operators. Overall results and descriptive statistics are first shown in this section. The following subsections present results related to each AM phase, estimates of progress ratios and application of a proposed labour cost model based on these estimates.

Overall, the total duration of all build experiments at full capacity performed by the novice operator, including machine warm up, build time and cool down, was 14,811 minutes. The total duration for all experiments undertaken by the expert was 17,559 minutes. This somewhat counterintuitive result is explained by the novice operator spending less time supervising the machine compared to the expert operator. This step is usually undertaken with no predefined time limits since it is based on prior experience and actual assessment of the current machine performance. Therefore, the expert is expected to be more vigilant and spend more time supervising the machine. The novice operator also spent less time in the Pre build phase due to the simultaneous mixing of powder material while cleaning the AM machine. The expert carried out both steps in sequence. When excluding activities associated with autonomous machine operation (i.e. Steps 5, 6 and 7 in Figure 3.2), however, total operator time

spent by the novice was 736 minutes, exceeding the 686 minutes spent by the expert in total, excluding the ramp-up experiments. Although this study of learning is limited to operator time, the build experiments showed that the expert operator used far less build material in the experiments, with significant implications for unit cost.

Two build failures occurred in the build experiments performed by the novice operator, likely due to powder degradation. Coincidentally, the same number of build failures occurred for the expert operator. The parity between the expert and the novice in terms of build failure provides some indication of the effectiveness of the training offered to the novice operator with respect to successful process execution.

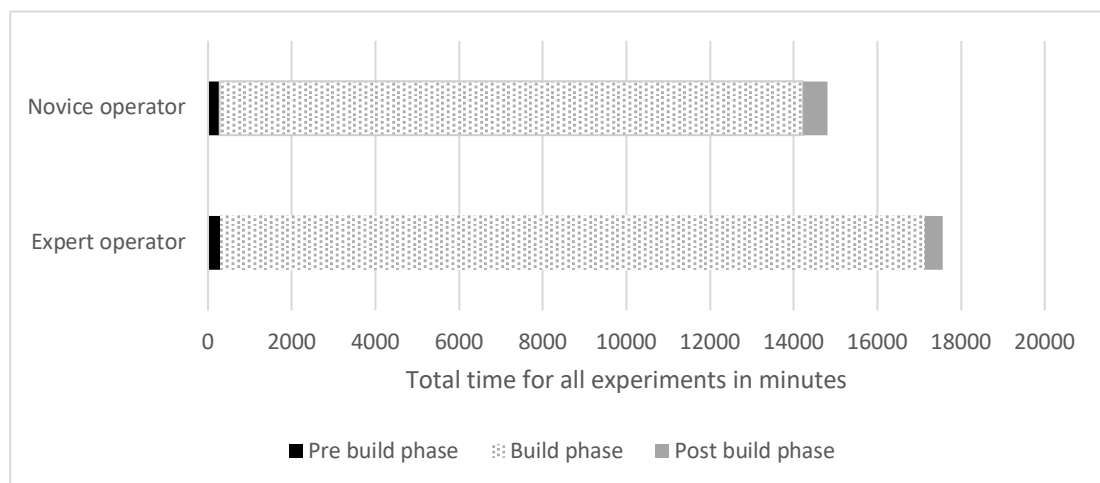


Figure 4.1. The contribution of the three main phases to the total time by both the expert and the novice.

Figure 4.1 summarises the total time requirements of the three main phases of the build. Table 4.1 presents descriptive statistics of each step for both the novice and the expert operator. The following subsections presents detailed results for all three phases of the build process, highlighting counterintuitive observations and offering explanations.

Table 4.1. Descriptive statistics of each step for both the novice and the expert.

Phase and step no.	Description	Time spent by the novice operator in minutes				Time spent by the expert operator in minutes			
		Mean	Maximum	Minimum	Standard deviation	Mean	Maximum	Minimum	Standard deviation
Pre build phase	1 File preparation	1.38	10.27	0.00	3.14	0.40	4.00	0.00	1.26
	2 Build setup	4.82	9.67	3.50	1.83	1.50	15.00	0.00	4.74
	3 Machine preparation	12.75	45.30	0.00	15.18	19.80	32.00	10.00	7.89
	4 Build release	0.68	1.00	0.38	0.26	1.00	1.00	1.00	0.00
Build phase	5 Machine warm-up	214.92	271.00	199.00	21.13	190.02	290.63	220.57	23.39
	6 Build process	149.18	152.00	146.00	1.82	149.98	152.28	148.37	1.42
	7 Machine cool-down	600.00	600.00	600.00	0.00	840.00	1080.00	600.00	159.61
	8 Machine supervision	9.10	31.00	3.00	8.46	12.30	20.00	10.00	3.23
Post build phase	9 Build removal	6.89	53.14	0.92	16.26	1.90	3.00	2.00	0.33
	10 Machine clean-up	11.02	18.10	8.28	2.69	7.50	14.00	6.00	2.45
	11 Unpacking and powder handling	7.54	14.78	4.00	3.24	7.90	15.00	7.00	2.64
	12 Shot blasting	8.16	9.77	7.35	0.72	6.30	13.00	3.00	3.08
	13 Parts washing	6.73	8.13	6.00	0.64	3.80	6.00	3.00	0.97
	14 Commission parts and packing	4.50	5.00	2.00	0.97	2.80	5.00	2.00	0.93

4.1.1. Pre build phase

As discussed in the Section 3.1, the Pre build phase includes all steps that need to be undertaken before the machine warm-up. The mean of the first step for the novice operator was 1.38 minutes, with a

Standard Deviation (SD) of 3.14 minutes as opposed to a mean of 0.4 with an SD of 1.26 minutes for the expert operator. A mean of 4.82 (SD = 1.83) minutes the novice operator spent on the second step while the expert operator spent a mean of 1.50 (SD = 4.74) minutes. Surprisingly, the novice operator spent a mean time of 12.75 minutes with SD of 15.18 minutes to prepare the machine for the build as compared to the expert operator who spent a mean of 19.80 minutes with an SD of 7.89 minutes. This occurred since the novice, in attempting to be efficient, turned on the powder mixing machine while cleaning the machine, unlike the expert who performed these operations in sequence to ensure appropriate timing of each activity. A mean of 0.68 and 1 minute was spent on releasing the build by the novice and the expert, respectively. Figure 4.2 presents a comparison of the total time spent throughout all build experiments in this phase.

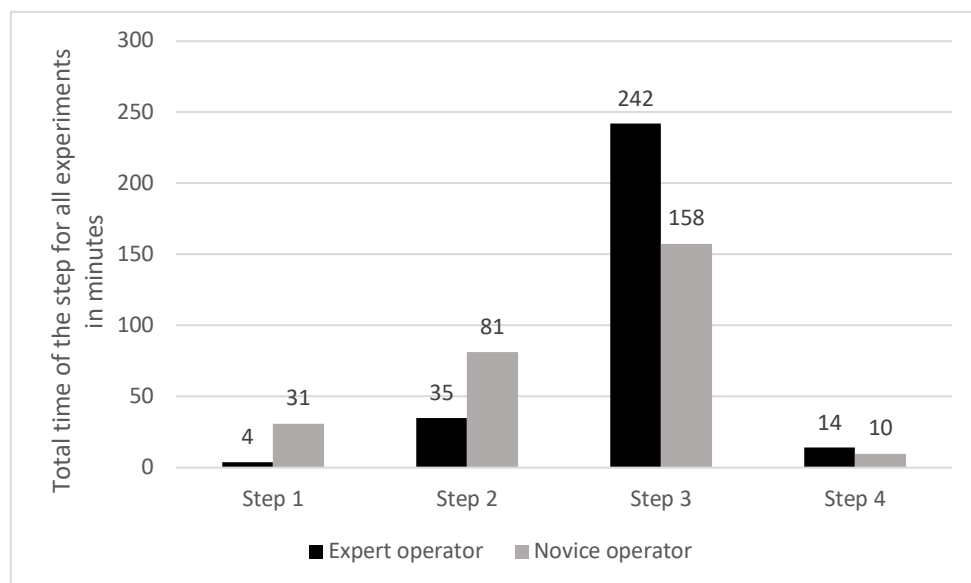


Figure 4.2. Comparison of the total time spent throughout all build experiments in the Pre build phase.

4.1.2. Build phase

For Step 5, machine warm-up, the mean is 214.92 minutes for the novice operator and 190.02 minutes for the expert operator. For Step 6, build process, the duration for both the novice operator and

the expert operator experiments took a mean of 149.18 and 149.98 minutes respectively to complete while it took a mean of 840 and 600 minutes respectively for the machine to cool down (Step 7). Figure 4.3 presents a comparison of the machine time for both the novice and the expert. The similarity in machine time reflects the independence of the build phase time from operator interventions. On the other hand, the novice spent a mean of 9.10 minutes for intermittent build supervision whereas the expert spent a mean of 12.30 minutes for the same task.

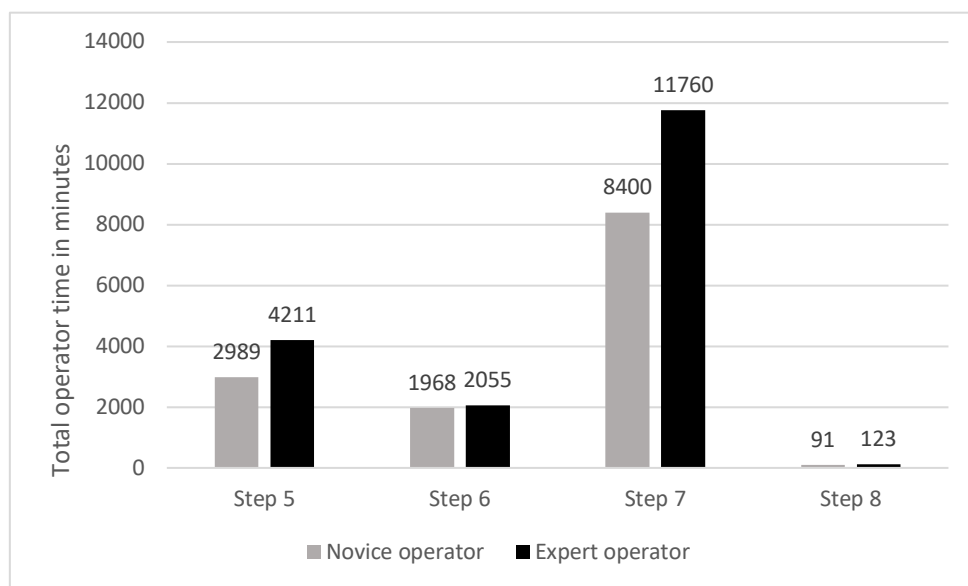


Figure 4.3. Total machine time for all experiments in minutes for both the novice and the expert.

4.1.3. Post build phase

This phase includes Steps 9, 10, 11, 12, 13 and 14, which took place after the machine cool down. The novice operator spent an average of 42.37 minutes to complete the post processing steps while the expert operator spent an average of 30.29 minutes for the same steps. Figure 4.4 presents the total time each operator spent on each one of these steps for all experiments.

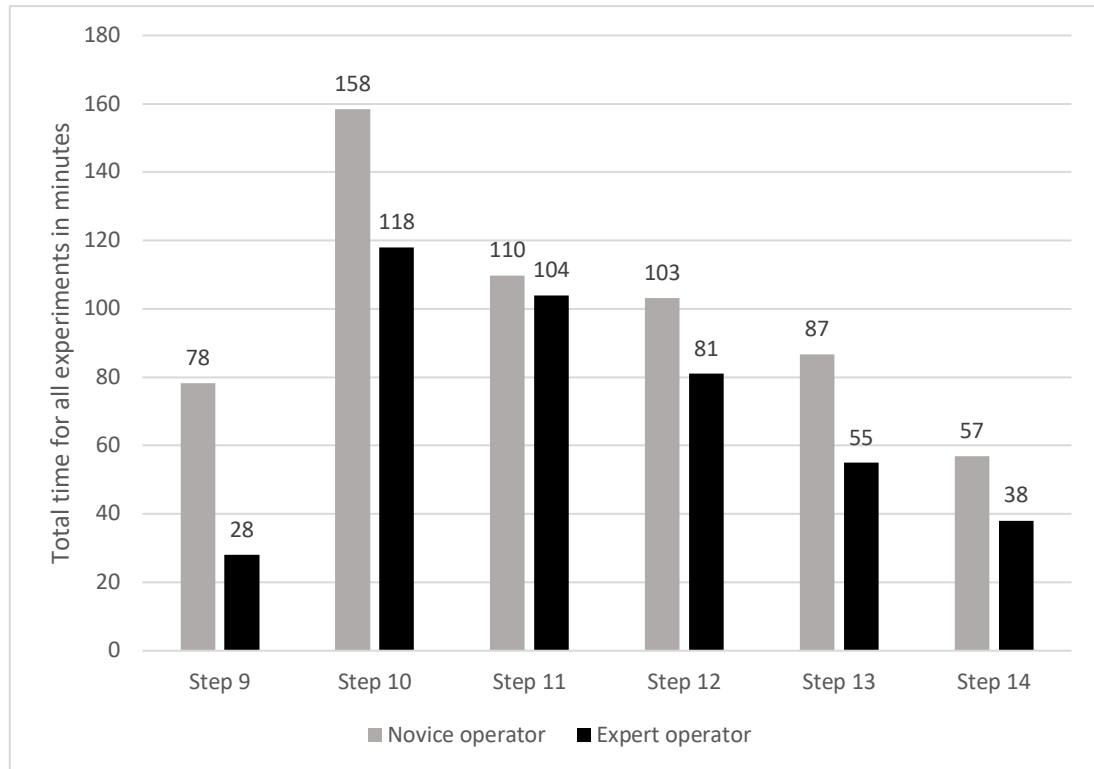


Figure 4.4. The total time each operator spent on each one of Steps 9, 10, 11, 12, 13 and 15.

4.1.4. Estimation of progress ratios

To estimate the progress ratio, the machine time, which includes warm-up, build and cool down time, was excluded from each experiment and the total operator time then was calculated. Figure 4.5 shows the total operator time for both the novice and the expert for each experiment at full capacity, thereby excluding ramp-up builds. Following the practical approach developed by van Sark (2008), progress ratios and errors in these ratios were estimated.

By fitting the learning curve power function to the collected data set, a progress ratio of 0.67 ± 0.08 was estimated for the novice operator with $R^2 = 0.72$ for an optimal value of 0.56 for b and 155.21 minutes for a . The corresponding progress ratio estimated for the expert operator is 0.80 ± 0.05 with $R^2 = 0.68$ for an optimal value of 0.31 for b and 107.28 minutes for a . The 67.73% progress ratio represents a reduction of 32.26% in labour time with each repetition

of the build process. This ratio contrasted with the expert progress ratio of 80.42%, which represents a reduction of 19.57% in the labour time with each build repetition. Table 4.2 presents the observed and estimated data for both the novice and expert operators.

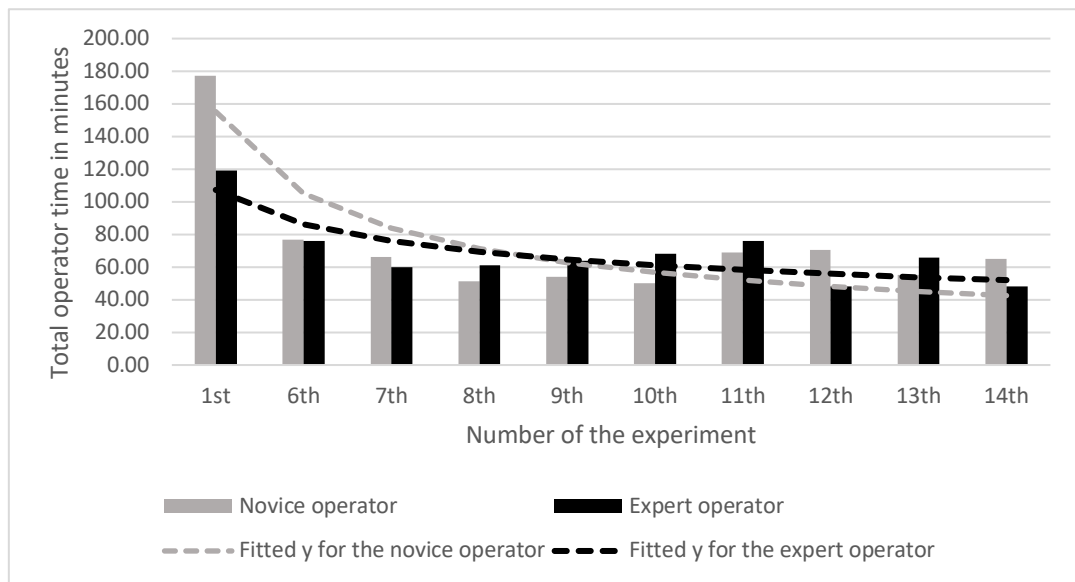


Figure 4.5. The total operator time of each experiment for both the novice and the expert operators.

Table 4.2. Comparison between the observed and estimated operator time for both the novice and the expert.

Experiment number	Time spent by the novice operator in minutes		Time spent by the expert operator in minutes	
	y	y_{fit}	y	y_{fit}
1 st	177.12	155.21	119.00	107.28
6 th	76.73	105.13	76.00	86.28
7 th	66.26	83.70	60.00	75.96
8 th	51.27	71.21	61.00	69.39
9 th	53.99	62.81	64.00	64.69
10 th	50.30	56.70	68.00	61.09
11 th	69.05	51.99	76.00	58.20
12 th	70.48	48.23	48.00	55.81
13 th	55.36	45.14	66.00	53.78
14 th	65.13	42.55	48.00	52.03

For the Pre build phase, the learning curve power function was fitted also to the collected data of this phase. This resulted in an estimated progress ratio of 0.50 ± 0.11 for the novice operator with $R^2 = 0.72$ for an optimal value of 0.99 for b_{pre} and 63.67 minutes for a_{pre} . This is contrasted with the 0.69 ± 0.08 progress ratio estimated for the expert operator with $R^2 = 0.60$ and optimal values of 0.53 for b_{pre} and 46.61 minutes for a_{pre} . Figure 4.6 shows the Pre build time for both the novice and the expert for each experiment while Table 4.3 presents the observed and estimated data for both the novice and the expert operators.

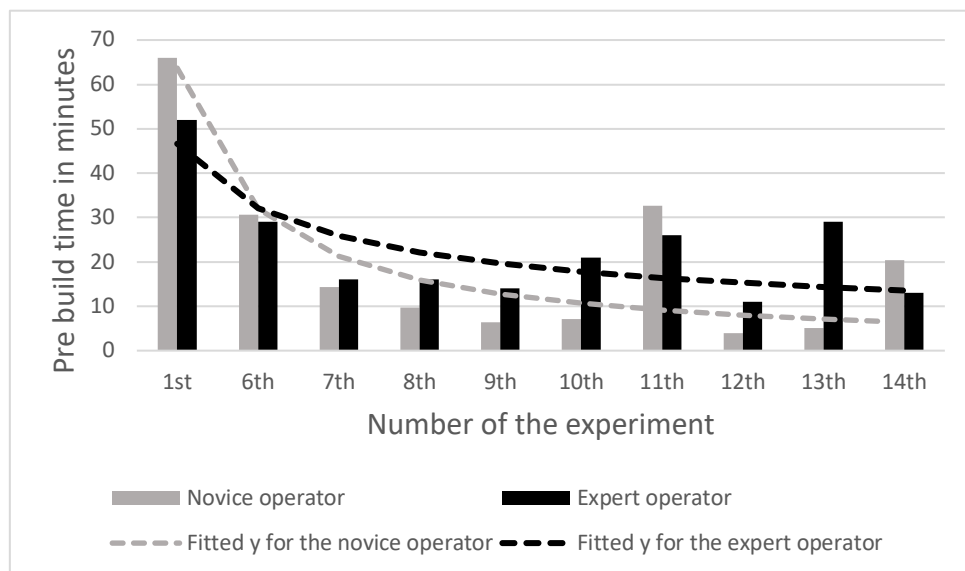


Figure 4.6. The Pre build time of each experiment for both the novice and the expert operators.

Table 4.3. Comparison between the observed and estimated Pre build time for both the novice and the expert.

Experiment number	Time spent by the novice operator in minutes		Time spent by the expert operator in minutes	
	y_{Pre}	y_{fit}	y_{Pre}	y_{fit}
1 st	65.98	63.67	52.00	46.62
6 th	30.66	31.88	29.00	32.13

7 th	14.33	21.27	16.00	25.85
8 th	9.75	15.96	16.00	22.15
9 th	6.40	12.78	14.00	19.65
10 th	7.10	10.65	21.00	17.82
11 th	32.72	9.13	26.00	16.40
12 th	3.95	7.99	11.00	15.27
13 th	5.03	7.11	29.00	14.33
14 th	20.38	6.40	13.00	13.55

Learning also was investigated in the Post build phase for both the novice and the expert. This resulted in an estimated progress ratio of 0.72 ± 0.07 for the novice operator with $R^2 = 0.75$ for an optimal value of 0.47 for b_{post} and 85.91 minutes for a_{post} whereas a 0.86 ± 0.03 progress ratio was estimated for the expert operator with $R^2 = 0.65$ and optimal values of 0.21 for b_{post} and 45.83 minutes for a_{post} . Figure 4.7 shows the Post build time for both the novice and the expert for each experiment while Table 4.4 presents the observed and estimated data for both the novice and the expert operators for this phase. By aggregating y_{Pre} with y_{Post} in one model and comparing them to y (as a non-aggregated model) using R^2 , the non-aggregated model showed higher accuracy for both the novice and the expert with R^2 values of 0.68 and 0.26 compared to the 0.72 and 0.68 values estimated for the aggregated model, respectively.

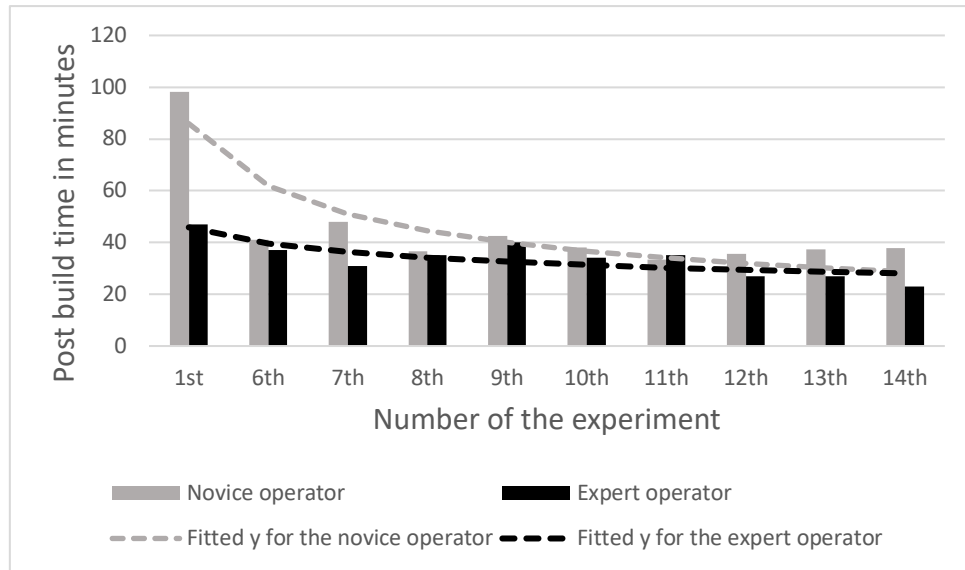


Figure 4.7. The Pre build time of each experiment for both the novice and the expert operators.

Table 4.4. Comparison between the observed and estimated Post build time for both the novice and the expert.

Experiment number	Time spent by the novice operator in minutes		Time spent by the expert operator in minutes	
	y_{Post}	y_{fit}	y_{Post}	y_{fit}
1 st	98.14	85.91	47.00	45.84
6 th	41.08	61.77	37.00	39.54
7 th	47.93	50.93	31.00	36.27
8 th	36.52	44.41	35.00	34.11
9 th	42.60	39.94	40.00	32.53
10 th	38.20	36.62	34.00	31.29
11 th	33.33	34.03	35.00	30.28
12 th	35.53	31.93	27.00	29.43
13 th	37.33	30.19	27.00	28.70
14 th	37.75	28.71	23.00	28.06

4.1.5. Application of the results in a simple model of labour cost

To demonstrate how the estimated parameters can be used for analyses of the cost performance of AM, a simple direct labour cost model can be constructed. The model is based on two different

labour cost rates for both the novice and the expert operators of €25.06/hr and €33.86/hr, respectively (Baumers and Holweg, 2019). The model thus considers the learning curve in AM by accounting for repetition of builds rather than the quantity of units manufactured. Since the direct labour cost is a function of process repetition, each repetition is expressed as a build here.

A number of additional assumptions are made to simplify the construction of the model:

- It is assumed that direct labour cost can be further decomposed into distinct labour costs elements: pre build cost (C_{Pre}), build cost (C_{Build}) and post build cost (C_{Post}). Hence, the total direct labour cost (TC) incurred for all builds can be estimated by multiplying the cumulative number of builds q (i.e. build experiments in this study) by the costs, as follows:

$$TC = q (C_{Pre} + C_{Build} + C_{Post}) \quad 4.1$$

- Further, it is assumed that the build phase, in which the operator is intermittently supervising the build process (i.e. Step 8 in Figure 3.2), is not subject to learning effect. Therefore, C_{Build} simply enters the models as a constant. This gives further distinction to TC as follows:

$$TC = q (\dot{C}y_{Pre} + C_{Build} + \dot{C}y_{Post}) \quad 4.2$$

where $\dot{C}$ denotes an hourly labour rate (€/hr). Incorporating the Equations 3.2 and 3.3 in Chapter 3 of this thesis, Equation 4.2 is revised as follows:

$$TC = \dot{C}a_{Pre}q^{1-b_{Pre}} + C_{Build} + \dot{C}a_{Post}q^{1-b_{Post}} \quad 4.3$$

To express the change in the direct labour cost arising from each build repetition, the direct labour cost of the q th build (BC_q) can be expressed as the difference between the total direct labour costs of the q th build and its preceding build $(q - 1)$ th (Badiru, 1991), as follows:

$$BC_q = (\dot{C}a_{pre}q^{1-b_{pre}} + C_{Build} + \dot{C}a_{post}q^{1-b_{post}}) - (\dot{C}a_{pre}(q - 1)^{1-b_{pre}} + C_{Build} + \dot{C}a_{post}(q - 1)^{1-b_{post}}) \quad 4.4$$

This resulting cost model can be used to explore the effect of learning on labour cost across several AM builds. Figure 4.8 presents the resulting build direct labour cost against the number of the AM build. As an illustration, the 14th build experiment implied the repetition of 10 build experiments for the novice operator; hence, the labour cost is spread over these build experiments, resulting in a direct labour cost of €389.8 for the 14th build (BC_{14}). The initial decrease in the direct labour cost for both the novice and the expert is a representative of the observed difference in operator time between the 1st and the subsequent build experiment. As can be seen, less direct labour cost is anticipated by the novice operator compared to the expert for each build after the first one. This is, in part, because the hourly rate for the novice operator in this research is less expensive than the expert. This cost model also ignores the far lower material consumption by the expert, which affects the direct labour cost (Baumers and Holweg, 2019).

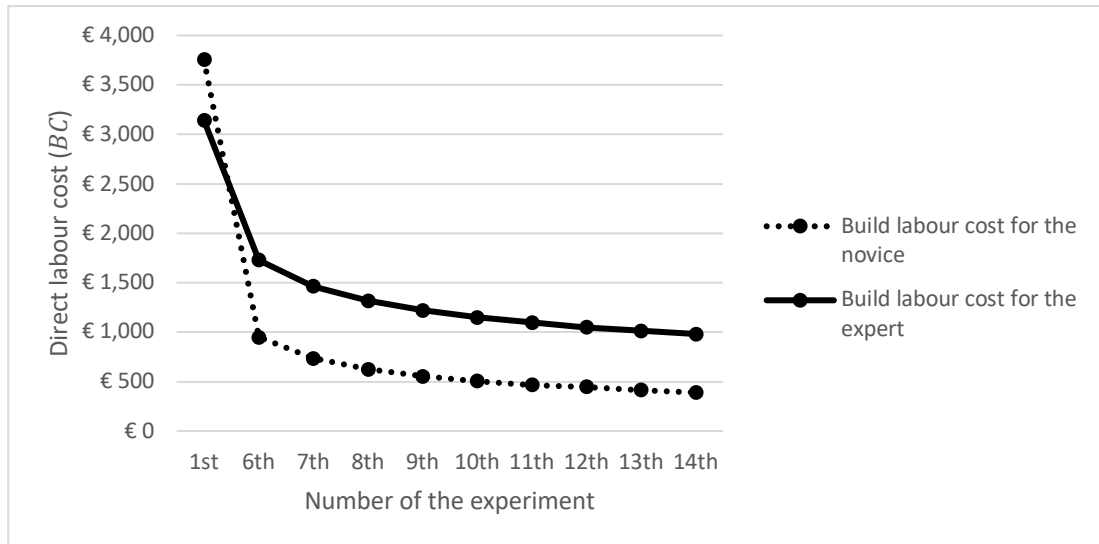


Figure 4.8: The batch direct labour cost for both the novice and the expert for each build experiment.

Next section presents the findings pertaining to the second research objective of this doctoral project.

4.2. Results on the impact of AM on inventory-related costs

This section presents the conceptual model developed that matches the possible production configurations of AM and conventional manufacturing technologies in relation to the demand volume level and stockout cost. The findings of the case study then are presented to obtain insights into the developed conceptual model.

4.2.1. The developed conceptual model of supply chain costs in AM

A conceptual framework is developed in this research to identify the relevant variables (i.e. demand volume and stockout cost) for the 2nd research objective. This is to map out how these two decisive factors might link to each other and dictate the possible production configurations of AM and conventional manufacturing technologies. Figure 4.9 presents the constructed conceptual model.

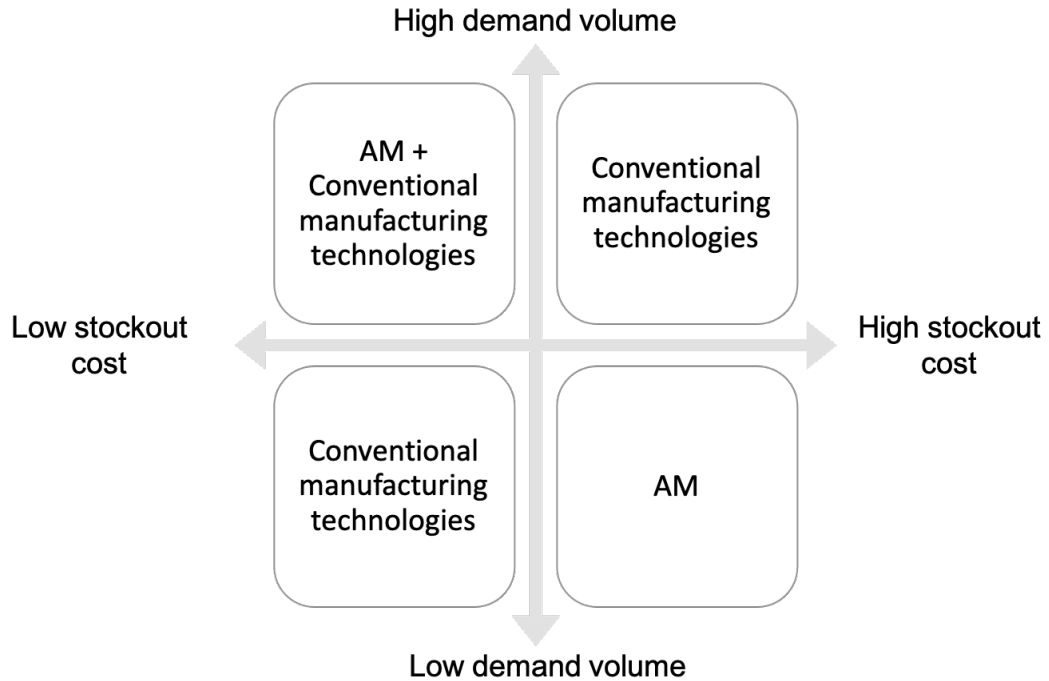


Figure 4.9: A conceptual model that matches possible production configurations in relation to demand volume level and stockout cost.

This conceptual model presents a matrix with four distinct quadrants each of which is dictated by the interaction of the demand volume level with the severity of the stockout cost. If high demand volume is anticipated in markets where stockout costs are high, then conventional manufacturing technologies such as IM is well-suited in such contexts. This is unlike when demand orders are received in low volumes but with associated high stockout cost; in this case, AM alone is a well-fitted choice. If the stockout cost is expected to be high with demand orders that are low in volumes, conventional manufacturing technologies are well-matched in these contexts. This is contrary to the case when orders are received in high volumes with low associated stockout cost, a combination approach of AM and a conventional manufacturing technology in this case is more effective.

4.2.2. Case study findings on inventory-related costs

This section presents the findings of the case study that serve as an investigated situation that can be analyzed in relation to the developed conceptual model shown in the previous section. The execution of the models of the three pathways in Arena detailed in Section 3.3.3 allowed the estimation of manufacturing quantities and the corresponding inventory-related costs for each technology.

The 1st pathway estimates the production of a total of 361,392 parts in the investigated 5-year period. For the same time period, the 2nd pathway predicts a total production quantity of 331,330 parts. Despite all orders being met in the 2nd pathway (unlike the 1st pathway), the model in this thesis suggests that the overall output of the 2nd pathway is lower than that of the 1st pathway in four out of five years. The main explanation for this result is that in the 1st pathway the system is initiated for batch production. This leads to the accumulation of excess inventory, while in the 2nd pathway only ordered quantities are produced.

In the 3rd pathway, a total production volume of 345,630 parts is predicted by the simulation model. Out of these, AM was utilised to produce 18,270 parts to offset shortages in the available inventory produced by IM. Note should be made that the amount lost due to stockout in the 1st pathway does not equate to the amount produced by AM in the 3rd pathway. This is because even though AM was adopted to prevent stockout penalties from occurring, it only produced the difference between the order quantity and the remaining available inventory, which is added to the shipped order.

Table 4.5 compares the main model results for all three pathways occurring over the investigated five-year period. As can be seen, the model suggests that the overall output quantity of the 3rd pathway

(345,630 units) is larger than both the 1st pathway (361,392 units) and the 2nd pathway (331,330 units). Additionally, when utilised as stand-alone technology and stockout are allowed as in the 1st pathway, IM benefits from the amortisation of tooling expenses across the manufactured volume of products, leading to a lower manufacturing unit cost of €0.79 versus €2.72 for the 2nd pathway and €0.89 for the 3rd pathway. It is noted that the observed cost levels for both the 1st and 2nd pathways are broadly in line with the cost performance reported by Atzeni et al. (2010).

Table 4.5: Comparison of cumulative model results after five years.

Model element	Unit	1 st pathway	2 nd pathway	3 rd pathway
Production volume	pcs	361,392	331,330	345,630
Manufacturing unit cost	€	0.79	2.72	0.89
Total manufacturing costs		283,769	901,218	309,479
Inventory holding costs		14,853	-	15,195
Order costs		1,768	3,051	1,680
Stockout costs		23,190	-	-
Total supply chain cost		323,580	902,678	326,354
Supply chain unit cost		0.90	2.72	0.94

As per the model specification, inventory and stockout costs do not occur in the 2nd pathway. The stockout cost also does not occur in the 3rd pathway. The model suggests, however, that these cost savings are not great enough to outweigh the manufacturing cost advantage of IM, as shown by the total supply chain unit cost estimates of €2.72 for the 2nd pathway and €0.94 for the 3rd pathway compared to €0.90 in the 1st pathway. The model thus indicates that, on a cost basis, the conventional IM route is more attractive than the adoption of AM, especially if it assumed that the sales price for the investigated component is independent of the used technology.

4.2.2.1. Parametric analysis

Parametric analysis describes the conduction of sensitivity analysis activities by running a simulation model several times, each of which with different input parameters. To understand the effect of the inventory parameters on the findings obtained from the execution of the three simulation models, parametric analysis was conducted as described in Section 3.3.7. In particular, three input parameters were selected: inventory holding cost, order cost and stockout cost. Each one of these parameters has been repeatedly altered to different prescribed values, and the simulation then was replicated while all the other parameters and variables remained constant. This experimentation resulted in a collection of scenarios pertaining to each input parameter in each pathway. The following subsections present the parametric analysis results for each input parameter.

4.2.2.1.1. Parametric analysis for inventory holding rates

The first input parameter is the inventory holding cost. In this study, this parameter was set at a cost factor of 0.25 to the manufacturing cost estimate of the annual average inventory. This rate, however, differs from one manufacturing firm to another based on the estimation method (Berling, 2005) but typically ranges from 0.25 to 0.45 (Durlinger and Paul, 2012).

Since the 2nd pathway does not incur an inventory holding cost, a set of scenarios for both the 1st and the 3rd pathways was performed with each scenario stepping up the inventory holding rate by a value of 0.05.

Table 4.6: A collection of scenarios with different inventory holding rates for the 1st pathway.

Scenario number	Inventory holding rate	Inventory holding cost (€/5 years)	Corresponding supply chain unit cost (€/part)
Scenario 1	0.30	17,824	0.90
Scenario 2	0.35	20,794	0.91
Scenario 3	0.40	23,765	0.92
Scenario 4	0.45	26,736	0.93

Table 4.7: A collection of scenarios with different inventory holding rates for the 3rd pathway.

Scenario number	Inventory holding rate	Inventory holding cost (€/5 years)	Corresponding supply chain unit cost (€/part)
Scenario 1	0.30	18,235	0.94
Scenario 2	0.35	21,274	0.96
Scenario 3	0.40	24,313	0.97
Scenario 4	0.45	27,352	0.98

Table 4.6 and Table 4.7 present the results of the parametric analysis performed to measure the effect of changing the inventory holding rate in the 1st and 3rd pathways. According to these results, the same rate of increase is observed for both pathways with each added value of 0.05 to the holding rate (i.e. 16.6%, 14.2% and 12.5% for scenarios 2,3 and 4, respectively). For the 1st pathway, even if the holding rate was set to the highest value (i.e. 0.45), its corresponding supply chain unit cost still outperforms their counterparts in the 2nd and 3rd pathways under the same conditions.

4.2.2.1.2. Parametric analysis for order cost values

Table 4.8, Table 4.9 and Table 4.10 present the findings of the parametric analysis undertaken for another critical input parameter which is the order cost. Durlinger and Paul (2012) reported that order costs in businesses range from €50 per order request to €100. Thus, the parametric analysis here assembled six distinct scenarios of different order cost values with an increase by €10 with each scenario. As evident in Table 4.8, Table 4.9 and Table 4.10, changing

the order cost from €50 to €100 did not have significant impacts on their corresponding supply chain unit cost for all pathways.

Table 4.8: A collection of scenarios with different order cost values for the 1st pathway.

Scenario number	Order cost values (€/order)	Inventory order cost (€/5 years)	Corresponding supply chain unit cost (€/part)
Scenario 1	50	2,000	0.90
Scenario 2	60	2,400	0.90
Scenario 3	70	2,800	0.90
Scenario 4	80	3,200	0.90
Scenario 5	90	3,600	0.90
Scenario 6	100	4,000	0.90

Table 4.9: A collection of scenarios with different order cost values for the 2nd pathway.

Scenario number	Order cost values (€/order)	Inventory order cost (€/5 years)	Corresponding supply chain unit cost (€/part)
Scenario 1	50	3,450	2.73
Scenario 2	60	4,140	2.73
Scenario 3	70	4,830	2.73
Scenario 4	80	5,520	2.73
Scenario 5	90	6,210	2.73
Scenario 6	100	6,900	2.74

Table 4.10: A collection of scenarios with different order cost values for the 3rd pathway.

Scenario number	Order cost values (€/order)	AM inventory order cost (€/5 years)	IM inventory order cost (€/5 years)	Corresponding supply chain unit cost (€/part)
Scenario 1	50	150	1,750	0.98
Scenario 2	60	180	2,100	0.98
Scenario 3	70	210	2,450	0.98
Scenario 4	80	240	2,800	0.98
Scenario 5	90	270	3,150	0.98
Scenario 6	100	300	3,500	0.99

4.2.2.1.3. Parametric analysis for stockout penalties

The last parametric analysis that was performed dealt with the effect of changing the number of future lost customers from 3 to 5. This is

only applicable in the 1st pathway, since stockouts only occur in this pathway. If with each stockout event four future orders are lost, as shown in Table 4.11, the supply chain unit cost of the 1st pathway increases to €0.97. This makes the supply chain unit cost of the 3rd pathway (i.e. €0.94) is more attractive than the 1st pathway in this scenario. However, with all the above parametric changes, the 2nd pathway did not show cost-effectiveness from a supply chain level in comparison with the 1st and 3rd pathways.

Table 4.11: A collection of scenarios with different numbers of future lost customers for the 1st pathway.

Scenario number	Future loss (customers)	Stockout cost (€/5 years)	Corresponding supply chain unit cost (€/part)
Scenario 1	3	34,785	0.93
Scenario 2	4	46,380	0.97
Scenario 3	5	57,975	1.00

This section presented the results obtained following the execution of the inter-process comparison between the three pathways described in Chapter 3. Now that the results on the 2nd research objectives have been presented, the next section shows the findings on the 3rd research objectives regarding the impact of AM on the four types of supply chain flexibility. It also shows the results related to the relationship between volume flexibility and unit cost.

4.3. Results on the impact of AM on supply chain flexibility

This section presents the conceptual model developed that maps the AM characteristics relevant to flexibility to key disruption scenarios faced by managers and originate from the market. Following this, the findings of the case study that pertain to flexibility are presented.

4.3.1. The developed conceptual model of supply chain flexibility in AM

A conceptual model is constructed in this research to clarify how the four supply chain flexibility aspects (i.e. volume, mix, delivery and new product) are developed by mapping out the AM characteristics relevant to flexibility (i.e. freedom of geometry, parts consolidation, absence of tooling and on-demand production) to the four key market requirements (i.e. demand uncertainty, demand variability, product variety and lead-time compression). Figure 4.10 presents the constructed conceptual model.

AM characteristics	Market requirements			
	Demand uncertainty	Demand Variability	Product variety	Lead-time compression
Freedom of geometry			New product flexibility	
Parts consolidation				
Absence of tooling	Volume flexibility		Mix flexibility	
On-demand production				
				Delivery flexibility

Figure 4.10: A conceptual model that maps AM characteristics relevant to supply chain flexibility against key market scenarios faced by managers.

As seen in Figure 4.10, AM exhibits various characteristics that can affect certain aspects of flexibility. The first of these characteristics

is freedom of geometry, which helps managers facing market trends that necessitate adopting product proliferation strategy or continuously introducing new products to the market to achieve higher levels of mix and new product flexibility. These two flexibility aspects are also achieved via part consolidation, the second of these AM characteristics. The third AM characteristic relevant to flexibility is the absence of tooling (i.e. moulds) in this technology. Through this feature, higher levels of mix flexibility, new product flexibility and volume flexibility can be achieved. The last AM characteristic is on-demand production, and through this feature, the four supply chain flexibility aspects can be developed/improved. Next section shows the case study findings obtained to gain in-depth insights into this conceptual model.

4.3.2. Case study findings on supply chain flexibility

Interesting insights into the performance of both technologies is obtained from comparing the estimation of the four supply chain flexibility metrics: (i) volume flexibility, (ii) mix flexibility, (iii) delivery flexibility and (iv) new product flexibility. As evident from Table 4.12, the supply chain employing IM shows higher volume and delivery flexibility with 65.68% and 92.8% compared to 58.70% and 75.35% for AM, respectively. This is largely due to the existence of buffer inventory in the IM supply chain which gives the ability to fulfil orders with volume as low as 200 and instant shipping of parts from the warehouse. This is unlike the AM route, which requires at least 82 hrs of production to processing any order.

Table 4.12: Comparison of the flexibility metrics.

Flexibility metric	Unit	AM	IM
Volume flexibility	%	58.70	65.68
Mix flexibility	hr	0.33	4.91
Delivery flexibility	%	75.35	92.85
New product flexibility	€	0	30,000

4.3.2.1. Volume flexibility and the cost penalty

As pointed out by Upton (1994), flexibility as a strategic orientation to the market can be developed only by considering the cost penalty it might cause. In this study, one important cost factor is the scale of production size or quantity. It is anticipated, based on the economies of scale phenomenon, that higher production volumes lead to lower unit costs (i.e. cost per part) (Carlino, 2012). This phenomenon, however, does not relatively manifest itself in parts fabricated by AM due to the lack of tooling (Petrick and Simpson, 2013), which is amortised over production quantity in other conventional manufacturing technologies, such as IM in this case. In this study, the effect of different maximum possible production volumes (O_{max}) on volume flexibility level and its corresponding manufacturing unit cost is analyzed. Table 4.3 shows the results of this analysis for the IM supply chain and it can be observed that at $O_{max} > 25,200$, volume flexibility level remains the same despite the corresponding continuous reduction of the manufacturing unit cost. Table 4.14 shows a similar pattern for AM at $O_{max} > 26,584$ but with corresponding constant manufacturing unit cost.

Table 4.13: The corresponding volume flexibility level and manufacturing unit cost of the maximum production quantity produced by IM.

O_{max}	Volume flexibility (F_v)	Manufacturing unit cost (€)
200	0%	150.70
2,700	13%	11.81
5,200	26%	6.47
7,700	38%	4.60
10,200	48%	3.64
12,700	55%	3.06
15,200	60%	2.68
17,700	63%	2.40
20,200	64%	2.19
22,700	65%	2.02
25,200	66%	1.89
27,700	66%	1.79
30,200	66%	1.70
32,700	66%	1.62
35,200	66%	1.55
37,700	66%	1.50
40,200	66%	1.45
42,700	66%	1.40
45,200	66%	1.37
47,700	66%	1.33
50,200	66%	1.30
52,700	66%	1.27
55,200	66%	1.25
57,700	66%	1.22
60,200	66%	1.20
62,700	66%	1.18

Table 4.14: The corresponding volume flexibility level and manufacturing unit cost of the maximum production quantity produced by AM.

O_{max}	Volume flexibility (F_v)	Manufacturing unit cost (€)
1,584	0%	2.72
4,084	13%	
6,584	26%	
9,084	37%	
11,584	45%	
14,084	51%	
16,584	55%	
19,084	57%	
21,584	58%	
24,084	58%	
26,584	59%	
29,084	59%	
31,584	59%	
34,084	59%	
36,584	59%	
39,084	59%	
41,584	59%	
44,084	59%	
46,584	59%	
49,084	59%	
51,584	59%	
54,084	59%	
56,584	59%	
59,084	59%	
61,584	59%	
64,084	59%	

To further comprehend the relationship between volume flexibility (F_v) and unit cost in this study, the unit cost curve is plotted against the volume flexibility level at each production quantity scenario as in Figure 4.11A and Figure 4.11B.

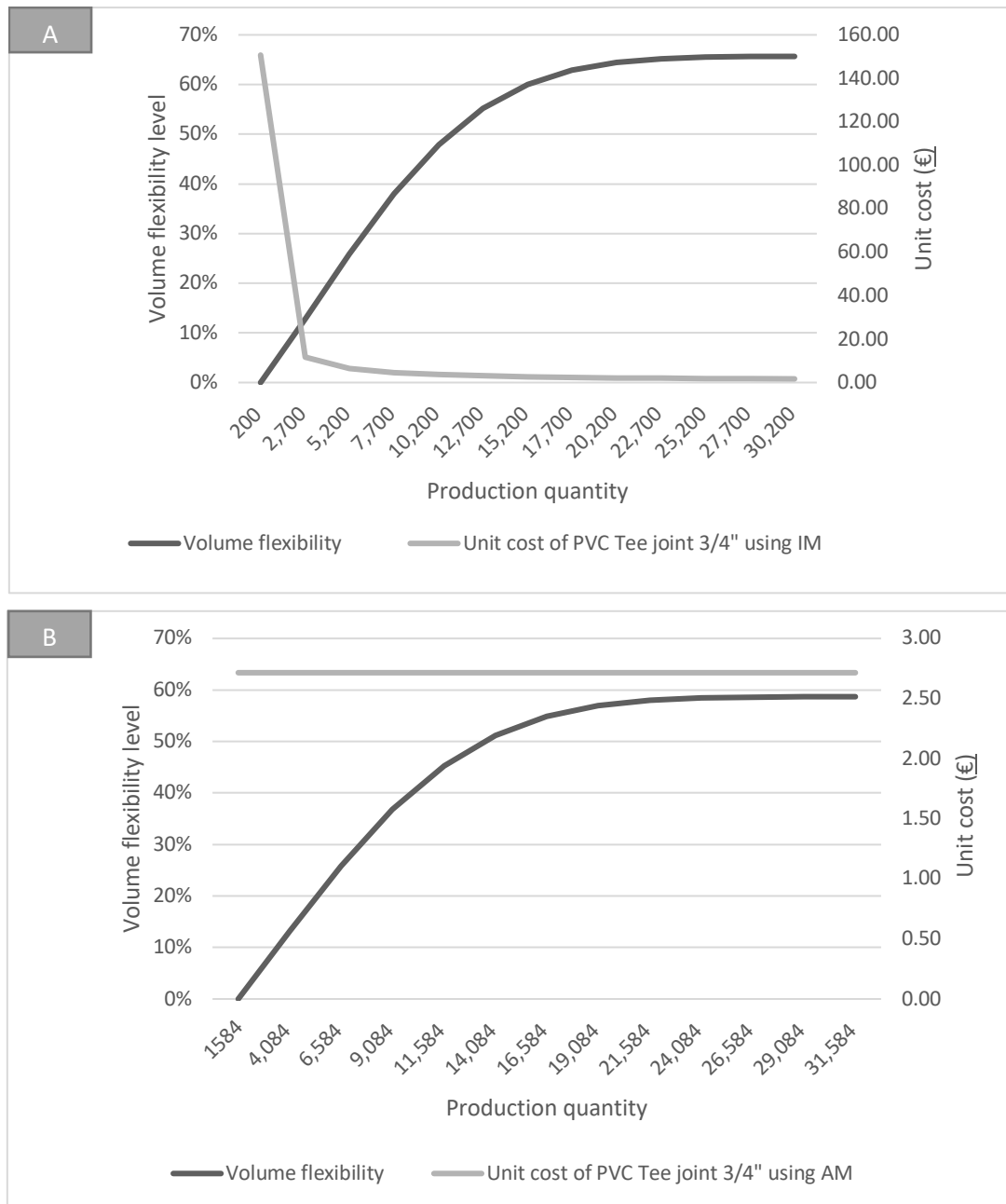


Figure 4.11: Relationship between volume flexibility and unit cost of the studied part for (A) IM and (B) AM.

As can be seen in Figure 4.11A and Figure 4.11B, the unit cost of AM is not reduced with each increase in production quantity compared to IM. In both supply chains, volume flexibility level shows the same pattern of sharp increase at the beginning before it starts to plateau once reaching a certain production quantity. This is because the volume flexibility level is estimated based on a minimum production quantity and a maximum production quantity in relation to the mean

$\bar{D}$ of the historical demand, which is 3,240 parts a month in this research. Therefore, such diminishing of increase in the volume flexibility level is expected since the increase in production quantity is rendered useless relative to the market demand. A supply chain that utilizes IM would, thus, be more attractive when aiming at increasing volume flexibility level due to the inverse proportion between the unit cost of its products and its volume flexibility.

This section presented the findings pertaining to the impact of AM on supply chain flexibility in comparison with an IM supply chain. It also examined the relationship between volume flexibility and manufacturing unit cost for both IM and AM. A summary of this chapter is presented in the following section.

4.4. Summary of results

This chapter presented the results obtained to address each of the three research objectives outlined in Chapter 1 of this thesis. These findings thus add more clarity to the overarching aim of this thesis, which is to examine the impact of adopting AM on the performance of supply chains that operates under demand uncertainty.

In particular, by assessing the aspect of operator learning in AM, this thesis adds a practical perspective which is highly relevant to the adoption of AM technologies. The estimation of learning curve models demonstrates that it is possible to establish, albeit tentatively, a rate by which operator labour inputs are reduced as an AM operator becomes more productive, which then can inform realistic modelling of the direct labour cost for each build repetition. According to the model shown in this chapter, it indicates a reduction of 32.26% of labour time with each repetition of a build performed by the novice operator compared to a reduction of 19.57% for the expert operator. By analyzing the learning effect for each phase

independently, this model indicates a higher rate of reduction for both the novice and the expert in Pre build phase compared to the Post build phase. Additionally, these results were utilised in a proposed direct labour cost model to demonstrate the impact of this learning effect on labour costs.

To address the 2nd research objective concerning the impact of AM on inventory-related costs, the constructed conceptual model was first shown in this chapter and followed by the results obtained following the conduction of the inter-process comparison between AM and IM. The estimated total supply chain costs suggest that the lower unit cost of a supply chain utilizes IM as a sole manufacturing method is more cost-effective, chiefly the result of the amortisation of tooling expenses and hence a form of economies of scale, as opposed to a supply chain that adopts AM either as a sole or complementary manufacturing method.

Following the execution of the methodology designed to address the 3rd research objective of this thesis, a conceptual model also was presented in this chapter that maps AM characteristics relevant to flexibility to key market requirements. Further insights were possible through the case study, which revealed that an AM supply chain without inventory seems to be relatively ineffective in responding rapidly to different demand volumes (i.e. 58.70% for AM compared to 65.68% for IM) and/or delivery times (75.35% for AM compared to 92.8% for IM). Also, a supply chain that utilizes IM would be more attractive when aiming at increasing volume flexibility due to the inverse proportion between the unit cost of its products and its volume flexibility. However, due to the lack of tooling, AM provides more flexibility in producing a wide range of products with less time (i.e. 0.33 hrs for AM compared to 4.91 hrs for IM) and in cheaper

introduction of new products to the system (and €0 for AM compared to €30,000 for IM).

5. Discussion

The overall aim of this doctoral project is to examine the impact of adopting AM on responsive supply chain performance. This impact is examined from three central outlooks: the existence of learning effect in AM, inventory-related costs and supply chain flexibility. Now that chapter 4 presented the results obtained associated with each one of these outlooks, this chapter discusses and contextualizes the research findings in their relevant streams of literature.

This chapter starts with Section 5.1 where the results on the learning effects are discussed in relation to various aspects in the literature, such as organizational learning and the skill gap in AM. This section is followed by Section 5.2 where the inventory-related findings are discussed in the context of three main streams of literature: demand volatility, supply chain complexity and absence of inventory. This chapter ends with Section 5.3 in which a discussion of the results obtained on the effect of AM on supply chain flexibility are discussed and contextualized.

5.1. Discussion of learning in AM

This section discusses the learning effect results of both the novice and the expert operators. An overall discussion of these results is first laid down in this section and followed by subsections that deal with these results in the context of organizational learning and the skill gap in AM.

Unsurprisingly, the estimated progress ratios suggest a faster learning rate by the novice operator which can be explained by significant progress novices usually make when they acquire new skills (Jarkas, 2010). Additionally, more operator time in total (736 minutes) was spent by the novice than the expert (686 minutes),

which was anticipated since lack of experience requires conscious and slow actions during the first few repetitions. Indeed, the novice operator spent less time in late experiments (e.g. 5th, 6th and 9th experiments) than the expert operator, which demonstrates the higher productivity gained with increasing experience. While the novice has shown lower unit costs for each build subsequent to the 1st one, it is important to note that this does not imply lower costs of operation since this ignores the far lower raw material consumption by the expert.

These results reflect two important insights. First, an inexperienced operator who is hired to implement AM activities would be expected to show a learning effect. Second, an expert operator would also be expected to show a learning effect whenever a repetition of the same build happens. The progress ratio for the expert operator supports - to some extent - the general assumption of the "80% Learning Curve" proposed by (Wright, 1936), suggesting a learning rate at this level for a wide range of processes. A progress ratio at this level is consistent with similar studies that investigate the learning effect in technologies (e.g. McDonald and Schrattenholzer, 2001; Nakicenovic, 2002).

The learning effect was not only exhibited with the novice operator but also with the expert, following the first build experiment in particular. As several publications have emphasized that interruption causes what is known as the "forgetting curve" (Bailey and McIntyre, 2003; Jaber and Kher, 2004), the expert in this study showed a relearning effect that followed an inactive period. Davidovitch et al. (2008) provide an account of how the learning-forgetting-relearning effect can be modelled. Another noteworthy point is that, for the novice operator experiments, the machine was interrupted and occupied for other purposes before the 11th experiment. This

resulted in a 15-day break throughout which the novice operator was not using the machine. This correlated with a sudden increase in the total operator time as shown in Figure 4.3, causing an increase in the processing time. It would appear that this is due to the “forgetting by not doing” phenomena, where an interruption in the production causes experience loss (McDonald and Schrattenholzer, 2001). Such interruption can occur in real manufacturing settings for several reasons. Demand fluctuation is one important reason that can disrupt the production schedule, occasionally resulting in longer inactive periods and a gradual forgetting. Afshari et al. (2019) proposed a realistic measurement of such interruption impact on time, cost and capacity in AM supply chains.

The resulted estimations of progress ratios for each phase that requires a high level of operator engagement suggest asymmetric exhibiting of the learning effects in these phases. In the Pre build phase, for instance, the novice operator showed a progress ratio of 0.50 implying a 50% reduction of time with each repetition of the build. The novice, however, showed a 0.69 progress ratio in the Post build phase. Considerable difference in the progress ratios also was estimated for the expert in these two phases. This can be explained by the fewer variations found in the Pre build phase compared to the Post build phase. In the Pre build phase, the operator goes through identical activities regardless of any changes in build content (i.e. product geometry or the number of products). In the Post build phase, however, the operator is faced with a variety of options that causes him/her to have the tendency to try one option in one build experiment and another in the following experiment. For instance, the operator can put one part only in the shot blasting machine (i.e. Step 12 in Figure 3.1) and can put multiple parts at once. This is also true for the parts washing activity (i.e. Step 13 in Figure 3.1). With

each trial of a new option in a repeated build, impeding the repetition of the past option, less learning rate is anticipated.

Putting the AM activities into a production management perspective, the utilization of the progress ratios for the Post build can help to solve the lot-size problem in Economic Production Quantity (EPQ) models. The two main trade-offs the EPQ formula optimizes is the setup cost and the holding cost. The application of the learning curve in these models has been widely discussed in the literature (e.g. Jaber, 2016; Jaber and Peltokorpi, 2020). Incorporating learning in this formula implies the addition of a production cost that decreases with learning (Jaber and Bonney, 1999). The learning effect estimated for the Post build phase can be used in this production cost; thus, improving the performance of EPQ formula.

On the other side, the Pre build phases in AM represents a “setup” time where the operator goes through preparation activities for the build. Based on this, the learning rate estimated in the Pre build phase can be used in the setup cost part of the EPQ. Jaber and Bonney (2003) for instance investigated the impacts of learning and forgetting on the setup time and concluded that higher learning rate promotes more frequent production of smaller batches. Since this constant rate of low volume production is widely desirable for stabilizing production planning (Gunasekaran et al., 2007), the estimation of the learning rate in the Pre build phase for both the novice and the expert in this study can inform the decision-making on this field. As discussed earlier however, demand fluctuation usually disrupts production planning and such disruption might lead to inactive periods where the operator’s learning rate deteriorates with forgetting.

It is worth noting, however, that the machine time, which constitutes a major part of the total process time, was not included in this

learning curve since build time is independent of operator experience. In this specific domain, however, Baumers et al. (2016) studied the static economies of scale that can be found in the machine throughput, which makes this study a complementary piece to other investigations of the scalability of AM. Furthermore, while AM is appropriate for customizable and geometry-complexed products (Conner et al., 2014), this study utilizes the production of identical parts informing decision making in low volume production scenarios, as in the case of AM in the spare parts industry (Gibson et al., 2010; Mellor et al., 2014).

5.1.1. Organizational learning

In the strategic management literature, the resource-based view describes resources as a key to deliver competitive advantages (Bromiley and Rau, 2016). To remain competitive in the market, some organizations thus implement different practices and methods that facilitate and support learning. This gives them a capability that has been commonly referred to in the literature as “organizational learning” or the “learning organization” (Serrat, 2017) which is marked by workers continually being empowered to acquire new knowledge, seek new solutions and receive feedback and learn new approaches as a result of the testing (Goh, 2003). The observed learning phenomena in this study demonstrate the process of knowledge acquisition by machine operators (Lapré and Van Wassenhove, 2003). For instance, if a reduction in unit cost occurs as a function of this acquired knowledge, while other variables (e.g. information distribution) remain uniform, an organization is considered to be learning (Argote, 2012).

Another important factor that lies at the heart of this sustainable competitive advantage is “time compression diseconomies” (Dierickx and Cool, 1989). For this learning effect to be completely shown,

time is needed. Therefore, late movers in the same market need to spend the same time in order to accumulate the same experience (Cool et al., 2012). In other words, reducing the learning time in AM would result in increases in the unit cost, giving additional protection to the organization that was first to gain this learning capability.

5.1.2. The skills gap in AM

Although the perception that AM processes are fully automated is widespread, this study shows that AM operator action is required in most of the steps in the process. In fact, Despeisse and Minshall (2017) proposed that a lack of appropriate workforce skills and appropriate training programs forms a barrier to mass AM adoption. They also observed a lack of sufficient systematic AM training programs that facilitate in building AM skills. In this context, the learning curve in this study can give guidelines for training program developers and managers regarding the optimum training hours to be spent by a new inexperienced operator so that maximum productivity is achieved after training.

Correspondingly, it has been emphasized in the operations management literature that variety in product mix causes a decrease in productivity; therefore, strategies and techniques have been developed to prevent such decrease (Hu et al., 2008). Apart from the first step, which requires coordinating the received CAD drawings in the specified build volume, all other steps that require direct involvement of the AM operator are almost the same for any desired 3D printed part and do not necessarily demand more experience. Therefore, the theory behind the decrease in productivity as a result of a higher variety in product mix might not be applicable in the AM context. Training managers therefore might utilise written, step-by-step manuals, known as Standard Operating Procedures (SOPs),

that illustrate how to perform a routine set of activities in their taught programs.

Having discussed the results on the learning effect in AM, the next section discusses the results obtained on the impact of AM on inventory-related costs.

5.2. Discussion of the effect of AM on inventory-related costs

As shown in Section 4.2, the results pertaining to the effect of AM on inventory-related costs reveal that inventory and stockout costs are not sufficiently high to cancel out the manufacturing cost advantage of IM, as shown by the total supply chain unit cost estimates. This supports the developed conceptual model presented in Section 4.2.1 where conventional manufacturing technologies are prescribed for market conditions where stockout cost is low and customer orders are received in low volumes. This section discusses the results in the context of four streams of literature: i) Demand volatility, ii) absence of inventory iii) effect of AM on supply chain complexity and iv) quality assurance aspects.

5.2.1. Demand volatility

In order to respond to customer demand in a timely manner, manufacturing companies procure raw materials and plan their work schedules ahead of actual demand, usually approached with the use of forecasting methods utilizing historical demand data (Syntetos et al., 2009). As identified by the seminal work of Davis (1993), disturbance to this readiness however can emerge from three main sources: supply, process and demand. In particular, Davis (1993) and McCutcheon et al. (1994) viewed disturbance caused by volatility on the demand-side as critical. Market demand that is

characterized by uncertainty or variability has been regarded as a driver of such disturbance (Gunasekaran et al., 2007).

Uncertainty in demand is identified when forecasting methods fail to predict future demand, be it high or low in volumes, which causes serious instability in production planning and scheduling (Tang and Grubbström, 2002). Consequently, mismatches and inefficiency occur in the process of determining the appropriate sequence and allocation of expected customer orders to the existing workload and machineries (Herrera et al., 2016). On the other hand, variability in demand prevents the production rate from being constant, which is undesirable from a lean manufacturing perspective (Bray and Mendelson, 2015). This research has studied a product with a demand that is attributed by both uncertainty and variability. If all product variants manufactured by the host company have been considered, then such attributes in demand can magnify the disturbance to their production planning and scheduling.

This study however confined the analysis to one product only. Particularly in the 3rd pathway, AM is found to be valuable in mitigating the effect of demand uncertainty by preventing unpredictable stockout events from happening. This in turn causes more stability in production scheduling as production managers can be confident that errors in their forecasts, which is in volatile markets deemed inevitable, will not be disruptive to their assignment of production schedule to the dedicated technology they utilised due to the coexistence of AM as a side flexible technology. In other words, using AM to cater for unpredictable demand will allow them to allocate the production resources to expected customer requests without concern for stockouts.

AM in the simulation model however did not relieve the effect of demand variability, which could have resulted in a more levelled and

smooth production, hence fewer quality issues (Smalley, 2004). If such relieve has occurred in this simulation model, repeated production of similar batch quantity via IM would have been observed. Sasson and Johnson (2016) nonetheless studied the coexistence of AM with traditional mass manufacturing technology to produce a variety of items in one production line. They found that AM in fact can isolate demand variability through assigning products with disruptive low volume demand to AM while levelling the production for the conventional manufacturing technology. This suggests that AM can lessen the effect of demand uncertainty for manufacturing firms with one-product but would be more appealing to be adopted for multiproduct firms as a means of moderating the effect of both demand uncertainty and variability. Another key issue in the SCM realm is supply chain complexity. This study offers insights into the effect of AM on this subject, which is discussed in the next section.

5.2.2.AM and supply chain complexity

Supply chains have been evolving greatly in the past two decades resulting in more complex structure and content (Cannella et al., 2017; Modrak and Soltysova, 2017). Thus, the term supply chain complexity emerged referring to the degree of interrelation and connectedness within a system where an alteration in one part can lead to an impact on other parts of the system (Mariotti, 2007). Shedding more lights on its mechanism, Bozarth et al. (2009) differentiated between external sources of supply chain complexity that emerge from either upstream or downstream and internal manufacturing ones.

A main contributor to complexities emerging internally from manufacturing is unstable production scheduling and planning (Vollmann, 2005), which is, as discussed earlier, triggered by

uncertainty in demand. Demand variability also is another factor discussed by Bozarth et al. (2009) that drives more complexity to the supply chain as it changes the reordering points and therefore changing production rates. As elaborated in the previous section, the ability of AM to isolate, or mitigate, the impact of these two factors makes it an attractive option in simplifying the structure of its supply chain.

Accordingly, several publications have suggested that AM can streamline the supply chain by cutting down the number of processes and assemblies needed to create a product (Cotteleer and Joyce, 2014; Janssen et al., 2014; Mohr and Khan, 2015; Ford and Despeisse, 2016) mainly due to its unique feature known as parts consolidation, which describes the capability to produce several parts in one build (Yang et al., 2015). However, stating that AM can reduce supply chain complexity is inadequate without considering its adoption context. This argument for instance might hold true for certain scenarios where traditional manufacturing methods are completely replaced with AM, especially in an industrial setting where complex products with subcomponents pertaining to each product are manufactured and processed. This is nonetheless not necessarily true in contexts where products are standard, as the case in this study.

It should be illuminated therefore that AM does not necessarily simplify the supply chain. As demonstrated by Haghighat Khajavi et al. (2020), employing AM in a supply chain can result in varying degrees of negative or positive effects on supply chain complexity. In this study, AM was introduced in two distinct ways. In the 2nd pathway, for instance, the supply chain appeared simpler whereas it seems to attach more processes and steps to the system in the 3rd pathway, resulting in more supply chain complexity. This is not to mention the additional complexity incurred while planning the

process of each pathway. Furthermore, process planning is the activity of determining how a part will be manufactured (Basinger et al., 2019). This task involves setting the process parameters in a manner that ensures quality and productivity. AM and IM are different processes and each of which requires specific experience and know-how of the precision of the technology. Recent work has documented process planning challenges when combining AM with other subtractive manufacturing methods (Chen and Frank, 2019). This is particularly because the parameters required for AM (e.g. part orientation) that need to be optimized are different from those needed for the other manufacturing technologies (Chen and Frank, 2019; Rossi and Lanzetta, 2020). Therefore, the decision to adopt AM for the mere motive of lowering supply chain complexity level may not always be successful.

5.2.3. Absence of inventory

Keeping an inventory of finished goods for future sales is a decision that companies usually take for different motives. Hedging against demand uncertainty is an important reason (Hu et al., 2003) which has been shown to improve customer satisfaction (Jung et al., 2004). Two main questions however must be addressed before determining the optimal inventory level, as discussed in Section 2.5 of this thesis, these are: when to produce and how much (Cobb, 2017). The goal is to optimize for a satisfactory customer service level and at the same time minimizing inventory-related costs. As seen in this study, such costs are exhibited in three distinct forms: holding, ordering and stockout costs. Decision making in this realm is heavily reliant on finding a desirable trade-off between these costs.

Before embracing one trade-off over another however, a service level is usually agreed upon, which is typically represented in the

form of a ratio between zero and one representing the probability that future customer orders will be fulfilled (Chakraborty and Bhuiya, 2017). Furthermore, diminishing returns is exhibited in the service level curve where the higher the service level the more inventory is required to be held with a lesser probability of preventing stockout events from happening (Akçay and Xu, 2004). Therefore, from a theoretical perspective, achieving 100% service level is deemed unfeasible, as infinite inventory level is needed to account for all future stockout possibilities.

This study however reveals an interesting insight pertaining to the service level. Achieving a high service level without holding large inventories can be an option with the adoption of AM. Employing AM in production lines to improve the customer service level, mainly through reducing the possibility of future stockout, is one possible solution to alleviate the dilemma of choosing between incurring the cost of holding large amount of inventory or holding low inventory level but accepting lost profits caused by probable stockout events (Christopher, 2016). This also in turn should positively impact the determination of the amount of safety stock, which companies usually hold to fulfil orders that might be received during the replenishment periods (Radasanu, 2016). The coexistence of AM as a flexible manufacturing technology in production lines permits safety stock level to be dropped to its minimal level since orders during the replenishment period can be met utilizing AM. From a quality management perspective however, certain aspects pertaining to the adoption of AM must be carefully dealt with. These aspects are discussed next.

5.2.4.AM quality assurance aspects

While this research takes a supply chain perspective, practical considerations related to AM implementation should be noted. One

main practical issue is related to the quality management of parts produced by the pathways that employ AM (i.e. 2nd and 3rd pathways). Adopting AM in various industries has been hindered by several issues, mainly revolving around reliability and quality assurance (Brajlih et al., 2011). In this research, AM is utilised for production settings where demand is received in low to high volumes. This has led to the utilization of AM for batch production, which entails certain quality risks. The first of these risks is related to the quality control aspect of the manufactured parts. In each AM build, a higher number of layers, which is a necessity in this research case, increases the probability of defects in the form of various types of voids. These voids can be caused by certain environmental factors or inherent process variation (Roy and Wodo, 2019). This means that there expected to be defected parts with each AM build. A point was made by Tofail et al. (2018) who pointed out that there is an observed variation in the quality of parts produced via AM from one build (i.e. batch) of parts to another.

Besides, achieving an appropriate level of quality assurance with AM varies from one part to another. The complexity of geometry, the required surface finish, and the interior lattice structure are all contributing factors to the capability of AM to produce reliable and quality assured parts (Pereira et al., 2019). Quality, therefore, is assessed differently based on the part feature and its health and safety requirements. In this case study, the pipe fitting is relatively not a complex part neither a risky one; hence, quality is not a concern for this part as with parts, for instance, in the aircraft industry (Pereira et al., 2019). Therefore, it is essential to assess the level of quality assurance required for each part beforehand to ensure that manufacturing firms neither overestimate nor underestimate the needed quality assurance activities (Wing et al., 2015). The necessity to develop quality assurance guidelines and

standards for AM has been recognized by scholars and practitioners (Bourell et al., 2009) and constant effort has been made in this area, albeit these guidelines are not fully established yet (Weller et al., 2015). These quality standards and guidelines form the cornerstone upon which precision manufacturing can be achieved (Russell, 2017).

Besides, this lack of industry-accepted quality standards for AM prevents regulators from certifying parts fabricated by AM (Seifi et al., 2017). Devolving the appropriate certification processes for AM has been discussed as a key success factor for its wider adoption (Gausemeier et al., 2011). Although efforts to develop certification processes for AM was made (e.g. Seifi et al., 2017; Bae et al., 2018), the complexity of each AM machine makes it challenging to maintain a high level of repeatability and reliability (Pereira et al., 2017; Pereira et al., 2019). When compared with the quality and reliability level of parts produced by IM therefore, AM is considered an inferior option (Newman et al., 2015). It is still possible, however, to take proactive measures to ensure AM produced parts conform to the quality requirements. For the AM machine proposed in this research (i.e. LS), powder, for instance, should be tested in advance for any inconsistencies in particle size. This is to avoid harming the structural integrity of the part by using incorrect process parameters such as laser power (Gibson and Shi, 1997). Another important consideration is that parts in the AM pathways must be designed in a way that ensures the ease of powder removal during post processing, which if left unremoved could cause further negative effects on structural integrity (Diegel et al., 2010). AM parts can be tested in a similar manner that IM parts are tested. For IM, batch testing is performed through statistical sample testing where one part is selected to test its tensile and compression, representing the mechanical properties of the entire batch (Breyfogle III, 1992).

While not yet widely adopted for AM, Non-Destructive Testing (NDT) also is a key test for quality assurance of batch production that has recently captured the attention of AM researchers (Lu and Wong, 2018).

Having discussed the results on the impact of AM on inventory-related costs, the next section provides a discussion of the results obtained on the impact of AM on supply chain flexibility.

5.3. Discussion of the effect of AM on supply chain flexibility

This section discusses the findings presented in Section 4.3 related to the impact of AM on the four distinct supply chain flexibility types: i) volume, ii) mix, iii) delivery, and iv) new product.

While the developed conceptual model presented in Section 4.3.1 suggests a positive effect of AM on volume and delivery flexibility, the findings obtained through the case study offer different insights. When compared with another conventional manufacturing technology, AM's positive effect on supply chain flexibility might not be sufficient. IM, in the case study, showed higher levels of volume and delivery flexibility compared to AM. Further discussion of these results in relation to the internal flexibility competency literature is offered in the next section. This is followed by a particular contextualization of the results related to the AM effect on the mix and new product flexibility.

5.3.1. Internal flexibility competencies

In terms of volume flexibility, the lower level shown by the proposed AM route in this study contradicts the proposition advocated by Verboeket and Krikke (2019) that AM increases volume flexibility from a supply chain perspective. While this might be accurate from a manufacturing perspective, a supply chain perspective

necessitates the inclusion of inventory as one important input in measuring flexibility, as pointed out by Lau (1999) who emphasized the need to incorporate other functions in the company when targeting higher flexibility level. The lower level of volume flexibility in the AM supply chain is in alignment with the results presented by Evers et al. (2018) who found moderate evidence of the capability of industrial AM system to flexibly vary the production volume.

It should be noted, however, that while these flexibility capabilities are required from a supply chain perspective, established from the customer standpoint, they are still caused by internally developed competencies. Some of these internal competencies are found in the form of machine, material handling, routing and labour flexibilities. As indicated by Zhang et al. (2003), these competencies are strongly and positively correlated with two external capabilities: mix flexibility and volume flexibility. The existence of the labour flexibility in the AM systems was evident in recent research (Evers and Potter, 2017; Evers et al., 2018) which should correlate with high volume flexibility level. Nonetheless, when compared with a supply chain that relies on dedicated production lines, as in the case of IM in this study, the AM supply chain does not commensurate to the same flexibility level that of IM. This shows the significance of holding a buffer stock to flexibly respond to rapid changes in volume and delivery, a point that has been repeatedly emphasized in the literature (Jack and Raturi, 2003; Reichhart and Holweg, 2007; Angkiriwang et al., 2014).

5.3.2.A flexibility aspect of AM

AM shows lower changeover time and cost of new product introduction to the system, which is indicated by the greater mix and new product introduction flexibility compared to IM (i.e. 0.33 hrs and €0 for AM compared to 4.91 hrs and €30,000 for IM, respectively).

As observed in the high rate of AM adoption in industries that entail the need for either mass customization or economically low production volumes (Berman, 2012), this study provides insights into possible aspects that led to such adoption. From a flexibility perspective, the important aspect of lack of tooling in the AM technology fosters: (i) easier introduction of new products into the system and (ii) achievable product proliferation strategies. Whilst the latter has great benefits associated with preserving and acquiring additional market share (Mainkar et al., 2006), it leads to substantial operational problems linked with less responsive delivery performance (Salvador et al., 2002). This might explain the lower delivery flexibility level for the AM supply chain in this study (i.e. 75.35% compared to 92.85% for IM) as it seems to be impacted by the lack of instant shipment using buffer stocks.

The lack of tooling in AM makes it a qualified manufacturing technology to address a challenge that has emerged in the manufacturing realm recently. Moreover, the development of industrial new technologies in connection with the Internet of Things (IoT) has driven the 4th industrial revolution, collectively known as Industry 4.0. One important concept that has emerged from this revolution is the smart factory, an interlinked and flexible manufacturing system that utilizes constant feedback from linked processes and production methods to adapt and cope with new market and environment conditions (Mehrpooya et al., 2019). Sjödin et al. (2018) have reported several challenges that hinder the successful implementation of the smart factory. One major challenge was the need for adopting contemporary approaches that support more agile and rapid products to the marketplace. In addressing this challenge, Sjödin et al. (2018) urged the introduction of agile product development approaches as opposed to the traditional Stage-Gate one. One implication of adopting Agile product

development approach is the production of a Minimum-Viable-Product (MVP) (Gielisch et al., 2019; Nguyen-Duc et al., 2019) for faster launch to the market. The unique characteristic of the lack of tooling in AM facilitates the successful production of MVPs and, hence, flexible iterative product development processes in the smart factory. The utilization of AM for creating MVPs has been recently validated by Storbacka (2018) and described in details by Reichwein et al. (2020).

Based on these results, a model that captures the fitness of the different flexibility capabilities with major supply and demand characteristics is offered here in Figure 5.1. Based on this model, a supply chain can be either in a strategic fit or lack thereof. A flexible manufacturing technology such as AM would be most appropriate for market environments with low demand volumes as widely suggested in the AM literature (e.g. Ruffo et al., 2006; Atzeni and Salmi, 2012). This, in turn, can result in attaining higher mix and new product flexibility levels, which are the proper flexibility metrics to be approached in such environments. Utilizing flexible manufacturing technologies, such as AM, in markets with high demand volumes however would result in a lack of strategic fit. As seen in this research, volume and delivery flexibility can deteriorate if AM was utilised for high demand volumes.

On the other hand, a dedicated manufacturing technology such as IM would require higher demand levels to ensure the appropriate realization of economies of scale (e.g. Achillas et al., 2017). Hence, greater volume and delivery flexibility levels can be achieved in response to sudden changes in market requirements. Conversely, utilizing dedicated manufacturing technologies to cater for orders received in low volumes is a misfit from a strategic perspective.

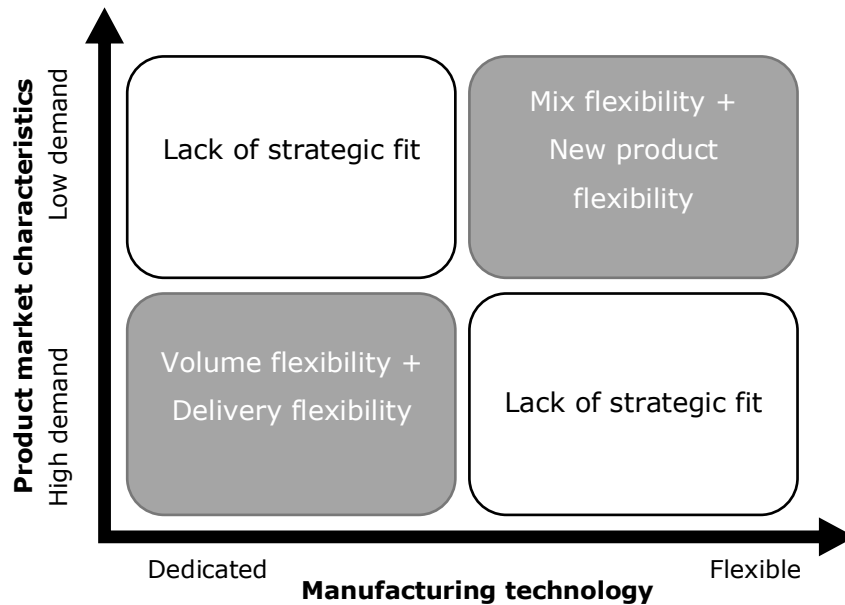


Figure 5.1: The relationship between the external flexibility capabilities, manufacturing technology and demand volume level.

To sum up, demand can be characterized based on the expected volume level. For markets with high demand levels, dedicated manufacturing technologies are well-suited to achieve higher levels of volume and delivery flexibility, mainly due to the flexibility offered by the produced buffer inventory. Conversely, for markets with low demand volumes, flexible manufacturing technologies are compatible to achieve higher levels of mix and new product flexibility. These two types of technologies (dedicated and flexible) both help realize distinct supply chain flexibility aspects. Flexible manufacturing technologies can work as “*capacity buffer*” (Van Kampen et al., 2010; Angkiriwang et al., 2014) while dedicated manufacturing technologies can be utilized to cope with uncertainty through building safety stocks (Manuj and Sahin, 2011), hence both technologies can increase flexibility but for different conditions. The same distinction applies to the commonly known philosophies: lean and agile, where lean increases responsiveness with minimum inventory while agile employs buffer stocks to respond to the

changes in demand volumes (Christopher, 2000; Qamar et al., 2018).

5.3.3. Summary of discussion

This chapter discussed and contextualized the results presented in Chapter 4 in their relevant streams of literature. In this chapter, a proposition is made that the results obtained in the examination of the learning effect in AM can be utilised to enhance the performance of the EPQ formula. These results also suggest that since the learning effect is found in AM operations, adopting AM contributes to the development of the learning organization and, hence, the attainment of competitive advantage based on the dynamic capability perspective of the RBV theory. These results related to learning in AM also supports the facilitation of training programs to address the skill gap reported in the literature.

Section 5.2 discussed the results pertaining to the effect of AM on inventory-related cost. Based on these results, it is suggested that AM can be utilised to moderate the effect of demand uncertainty and facilitates stable production scheduling and planning. The results also suggest that AM can either increase or decrease the supply chain complexity based on its orientation within the chain. Finally, these results indicate that AM can contribute to the realizing of higher service levels that are difficult to achieve with other conventional manufacturing technologies.

Section 5.3 discussed the results obtained on the effect of AM on supply chain flexibility in relation to previous studies that focused on internal flexibility aspects of AM. The results related to the positive effect of AM on flexibly introducing new products to the system suggest the appropriateness of this technology to address a challenge that is faced when implementing the concept of the smart factory. A proposed model also is shown at the end of this section

that elaborates the flexibility measures and context in which AM is well-suited.

Having discussed the findings of this thesis, the next chapter concludes this research by providing a summary of this thesis, the original contributions realized, the limitations and recommended future work.

6. Conclusion

This chapter concludes and summarizes the key findings of this research. It begins by reviewing the progress made to address the principal research objectives of this doctoral project. It then proceeds by detailing the original contribution made by this research. This chapter ends by acknowledging the limitations of this research and provides recommendations for future work.

6.1. Thesis summary

In an attempt to bring more clarity to the impact of adopting AM in markets that are characterized by demand volatility, this thesis presented a systematic examination of AM's impact on responsive supply chain performance. The three research objectives identified in Section 1.3 have been addressed as follows:

- By assessing the often-overlooked aspect of operator learning in AM, which is reflected in the erroneous perception that AM is a largely automated technology, this research adds a practical perspective which is highly relevant to the adoption of AM technologies. The estimation of learning curve models demonstrates that it is possible to establish, albeit tentatively, a rate by which operator labour inputs are reduced as an AM operator becomes more productive. This informs realistic modelling of the direct labour cost incurred for each build repetition. According to the model utilised in this research, it indicates a reduction of 32.26% of labour time with each repetition of a task by a novice operator compared to a reduction of 19.57% for an expert operator. By analyzing the learning effect for each phase independently however, the built model indicates a higher rate of reduction for both the novice and the expert in the Pre build phase compared to the

Post build phase. By using these results in the proposed direct labour cost model, the novice operator showed lower direct labour cost compared to the expert in each build after the 1st build repetition. Using these estimates as inputs to the EPQ model can add a more accurate realization of the optimal balance between setup and holding costs.

- The constructed conceptual model offers a distinction of the possible production configurations that AM can take based on the expected stockout cost and demand volume level. In addition, the model constructed for the investigation of the impact of AM on inventory-related costs is based on the hypothesis that the adoption of AM in place of or beside IM permits the elimination of some supply chain costs, including the opportunity costs resulting from stockouts. Despite this cost reduction in the case study, the total supply chain costs suggest that a supply chain utilizing IM as the only manufacturing method is more cost-effective than the competing supply chains (AM only or AM combined with IM). This cost advantage is chiefly the result of the amortization of tooling expenses and hence a form of economies of scale, as opposed to a supply chain adopting AM as either a single or complementary manufacturing method. This investigation also suggests that AM can be employed to mitigate the severe effect of demand uncertainty hence facilitating stable production scheduling and planning, mainly due to its effectiveness in responding to customer orders that would otherwise be rejected when relied upon dedicated manufacturing technologies such as IM. While such advantage helps reduce the complexity of supply chains, the constructed models nonetheless imply that AM can either increase or

decrease the supply chain complexity depending on its orientation within the chain. Additionally, this study indicates that greater customer service level, in the form of more available inventory and less stockout probability, can be reached utilizing AM as a flexible technology capable of catering production orders on-demand.

- In the supply chain literature, it has been emphasized that managing manufacturing systems should incorporate flexibility aspects as a core objective along with cost, quality and dependability. There were no studies, however, that examined how adopting AM affects these flexibility aspects in comparison with other conventional manufacturing technologies. This thesis provides a conceptual framework that maps how certain AM characteristics can positively affect supply chain flexibility aspects based on key market requirements. In addition, by conducting an inter-process comparison between AM and IM using the data collected from the host company, this thesis provides quantification of these aspects. The findings obtained in this case study indicate that an AM supply chain without inventory seems to be relatively ineffective in responding rapidly to different demand volumes (i.e. 58.70% for AM compared to 65.68% for IM) and/or delivery times (75.35% for AM compared to 92.8% for IM). Also, a supply chain that utilizes IM would be more attractive when aiming at increasing volume flexibility due to the inverse proportion between the unit cost of its products and its volume flexibility. However, due to the lack of tooling, AM provides more flexibility in producing a wide range of products with less time (i.e. 0.33 hrs for AM compared to 4.91 hrs for IM) and in cheaper introduction of new products to the system (and €0 for AM

compared to €30,000 for IM). Furthermore, this study suggests that lead-time compression enabled by the instant production of AM technology will not be sufficient to outweigh the lead-time compression attained by a supply chain employing a buffer stock strategy produced by IM. On the other side, AM can significantly increase supply chain flexibility in production settings where customized products or low production volumes are demanded. This is attributed mainly to the lack of tooling in AM, permitting a cheaper and faster introduction of new products to the system.

6.2. Original contributions made by this research

To assess the costs and benefits of AM, various studies have examined certain aspects of this technology with increasingly ill-structured aspects are being taken into account (Thompson et al., 2016). This thesis contributes to the knowledge base by assessing the costs and benefits of AM from a supply chain perspective. Figure 6.1 shows the contribution of this research in relation to the literature that deals with the costs and benefits of AM.

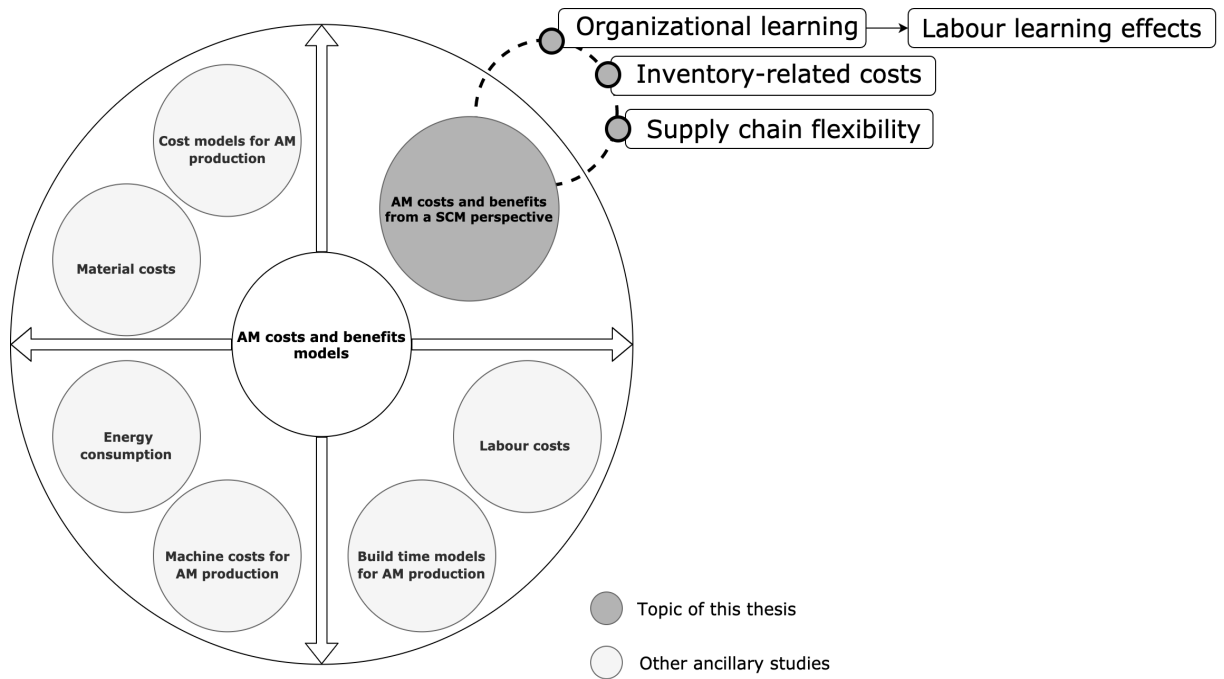


Figure 6.1: The positioning and contribution of this research to the AM literature. The outward movement characterizes the increase of the scope of models that assess the costs and benefits of AM.

This thesis has reviewed the recent literature that relates to and deals with the impact of adopting AM on responsive supply chain performance and has consequently identified three research gaps that were then addressed in this thesis. These reviews have shown a lack of detailed scholarly research that examines the impact of AM adoption on key aspects that relate to the responsive supply chain performance. These aspects are: the learning effect offered by AM, its impact on inventory-related costs and its impact on supply chain flexibility. Following the execution of this research, several original contributions are made, and they are summarized as follows

1. The examination of the learning effect in AM for both novice and expert operators and the development of a labour cost model that considers this effect.

Perhaps contrary to AM's public image as an "automatic" process, significant labour inputs are required in the AM process (Ruffo et al., 2006; Baumers et al., 2017). However, the literature still falls short

on examining the existence of learning effect in AM and on discussing systematically how operator learning can result in economies of scale of the dynamic type, as described by Haldi and Whitcomb (1967). In response to this gap in knowledge, this thesis offers two main contributions. First, it provides an experimental measurement of the learning rate to help explain production efficiency increases observed in AM. This rate can be, for instance, utilised for more efficient scheduling and planning of workload and initiatives to reduce quality defects as workers learn and improve their performance by repetition (Jaber, 2006; Jaber and Guiffrida, 2008), especially in processes that require significant labour inputs such as AM. Knowledge of such learning rates is highly actionable since it assists in increasing the realism of setting accurate labour standards and production targets (Smunt and Watts, 2003). The second contribution is the built cost model that incorporates these experimentally investigated learning rates into direct labour costs, thereby filling a gap in the AM literature relating to the dynamic part of the economies of scale. It is anticipated that these results pertaining to the learning effect in AM will inform researchers and decision-makers in a range of problem settings. These include improvements in manufacturing strategy (Anzanello and Fogliatto, 2011), the determination of appropriate pricing and marketing planning (Feng and Chan, 2019), informing the budgeting of training programs (Charland et al., 2011), establishing subcontracting relationships and transfer of production sites (Smunt and Watts, 2003) and the facilitation of production scheduling solutions (Mosheiov, 2001) and lot-size (Jaber and Peltokorpi, 2020). These results also guide supply chain managers on developing, through labour learning, the organizational learning capability which, alongside the characteristic of diseconomies of the time compression, forms a valuable resource that enables AM supply chains to gain a sustainable competitive advantage in markets with

demand volatility. As the lack of appropriate skills has been suggested as one of the main barriers for mass adoption of AM (Despeisse and Minshall, 2017), this thesis offers directions to this field by recommending a sufficient training period after which maximum productivity can be achieved by novice operators. Furthermore, this study suggests that more variety in the product mix in the operations of AM does not necessarily correlate with lower operator productivity as in many other manufacturing techniques. This further underlines the value of teaching standard operating processes in AM training programs.

2. The conceptual model of inventory-related costs in AM and the systematic examination of the effect of adopting AM on supply chain cost when operates in volatile markets.

AM is a process that does not require dedicated tooling, such as moulds, cutting implements or dies; therefore, there are no tooling costs that are amortised over production runs (Weller et al., 2015). This feature, the lack of tooling, indicates that AM can produce the exact customer quantity without the need of incurring the cost of holding excess inventory. It is thus argued that AM could reduce the inventory-related costs (Thomas and Gilbert, 2014). Baumers and Holweg (2016) also have argued that realistic cost models should be used as a basis for the statement of cost-quantity relationships in AM and should reflect ill-structured elements. Therefore, evaluating AM from a supply chain perspective raises the necessity to include inventory-related costs as an ill-structured part of the AM cost model.

To date, no studies have addressed the cost-effectiveness of AM in market environments that are characterized by demand volatility while accounting for inventory-related costs and the opportunity

costs resulting from stockouts. This thesis is therefore in line with the move towards increased realism in the investigation of the commercial aspects of AM through the inclusion of the cost impact of inventory and stockouts. It specifically contributes to production settings where demand is both uncertain and volatile and hence an assessment of the possible technology investments is usually undertaken that could mitigate the disruptive effect of such demand attributes. The investigation was undertaken to assess the impact of AM on inventory-related costs yields insight into the relative magnitude of supply chain costs compared to manufacturing costs which have been ignored in previous cost models of AM. On a general level, this shows that inter-process comparisons of the commercial performance of different manufacturing processes can be made more realistic by including such aspects. Especially if the differential in pure manufacturing cost is smaller than in the investigated case, order costs, carrying costs and stockout costs may form a decisive part of the overall case for or against the adoption of AM.

3. The conceptual framework of supply chain flexibility in AM and examination of the impact of AM on distinct supply chain flexibility aspects in comparison with another dedicated manufacturing technology under demand volatility.

Several studies have suggested that AM could increase manufacturing flexibility (e.g. Cotteleer and Joyce, 2014; Weller et al., 2015; Brettel et al., 2016). However, there was little research on systematically examining the impact of AM on supply chain flexibility in markets that are characterized by volatility in demand. Also, there were no studies that approached such examination in comparison with conventional manufacturing technology. The investigation executed in this research to fill this gap realistically demonstrates the feasibility of adopting AM in production

environments with demand volatility. When considering AM as a choice to increase supply chain flexibility in volatile environments that entails potentially high production volumes, AM might be ineffective compared to other conventional manufacturing technologies. The obtained results of this part of the thesis will inform both practitioners and scholars to accurately predict what effects the employment of AM will cause on distinct supply chain flexibility aspects in relation to demand attributes.

6.3. Limitations and future work

This thesis would be incomplete without an appreciation of its limitations. This section discusses these limitations and recommends various aspects that should be considered in future work. Each one of the research objectives outlined in Section 1.3 has its limitations and recommended future work. The limitations and future work for each one of these examinations, therefore, are discussed next in the order followed in this thesis.

For the examination of the learning effect in AM, certain process boundaries should be acknowledged. This investigation has focused on the manufacture of identical parts, therefore offering insight into AM application targeting standard components rather than customized one-off products. While this represents segments of the market under study (i.e. market with volatile demand) such as the spare parts industry, further incorporation of other product characteristics will include other segments of the market. This study also did not incorporate design activities preceding the first step in the process map and how the outputs of the AM process feed into wider downstream supply chains. Therefore, future work to determine the possibility of gaining similar increasing returns in these activities is needed. Incorporating these variations will enhance the representativeness of the developed model in real-

world scenarios. Increasing the number of experiments in future studies and eliminating any possibility of machine interruption will allow for a higher level of generalizability.

Future work also should consider the effect of learning on the supply chain from a strategic perspective, where the other entities in the supply chain are involved in the analysis. In addition, AM production scheduling and planning is still in its nascent stage (Li et al., 2017), and incorporating the learning rates for both the Pre build and Post build phases into the relevant equations of planning and scheduling (e.g. EOQ) will help establish this field. This can be approached by first constructing the planning and scheduling equations and then validate them by measuring their cost performance in comparison with the current AM scheduling practices, which is typically undertaken based on the operator prior experience.

For the examination undertaken to understand the impact of AM on inventory-related costs, several limitations also are recognized. First, the model of stockout costs is limited in that it ignores more severe consequences, such as the permanent loss of customer goodwill in the future (Schwartz, 1966). Second, other manufacturing companies will in reality cater for different types of customers, such as retailers, which was ignored in the model. Had this diversity been taken into account in the simulation, different outcomes related to inventory-related costs might have been observed. Third, from a technical point of view this investigation is limited in that it assumes that the two investigated technologies and their materials can simply be interchanged. This ignores knock-on changes in post processing and quality assurance which are likely to affect the overall adoption rationale. Future work should consider multiple product variants with more complex geometry to allow for more generalizable results. Additionally, while other ill-structured cost elements such as build failure are important, this study focused

on the inventory-related costs element and incorporating the other elements should be considered in future work.

Furthermore, the developed conceptual model (Figure 4.9) in this thesis should be validated in different industries. The case study in this thesis was performed in the pipe industry but other industries with different materials and conventional manufacturing technologies should be investigated to gain further insights into the developed model. Additionally, AM can be combined with IM in two distinct scenarios. The first was shown in this thesis, where AM is employed for orders that are otherwise will be rejected by the conventional manufacturing technology. The second scenario however was not examined in this thesis where AM is employed for products with disruptive nature while conventional manufacturing technologies serve predictable orders (Sasson and Johnson, 2016; Braziotis et al., 2019). It is imperative therefore to examine the feasibility of such scenarios in future studies in this area. These scenarios can be examined through scenario modelling to analyze the sensitivity of different parameters such as part geometries and supply chain structure.

For the examination of the AM effect on supply chain flexibility, this study is not inclusive of all possible aspects, and some limitations should be noted. First, as stated above the chosen product is standardized and usually ordered by wholesalers and stockiest in high volumes. Had different product with complex geometry and relatively low demand volumes been chosen, different flexibility metrics would have been observed. This option, however, could not be realised due to lack of industrial access and time constraints and should be left for future studies. Second, this study also did not consider other forms of responsive supply chains (i.e. supply chains that require flexibility). For instance, other production lines utilisepostponement strategies that allow for certain elements of a

modular product to be produced in batches whereas the production of the remaining elements is deferred to the latest point near to the customer request. In these cases, certain features of the manufactured product will be customized based on customer preference, which requires various degrees of customization. This will examine the capability of AM to increase certain flexibility aspects (i.e. internal ones such as process, program and labour or external ones such as delivery or postponement). Studying such cases and examining the effect AM would yield on flexibility will permit wider exploration. Future studies also should consider different product types within the same range of demand volatility to allow for more generalizable conclusions related to the effect of AM on flexibility.

Furthermore, to ensure a more realistic assessment of the impact of adopting AM, future studies should conduct pilot experiments where AM is employed for real-world production settings. Conducting such pilot studies will ensure that the various effects of certain practical issues are considered and thus preventive and proactive actions are proposed. Based on such studies, the development of safety measures helps to establish industry-accepted quality standards which are needed for regulators to certify parts produced via AM.

7. Appendices

7.1. Appendix A

Table 7.1: Percentage Points of the Chi-Square Distribution (ν) degrees of freedom (Rossetti, 2015).

$\nu \backslash \alpha$	0.1	0.05	0.025	0.01	0.005	0.0025	0.001	0.0005
1	2.706	3.841	5.024	6.635	7.879	9.141	10.828	12.116
2	4.605	5.991	7.378	9.210	10.597	11.983	13.816	15.202
3	6.251	7.815	9.348	11.345	12.838	14.320	16.266	17.730
4	7.779	9.488	11.143	13.277	14.860	16.424	18.467	19.997
5	9.236	11.070	12.833	15.086	16.750	18.386	20.515	22.105
6	10.645	12.592	14.449	16.812	18.548	20.249	22.458	24.103
7	12.017	14.067	16.013	18.475	20.278	22.040	24.322	26.018
8	13.362	15.507	17.535	20.090	21.955	23.774	26.124	27.868
9	14.684	16.919	19.023	21.666	23.589	25.462	27.877	29.666
10	15.987	18.307	20.483	23.209	25.188	27.112	29.588	31.420
11	17.275	19.675	21.920	24.725	26.757	28.729	31.264	33.137
12	18.549	21.026	23.337	26.217	28.300	30.318	32.909	34.821
13	19.812	22.362	24.736	27.688	29.819	31.883	34.528	36.478
14	21.064	23.685	26.119	29.141	31.319	33.426	36.123	38.109
15	22.307	24.996	27.488	30.578	32.801	34.950	37.697	39.719
16	23.542	26.296	28.845	32.000	34.267	36.456	39.252	41.308
17	24.769	27.587	30.191	33.409	35.718	37.946	40.790	42.879
18	25.989	28.869	31.526	34.805	37.156	39.422	42.312	44.434
19	27.204	30.144	32.852	36.191	38.582	40.885	43.820	45.973
20	28.412	31.410	34.170	37.566	39.997	42.336	45.315	47.498
21	29.615	32.671	35.479	38.932	41.401	43.775	46.797	49.011
22	30.813	33.924	36.781	40.289	42.796	45.204	48.268	50.511
23	32.007	35.172	38.076	41.638	44.181	46.623	49.728	52.000
24	33.196	36.415	39.364	42.980	45.559	48.034	51.179	53.479
25	34.382	37.652	40.646	44.314	46.928	49.435	52.620	54.947
26	35.563	38.885	41.923	45.642	48.290	50.829	54.052	56.407
27	36.741	40.113	43.195	46.963	49.645	52.215	55.476	57.858
28	37.916	41.337	44.461	48.278	50.993	53.594	56.892	59.300
29	39.087	42.557	45.722	49.588	52.336	54.967	58.301	60.735
30	40.256	43.773	46.979	50.892	53.672	56.332	59.703	62.162
31	41.422	44.985	48.232	52.191	55.003	57.692	61.098	63.582
32	42.585	46.194	49.480	53.486	56.328	59.046	62.487	64.995
33	43.745	47.400	50.725	54.776	57.648	60.395	63.870	66.403
34	44.903	48.602	51.966	56.061	58.964	61.738	65.247	67.803
35	46.059	49.802	53.203	57.342	60.275	63.076	66.619	69.199
40	51.805	55.758	59.342	63.691	66.766	69.699	73.402	76.095
50	63.167	67.505	71.420	76.154	79.490	82.664	86.661	89.561
60	74.397	79.082	83.298	88.379	91.952	95.344	99.607	102.695
70	85.527	90.531	95.023	100.425	104.215	107.808	112.317	115.578
80	96.578	101.879	106.629	112.329	116.321	120.102	124.839	128.261
90	107.565	113.145	118.136	124.116	128.299	132.256	137.208	140.782
100	118.498	124.342	129.561	135.807	140.169	144.293	149.449	153.167

7.2. Appendix B

Table 7.2: Kolmogorov–Smirnov Test Critical Values (Rossetti, 2015).

n	$D_{0.1}$	$D_{0.05}$	$D_{0.01}$
10	0.36866	0.40925	0.48893
11	0.35242	0.39122	0.46770
12	0.33815	0.37543	0.44905
13	0.32549	0.36143	0.43247
14	0.31417	0.34890	0.41762
15	0.30397	0.33760	0.40420
16	0.29472	0.32733	0.39201
17	0.28627	0.31796	0.38086
18	0.27851	0.30936	0.37062
19	0.27136	0.30143	0.36117
20	0.26473	0.29408	0.35241
25	0.23768	0.26404	0.31657
30	0.21756	0.24170	0.28987
35	0.20185	0.22425	0.26897
Over 35	$1.22/\sqrt{n}$	$1.36/\sqrt{n}$	$1.63/\sqrt{n}$

7.3. Appendix C

Table 7.3: Empirical and theoretical statistics for the inter-arrival time.

Bin number (j)	The interval $[l_j, r_j)$	IID observation (N_j)	Relative frequency ($\hat{p}_j$)	Cumulative relative frequency ($\hat{F}_X$)	Theoretical relative frequency (p_j)	Theoretical distribution (F_X)
1	[2,11)	10	0.34	0.34	0.37	0.37
2	[11,20)	5	0.17	0.51	0.19	0.57
3	[20,29)	4	0.14	0.65	0.13	0.70
4	[29,38)	3	0.10	0.75	0.09	0.80
5	[38,47)	0	0	0.75	0.06	0.86
6	[47,56)	2	0.06	0.82	0.04	0.90
7	[56,65)	1	0.03	0.86	0.02	0.93
8	[65,74)	0	0	0.86	0.02	0.95
9	[74,83)	0	0	0.86	0.01	0.97
10	[83,92)	0	0	0.86	0	0.98
11	[92,101)	0	0	0.86	0	0.98
12	[101,110)	0	0	0.86	0	0.99
13	[110,119)	0	0	0.86	0	0.99
14	[119,128)	0	0	0.86	0	0.99
15	[128,137)	0	0	0.86	0	0.99
16	[137,146)	0	0	0.86	0	0.99
17	[146,155)	1	0.03	0.89	0	0.99
18	[155,164)	0	0	0.89	0	0.99
19	[164,173)	0	0	0.89	0	0.99
20	[173,182)	0	0	0.89	0	0.99
21	[182,191)	1	0.03	0.93	0	0.99
22	[191,200)	0	0	0.93	0	0.9
23	[200,209)	0	0	0.93	0	0.9
24	[209,218)	1	0.03	0.96	0	0.9
25	[218,227)	0	0	0.96	0	0.99
26	[227,236)	0	0	0.96	0	0.99
27	[236,245)	0	0	0.96	0	0.99
28	[245,254)	0	0	0.96	0	0.99
29	[254,263)	0	0	0.96	0	0.99
30	[263,272)	0	0	0.96	0	0.99
31	[272,281)	0	0	0.96	0	0.99
32	[281,290)	0	0	0.96	0	0.99
33	[290,299)	0	0	0.96	0	0.99
34	[299,308)	0	0	0.96	0	0.99
35	[308,317)	1	0.03	1	0	1

7.4. Appendix D

Table 7.4: Empirical and theoretical statistics for the order quantities.

Bin number (j)	The interval $[l_j, r_j)$	IID observation (N_j)	Relative frequency ($\hat{p}_j$)	Cumulative relative frequency ($\hat{F}_X$)	Theoretical relative frequency (p_j)	Theoretical distribution (FX)
1	[200,400)	9	0.31	0.31	0.36	0.36
2	[400,600)	2	0.07	0.38	0.04	0.40
3	[600,800)	1	0.03	0.41	0.03	0.43
4	[800,1000)	1	0.03	0.45	0.02	0.45
5	[1000,1200)	1	0.03	0.48	0.02	0.46
6	[1200,1400)	0	0.00	0.48	0.01	0.48
7	[1400,1600)	0	0.00	0.48	0.01	0.49
8	[1600,1800)	0	0.00	0.48	0.01	0.50
9	[1800,2000)	0	0.00	0.48	0.01	0.51
10	[2000,2200)	0	0.00	0.48	0.01	0.52
11	[2200,2400)	0	0.00	0.48	0.01	0.53
12	[2400,2600)	0	0.00	0.48	0.01	0.53
13	[2600,2800)	0	0.00	0.48	0.01	0.54
14	[2800,3000)	0	0.00	0.48	0.01	0.55
15	[3000,3200)	0	0.00	0.48	0.01	0.55
16	[3200,3400)	1	0.03	0.52	0.01	0.56
17	[3400,3600)	1	0.03	0.55	0.01	0.57
18	[3600,3800)	0	0.00	0.55	0.01	0.57
19	[3800,4000)	0	0.00	0.55	0.01	0.58
20	[4000,4200)	0	0.00	0.55	0.01	0.58
21	[4200,4400)	0	0.00	0.55	0.01	0.59
22	[4400,4600)	0	0.00	0.55	0.01	0.60
23	[4600,4800)	0	0.00	0.55	0.01	0.60
24	[4800,5000)	0	0.00	0.55	0.01	0.61
25	[5000,5200)	0	0.00	0.55	0.01	0.61
26	[5200,5400)	0	0.00	0.55	0.01	0.62
27	[5400,5600)	0	0.00	0.55	0.00	0.62
28	[5600,5800)	0	0.00	0.55	0.00	0.63
29	[5800,6000)	0	0.00	0.55	0.00	0.63
30	[6000,6200)	0	0.00	0.55	0.00	0.64
31	[6200,6400)	0	0.00	0.55	0.00	0.64
32	[6400,6600)	0	0.00	0.55	0.00	0.64
33	[6600,6800)	1	0.03	0.59	0.00	0.65
34	[6800,7000)	0	0.00	0.59	0.00	0.65
35	[7000,7200)	0	0.00	0.59	0.00	0.66
36	[7200,7400)	0	0.00	0.59	0.00	0.66

37	[7400,7600)	0	0.00	0.59	0.00	0.67
38	[7600,7800)	0	0.00	0.59	0.00	0.67
39	[7800,8000)	0	0.00	0.59	0.00	0.68
40	[8000,8200)	0	0.00	0.59	0.01	0.68
41	[8200,8400)	0	0.00	0.59	0.01	0.69
42	[8400,8600)	0	0.00	0.59	0.01	0.69
43	[8600,8800)	0	0.00	0.59	0.01	0.70
44	[8800,9000)	0	0.00	0.59	0.01	0.71
45	[9000,9200)	0	0.00	0.59	0.01	0.71
46	[9200,9400)	0	0.00	0.59	0.01	0.72
47	[9400,9600)	0	0.00	0.59	0.01	0.72
48	[9600,9800)	0	0.00	0.59	0.01	0.73
49	[9800,10000)	1	0.03	0.62	0.01	0.73
50	[10000,10200)	0	0.00	0.62	0.01	0.74
51	[10200,10400)	0	0.00	0.62	0.01	0.75
52	[10400,10600)	0	0.00	0.62	0.01	0.76
53	[10600,10800)	0	0.00	0.62	0.01	0.76
54	[10800,11000)	0	0.00	0.62	0.01	0.77
55	[11000,11200)	9	0.31	0.93	0.01	0.78
56	[11200,11400)	0	0.00	0.93	0.01	0.79
57	[11400,11600)	0	0.00	0.93	0.01	0.80
58	[11600,11800)	0	0.00	0.93	0.01	0.82
59	[11800,12000)	0	0.00	0.93	0.02	0.84
60	[12000,12200)	0	0.00	0.93	0.03	0.86
61	[12200,12400)	2	0.07	1.00	0.14	1.00

7.5. Appendix E

1

Create

Name:

Customers Arrive

Entity Type:

Orders

Time Between Arrivals

Type:

Expression

Expression:

2 + Expo(23.5)

Units:

Days

Entities per Arrival:

1

Max Arrivals:

Infinite

First Creation:

0.0

OK

Cancel

Help

2

Assign

Name:

Customer Demand

Assignments:

Variable, Total Customers, Total Customers + 1

Variable, Demand, 200 + 1.1e+004 * BE(1A(0.147, 0.253))

<End of list>

Add...

Edit...

Delete

OK

Cancel

Help

3

Decide

Name:

Restart Production

Type:

2-way by Condition

If:

Expression

Value:

Inventory <= Reorder Point

OK

Cancel

Help

4

Assign

Name:

Lost Sales

Assignments:

Variable, Lost, Lost+1

Variable, Amount Lost, Amount Lost + Demand

<End of list>

Add...

Edit...

Delete

OK

Cancel

Help

5

Assign

Name:

Update Stockout Cost

Assignments:

Variable, Stockout Cost, Stockout Cost + Amount Lost * 0.204

<End of list>

Add...

Edit...

Delete

OK

Cancel

Help

7

Assign

Name:

Reduce Inventory

Assignments:

Variable, Demand Met, Demand Met+Demand

Variable, Inventory, Inventory - Demand

<End of list>

Add...

Edit...

Delete

OK

Cancel

Help

8

Decide

Name:

Restart Production

Type:

2-way by Condition

If:

Expression

Value:

Inventory <= Reorder Point

OK

Cancel

Help

9

Assign

Name:

Production Status

Assignments:

Variable, Production, 1

<End of list>

Add...

Edit...

Delete

OK

Cancel

Help

219

Create

10

Name: Entity Type:

Time Between Arrivals

Type: Expression: Units:

Entities per Arrival: Max Arrivals: First Creation:

Hold

11

Name: Type:

Condition:

Queue Type:

Queue Name:

Assign

12

Name:

Assignments:

<End of list>

Process

13

Name: Type:

Logic

Action: Priority:

Resources:

<End of list>

Delay Type: Units: Allocation:

Expression:

☒ Report Statistics

Process

14

Name: Type:

Logic

Action: Priority:

Resources:

<End of list>

Delay Type: Units: Allocation:

Expression:

☒ Report Statistics

Assign

15

Name:

Assignments:

<End of list>

Assign 16

Name:

Assignments:

Variable: Inventory, Inventory + Production Volume	Add...
<End of list>	Edit...
	Delete

OK Cancel Help

Decide 17

Name: Type:

If:

Value:

OK Cancel Help

Assign 18

Name:

Assignments:

Variable: Production, 0	Add...
<End of list>	Edit...
	Delete

OK Cancel Help

Figure 7.1: Collection of screenshots of the content of all the modules used in the 1st pathway simulation.

7.6. Appendix F

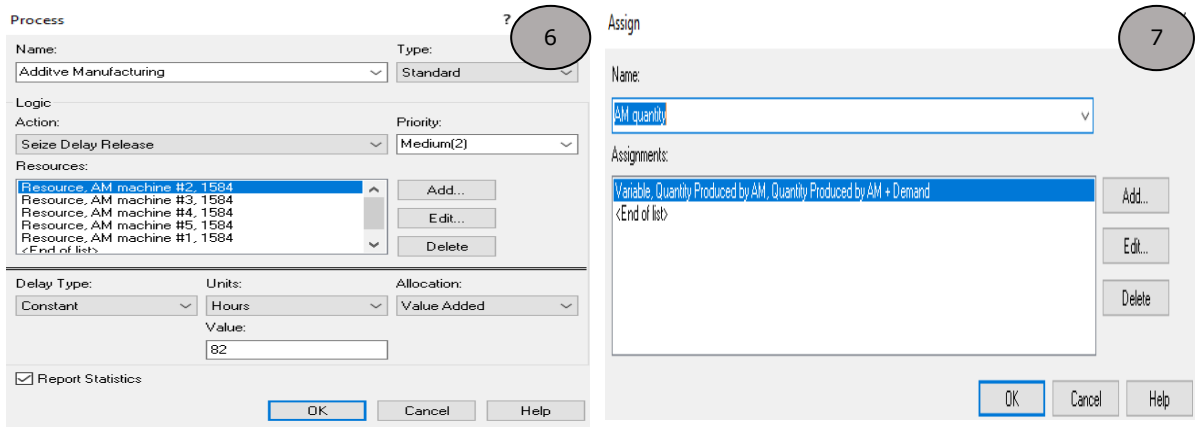


Figure 7.2: Screenshots of the content of Modules 6 and 7 used in the 2nd pathway simulation.

7.7. Appendix G

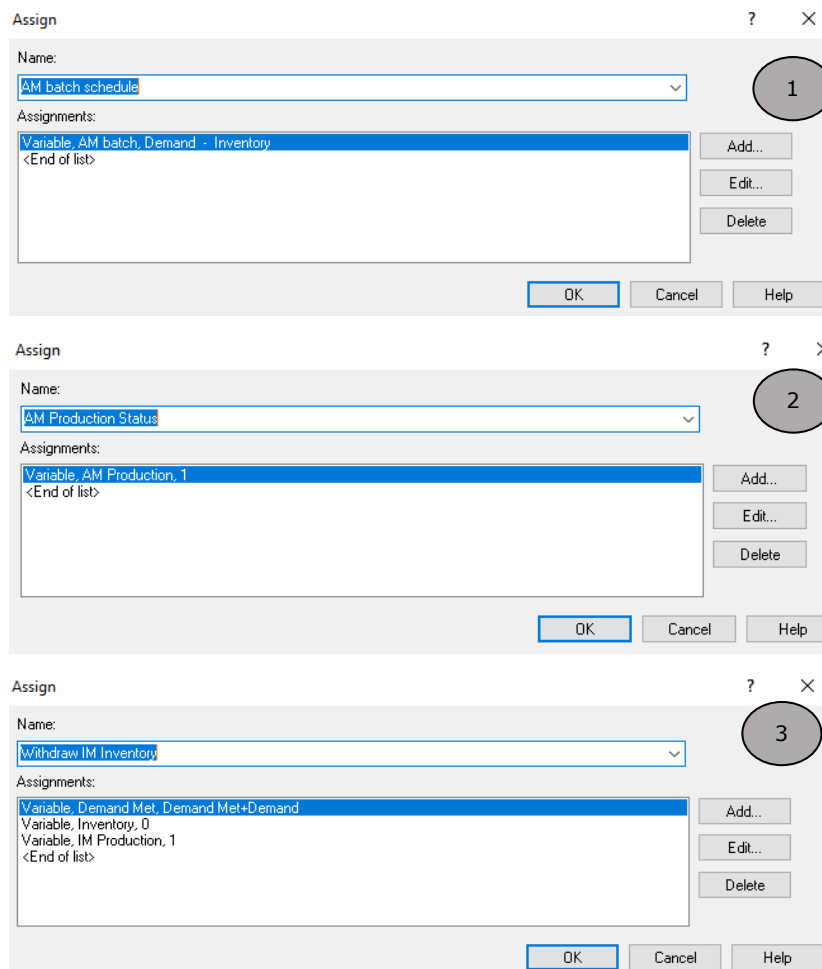


Figure 7.3: Screenshots of the content of Modules 1, 2 and 3 used in the 3rd pathway simulation.

8. References

Uncategorized References

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