MASTER

Additive manufacturing in spare parts supply chains
a comparison between in-house production, outsourcing and dual sourcing

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A comparison between in-house production, outsourcing and dual sourcing

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Abstract

Increasingly large and costly slow-moving spare parts inventories, caused by long supplier leadtimes, pose a problem to many organizations, among which the Royal Netherlands Army (RNLA). Additive manufacturing (AM) has the capability to supply the required spare parts with a relatively short leadtime. This reduces the need for high safety inventories, making AM deployment in the spare parts supply chain a potential solution to above problem. We investigate to what extent supply methods with AM can achieve inventory and cost reductions within the domestic spare parts supply chain of the RNLA. Four supply methods are compared: the current method, a method wherein spare parts are produced and supplied by an external AM provider, an in-house AM method and a dual source supply method that combines the last two options. A generic model is constructed to enable the comparison of these four supply methods based on costs and service levels. Two separate case studies are performed at the RNLA: one for polymer AM and one for metal AM. Both case studies indicate that AM can indeed bring about significant inventory reductions. Yet, these inventory reductions do not outweigh high part production costs associated with current AM technology. Especially for metal AM, these costs are disproportionately high. We conclude that AM supply methods can be very effective in achieving cost reductions in special cases, but do not show the same potential in the role of standard supply method for sourcing spare parts.

Executive summary

Introduction

Increasingly large and costly slow-moving spare parts inventories, caused by long supplier leadtimes, pose a problem to many organizations, among which the Royal Netherlands Army (RNLA). Additive manufacturing (AM) has the capability to supply the required spare parts with a relatively short leadtime, which could potentially aid in reducing inventory levels. The value of AM has already been proven for the RNLA in remote locations, but it is uncertain whether it could be the solution for the high spare parts inventory levels in the Netherlands. Although applications of AM are widening and associated costs decreasing, the technology is still significantly more costly than conventional manufacturing techniques. This results in the question whether the reductions in inventory holding costs that can be achieved through AM can in fact outweigh the extra costs that come with the technology.

Research design

The *supply sources* that we consider in this study are the original equipment manufacturer (OEM), external AM providers, and in-house AM. We consider four methods for supplying the central spare parts inventory, which we refer to as *supply methods*. These include:

- *Supply Method 1: OEM*
- *Supply Method 2: outsourced AM*
- *Supply Method 3: in-house AM*
- *Supply Method 4: in-house AM combined with outsourced AM*

The RNLA is uncertain as to what is the best supply method for its spare parts inventory in the Netherlands. The main research question (Main RQ) is:

Main RQ Which supply method must be used for spare parts if AM is an option?

In order to come to an answer to the Main RQ, a comparison is made between the four supply methods. The perspective taken is mainly economical; the focus lies on investigating to what extent AM can be financially beneficial to the spare parts supply chain of an organization.

The approach taken for the research is as follows. First, a generic mathematical model is constructed to facilitate a fair comparison between the four supply methods. We continue with the specification of each of the four supply methods. Thereafter, case studies within the RNLA are carried out to investigate the performance of each of the supply methods for several spare parts.

Generic model

The generic model we present for the comparison of supply methods has two performance indicators: costs and service level. The former is minimized while a specific value of the latter needs to be met. A continuous-review (R, Q) policy is considered, in which every time the inventory position drops to reorder level R an order for order size Q units is placed to replenish the inventory. Values for R and Q are determined based on several supply method-specific input variables. These include unit cost, fixed order cost and the demand during leadtime or the number of items that has been ordered but not yet delivered (pipeline inventory). If these variables are inserted in the generic model, the total costs of a supply method can be computed, while meeting a service level constraint. How the values for these input variables are obtained is covered per supply method, starting with the three single-source supply methods.

Single source supply methods

Under Supply Method 1, which relies on the OEM source, an order of one or more items is issued and generally arrives after several months. Under Supply Method 2, outsourcing AM, we assume a single part is ordered at the external AM provider and delivered within several days up to a few weeks, as is industry standard. Costs incurred are quoted by the external AM provider and usually exceed OEM costs. Under Supply Method 3, in-house AM, a spare part demand triggers a build job, which is placed in the job queue of the single AM system. Build jobs generally take several hours up to at most a few days. An important aspect taken into account is the $M/G/1$ queue, due to which waiting time may become substantial. Furthermore, build costs depend on an array of expenses, including AM machine costs, build material, labor and build time. These elements are factored into the eventual comparison.

A dual source supply method

The dual source supply method that we consider includes the option to use the in-house AM system and the option to outsource the AM job to an external provider. The function of this alternative source is to enable circumvention of the in-house AM system when the queue is long. We design a decision rule that selects the option that is expected to have the shortest leadtime. Leveraging prior research on $M/G/1/K$ queues, we then compute the input variables needed for the generic model, taking into account the designed decision rule.

Case studies

Two case studies are performed within the RNLA: polymer and metal AM. In the first, polymer AM is considered and three different spare parts of the Fennek reconnaissance and security vehicle are investigated. Two of these parts are special cases: they are small, relatively cheap and cannot be purchased separately at the OEM, but need to be bought along with the assembly to which they belong. For these parts, we find that both outsourced and in-house AM can achieve large costs reductions. For the regular polymer part, we find that the AM supply methods are more expensive under the current AM technology, but only slightly. It is further found that reductions in on-hand inventory of $73\% - 90\%$ can be achieved.

In the second case study, we consider metal AM and examine six different spare parts. Reductions in on-hand inventory under the AM methods are found to be equally large as in the polymer case. The resulting reduction in holding costs, however, is found to be insufficient to counterbalance strongly increased part costs associated with metal AM. The OEM supply method remains unequivocally the most cost-effective option for the metal parts considered, in the presence of several AM options.

Conclusions

First of all, we conclude that current AM is not cost-effective for rather low-complexity spare parts at the RNLA. We expect that AM part costs are better justified for more complex spare parts, and recommend future studies to take this into consideration. Furthermore, we consider a regular domestic environment with relatively low costs of holding inventory and – in line with previous studies – expect AM to better demonstrate its value in environments where holding inventory is more burdensome, which we recommend to shift the attention towards. Additional to these special environments, we recommended the RNLA and other organizations to continue investigating special cases for which AM can be leveraged to its full potential. One of these special cases for which AM can be valuable, as we find in our case studies, is AM of small sub-parts that cannot be bought separately at the OEM. Instead of being forced to replace the entire part to which the failed sub-part belongs, the sub-part can be replaced cost-effectively by an AM version. Other examples of special cases for AM that are worth revision are last time buys, obsolescence or temporary supply disruptions. Furthermore, for enabling top-down identification of AM business cases among its spare parts, we argue that data quality and structure are essential. Our second to last recommendation concerns cooperation between RNLA and AM specialist parties. Based on case study findings we conclude that, although experimenting with new technologies is a valuable activity for the RNLA, actual production should not be one of its core tasks. Moreover, involving external parties can be useful for gaining valuable knowledge. Finally, we suggest further investigation into the benefits of combining multiple AM sources, and recommend testing a dual AM source model under different conditions.

Preface

When I stood at the starting line of the master thesis project, the road ahead seemed full of obstacles and the end nowhere near. Now, seven months later, I am proud to say that this report marks the completion of the research project. Over the course of the project, I have spoken with numerous helpful people from whom I learned valuable lessons and gained interesting insights. Additionally, countless solitary hours were spent on calculations, programming, writing and rewriting these chapters. Although challenging at times, working on this research project has been truly enriching for my education, and I am grateful for having been given the opportunity to carry it out. All in all, it has been a worthy termination of my time at the Eindhoven University of Technology.

I could never have completed the project without the support of several people. First of all, I would like to thank Jelmar den Boer for helping me find my way around the Royal Netherlands Army organization, for the brainstorm sessions, for attentively reading several drafts and for providing me with valuable feedback. Furthermore, I wish to thank Rob Basten and Karel van Donselaar for supervising the project on behalf of the university. Your critical perspectives and constructive feedback have made me carefully consider and rethink assumptions and modeling choices, and significantly improved the thesis. I would also like to thank Claudia Fecarotti for her effort in evaluating the report in the capacity of third assessor. Finally, I want to express my gratitude to my girlfriend, parents, family and friends. Your support over the past months has kept me motivated till the end.

I hope you enjoy reading.

Koen Pijnappels
Prinsenbeek, April 2019

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Chapter 1

Introduction

In this chapter we introduce the research environment, the Royal Netherlands Army (RNLA), in Section 1.1. The subject of additive manufacturing (AM) is introduced in Section 1.2, after which we discuss current practises and future vision of the RNLA regarding AM in Section 1.3. The chapter is concluded in Section 1.4.

1.1 The Royal Netherlands Army

The research context for this study is the Royal Netherlands Army. The RNLA is one of the four armed forces of the Netherlands Ministry of Defense, the other three being the Royal Netherlands Navy, the Royal Netherlands Air Force and the Royal Netherlands Marechaussee (military and border police).

1.1.1 RNLA core tasks

The RNLA performs land operations in order to contribute to peace, freedom and security in the Netherlands and abroad. A distinction is made between tasks of the RNLA in the home country and on foreign terrain. In the Netherlands, the organization has two core tasks:

- to defend the territory of the Netherlands against hostile nations and groups;
- to provide assistance to government authorities in the event of disasters and crises.

Additional to activities of the RNLA in the Netherlands, the organization also cooperates with the other armed forces of the Netherlands or with foreign army units during missions abroad. Tasks of the RNLA when operating abroad include;

- to defend the territory of NATO Allies;
- to conduct peacekeeping or peace enforcement missions;
- to provide humanitarian aid;
- to support local population and local civil organizations.

1.1.2 RNLA spare parts supply chain

Performing these tasks requires the RNLA to operate a large fleet of (weapons) systems, each one containing numerous smaller parts. Part lifetimes are generally limited, prompting the need for spare parts. In this study, we consider the spare parts supply chain of the RNLA. The RNLA has its main spare parts inventories in the Netherlands. Parts are sourced from domestic and foreign suppliers and in many cases leadtimes are long. For parts supplied by overseas original equipment manufacturers (OEMs) leadtimes occasionally exceed 6 months. If a critical part fails, and cannot be repaired, a new part has to be taken from stock. When a stock-out of a critical part occurs, system downtime can be costly and may even endanger military mission objectives and lives; system availability is paramount.

1.2 Additive manufacturing

Additive manufacturing, also known as three-dimensional (3D) printing, is the official industry standard term for all applications of the technology, and is defined as the process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies (ASTM International, 2015). The global AM market exceeds US$7.3 billion in 2018 and grew with 21% relative to 2017 (Wohlers Report, 2018) and adoption is growing; "AM is moving from limited applications, such as prototyping and making conventional machine tools, to a central role in manufacturing for a growing number of industries" (Harvard Business Review, 2018).

1.2.1 AM technologies

Major AM process categories include fused deposit modeling (FDM), stereolithography (SLA) and powder bed fusion (PBF) processes such as selective laser melting (SLM) and sintering (SLS) (Prakash et al., 2018). Materials that can be used for AM are myriad and include countless types of polymers, metals, ceramics and composites. We choose to consider polymers and metals, as these are suitable for most applications within the RNLA. Due to the large cost difference between them, our analysis regards both material types separately. For polymer builds we assume the SLS process, which has been used successfully for experimental AM at the RNLA. Furthermore, a new generation of economical polymer SLS systems is arriving, interesting for this cost comparison study. For metal processing we consider the direct metal laser sintering (DMLS) process, one of the most widely applied process category in metal AM (Bhavar et al., 2014).

1.2.2 AM advantages and challenges

AM has several advantages over conventional manufacturing (CM) methods, which are listed by Attaran (2017). Suggested advantages include the ability to reduce product development and repair times, rapidly produce spare parts, manufacture small volumes, customize unique items and produce very complex parts. Another major advantage is the ability to do on-site and on-demand manufacturing of customized replacement parts.

Main challenges of AM are product size restrictions, long production times and high costs of machines and materials used (Attaran, 2017). Additionally, current regulations prohibit or complicate usage of AM parts in some cases; strict part and process certification processes exist in many sectors such as airline industry and defense. However, technological progress is fast and AM system and process costs are decreasing (Thomas, 2016). AM quality, consistency and capabilities will continue to improve (Thompson et al., 2016). Regulatory issues are being tackled by industry and safety regulators such as the U.S. Federal Aviation Administration (3DPrintingindustry.com, 2017) and it is expected that AM will continue to advance in its development and societal impact (Huang et al., 2013).

1.2.3 AM in spare parts supply chains

One of the areas in which AM application can be leveraged is spare parts supply chain management (Holström et al., 2010). The amount of capital tied up in spare parts inventories has increased over the years, triggering interest in more efficient methods for spare part management (Van Houtum and Kranenburg, 2015). Organizations in the aviation industry, large industrial companies and defense organizations – such as the RNLA – generally own tens of millions of euros in costly spare parts to prevent expensive downtimes (Basten and van Houtum, 2014). A number of studies numerically investigates and demonstrates the potential of AM in spare parts supply chains (Khajavi et al., 2014; Liu et al., 2014; Li et al., 2017; Knofius et al., 2017; Westerweel et al., 2018b). It is generally concluded that the potential for cost reductions with AM is particularly large for asset-critical slow-moving (i.e., having a low demand rate) spare parts associated with high downtime costs.

1.3 AM at the Royal Netherlands Army

1.3.1 AM at the RNLA: current status

Several AM systems have already been deployed at RNLA locations in the Netherlands and abroad for experimental purposes. Within the RNLA, current applications include prototyping, manufacturing small and relatively low-cost items that can no longer be ordered at the supplier (obsolescence), and producing customized *quick fixes* to solve small practical issues. Similar practises are conducted within the Royal Netherlands Air Force and the Royal Netherlands Navy. Current AM usage within RNLA takes place in a decentralized manner and a main objective is to raise awareness and understanding regarding the potential of AM within the organization.

1.3.2 AM on missions

The RNLA plans to develop and professionalize AM practises within the organization, and foresees that the technology can be leveraged to increase system availability during missions and reduce the logistic footprint by lowering inventory and transport costs. Several studies have been performed within the RNLA to investigate how this should be done. Den Boer (2018) lays out the advantages and challenges of AM in the spare parts supply chain of armed forces. Rooijakkers (2017) examines the impact of on-location temporary fix AM of spare parts on service supply chains at the RNLA, and develops a method to identify the most promising spare parts for this technique. Westerweel et al. (2018b) consider AM to print temporary parts for the RNLA and focus specifically on remote mission locations. They show that these locations are prime candidates for implementing AM to print spare parts on-site and on-demand, even if the printed parts possess a lower reliability than regular parts. Melman (2018) investigates how AM parts can optimize spare part availability under capacity constraints in remote locations. Each of the prior studies shows that on-location AM in or near missions can be of great value.

1.3.3 The domestic AM hub

The RNLA envisions an AM expertise hub in The Netherlands as well. This hub, named the AM Center, should become the AM nerve center of the RNLA, but its exact functions and facilities are still undetermined. One option considered by the RNLA is to let the AM Center serve as in-house spare part printing facility. Spare part inventories are high to hedge against expensive stock-outs. Printing spare parts in the AM center can potentially enable the RNLA to circumvent long OEM leadtimes and thereby lower inventories. Alternatively, RNLA considers outsourcing AM jobs to an external organization. This would serve the same purpose of avoiding OEM leadtimes and relieve the need to purchase high-cost AM equipment. The three options for sourcing spare parts – the OEM, outsourcing AM and in-house AM – all have advantages and drawbacks. A combination of two sources for sourcing a spare part – a dual source supply method – could be the key. Determining an optimal supply method for spare parts in the presence of AM options is the objective of this study.

1.4 Conclusion

AM technology is developing rapidly and recent studies suggest that its potential impact on the spare parts supply chain is significant, especially in terms of leadtime and inventory cost reductions. The RNLA is investigating deployment of AM applications within the organization, which have already proven their value in remote locations. As a consequence, the RNLA is interested in how the technology can be leveraged to optimize the organization's regular spare parts supply chain. Currently, the spare parts inventories in the Netherlands are supplied by OEMs, often with excessive leadtimes. AM of spare parts is generally associated with the trade-off between shorter leadtimes and higher production costs. The RNLA considers locating a main AM facility in the Netherlands as complementary supply source for its central spare parts inventories. Outsourcing AM of spare parts to external AM providers in the Netherlands is an alternative option. We consider the three supply sources – the OEM, outsourcing AM and in-house AM – and investigate which one, or which combination, is most beneficial for the spare parts supply chain of the RNLA.

Chapter 2

Research design

As described in Chapter 1, the potential of AM in optimizing spare parts supply chains has not gone unnoticed within the RNLA. The current state of AM at the organization sparks several questions about decisions on AM in the near future. For example, how should the RNLA leverage the possibility to print spare parts? Should the RNLA adopt AM of spare parts in-house, or is it more cost-effective to outsource such production to a third party? Is it better to stick with ordering at the OEM? Is there a combination of supply sources that is optimal? These questions illustrate the currently existing uncertainty within the RNLA, on which we base the research problem in Section 2.1. Research questions are presented in Section 2.2 and the scope is covered in Section 2.3. We discuss our contribution to the existing literature in Section 2.4 and discuss the thesis structure in Section 2.5.

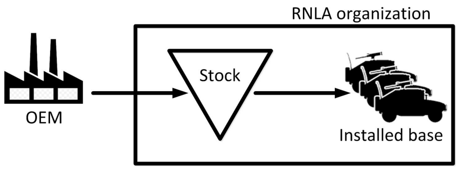
2.1 Research problem

It is unclear how AM can be used most effectively to optimize spare parts supply chain performance, in terms of total costs and service level. More specifically, the RNLA is uncertain as to what is the best *method for supplying its central spare parts inventory in the Netherlands* – which we refer to as *supply method* – if AM is an option. The complication lies in the fact that different supply methods all come with advantages and disadvantages. To further specify the research problem, we elaborate on the supply methods relevant to this research. A supply method can rely on one or multiple *supply sources*.

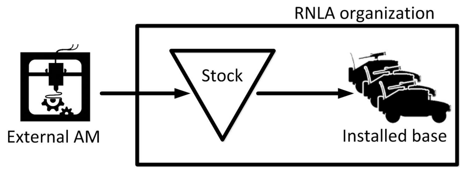
2.1.1 Supply sources

The three supply sources considered in this research are the OEM, an external AM provider and in-house AM capacity. We now briefly describe the main characteristics of the three supply sources:

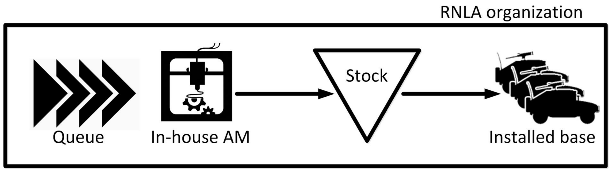
- *Supply source 1: OEM* The OEM supply source is associated with relatively long leadtimes and low part costs. For slow-moving parts, leadtimes at the majority of OEMs range from two months up to a year. Part costs are relatively low due to the fact that the OEM uses conventional manufacturing techniques, which are generally more cost-effective than current AM technology.



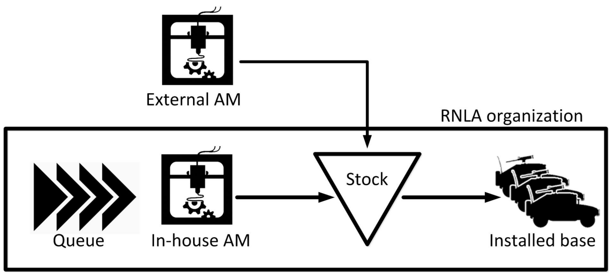
(a) *Supply Method 1: OEM*



(b) *Supply Method 2: Outsourced AM*



(c) *Supply Method 3: In-house AM*



(d) *Supply Method 4: in-house AM combined with outsourced AM*

Figure 2.1: The four supply methods considered in this study

- *Supply source 2: outsourcing AM* Outsourcing AM to an external AM provider is generally characterized by shorter leadtimes and higher part costs. High part costs are caused by expensive AM systems, costly build materials and the third party's profit margin. Short leadtimes can be explained by the relatively short setup time inherent to the AM process and short transport times due to geographic proximity. Furthermore, capacity at the third party is abundant due to their large industrial AM systems, so queuing effects can be ignored.

- *Supply source 3: in-house AM* Main characteristics of in-house AM include short leadtimes, high part costs and queuing effects associated with limited capacity in-house production. Short leadtimes of in-house AM can be explained by short AM setup times and no transport time. The high part costs in AM are a result of high AM system and build material costs. A key difference between in-house AM and outsourcing AM lies in the job queue, which arises when a new job arrives at the AM system while it is occupied. These queuing effects may have serious impact on the total leadtime.

2.1.2 Supply methods

We consider four supply methods, which are graphically represented in Figure 2.1. They include three single source methods — one for each of the supply sources listed. Additionally, we consider a supply method that combines the in-house AM supply source with the option of outsourcing AM. Especially in case of high utilization of the in-house AM facility, outsourcing AM can be useful to complement in-house AM capacity. Using this dual AM supply method, RNLA has the advantages of in-house AM while being able to prevent long queues at the AM system through outsourcing overflow spare part demand.

Other supply methods comprising multiple supply sources could also be formed, but will not be considered in this research. We argue that, for the RNLA, obtaining 3D drawings and licenses to print a certain spare part takes considerable investment. When these enablers for AM have been acquired for a specific spare part, it is not sensible to occasionally order this part at the OEM as well.

To summarize, the following four supply methods are studied:

- *Supply Method 1 (M1): OEM*
- *Supply Method 2 (M2): outsourced AM*
- *Supply Method 3 (M3): in-house AM*
- *Supply Method 4 (M4): in-house AM combined with outsourced AM*

Note that in each of the configurations of Figure 2.1 a stockpoint is included; even though printing results in short leadtimes, a small stock may still be required to prevent expensive downtime.

2.2 Research questions

In order to resolve the research problem of Section 2.1, we aim to answer the main research question (Main RQ):

Main RQ	**Which supply method must be used for spare parts if AM is an option?**

Admittedly, this is a very general research question. We choose to focus specifically on the RNLA spare parts supply chain, and then discuss to what extent conclusions can be generalized.

To gain better insight in the performance of the four considered supply methods, a mathematical model is created. Several important questions arise in the construction and application of this model. In this section we introduce the RQs and corresponding sub questions.

The first challenge in comparing the four supply methods is to construct a single model to accurately represent all four supply methods, even though there are key differences. A collection of assumptions is needed to support the generic mathematical model. A question that arises after having established the key assumptions in the model is how to evaluate the model with respect to cost and and service level. Lastly, we focus on the procedure of finding optimal values for decision variables in the generic mathematical model. RQ1 and associated sub questions are as follows:

RQ1	**How can the four considered supply methods be captured in a single generic mathematical model?**
A	Which key assumptions are needed in order to construct a generic model?
B	How can supply method costs be evaluated in the generic model?
C	How can the service level of a supply method be evaluated in the generic model?
D	What is a suitable optimization procedure for the generic model?

Each of the supply methods has its own unique properties that determine the value of input variables for the generic model.

It should be noted that, although these input variables are input to the generic model, a significant amount of supply method-specific modeling is needed for some of them. In this modeling, which is covered separately per supply method, the generic model input variables are naturally no longer input variables. Regardless of the fact that these variables are the product of these smaller supply method-specific models, they continue to be the input variables to the generic model. Consequentially, we continue to refer to them as such over the course of this thesis.

In determining values for these input variables, the topic of single source supply methods is touched upon first. By answering RQ2 and sub questions, model input variable values for the single source supply methods are derived.

RQ2	**What are the model input variable values for the single source supply methods?**
A	What are the model input variable values for the OEM supply method?
B	What are the model input variable values for the outsourced AM supply method?
C	What are the model input variable values for the in-house AM supply method?

We determine input variable values of the generic comparison model for the dual AM source supply method as well. Due to this method's more complex nature, a separate RQ is dedicated to it. In the dual AM supply method, first of all, a rule is established for deciding when to use which source. Then, the model input variable values can be derived for the dual AM source supply method. RQ3 and sub questions A and B read:

RQ3	**What are the model input variable values for a dual AM source supply method?**
A	What is a good rule for deciding when to use in-house AM and outsourcing AM in a dual source supply method?
B	How can model input variable values for a dual AM supply source be derived?

After RQ1-3 have been answered, we can compute costs and service level of the four supply methods for a given set of spare parts, using the generic model and specific input variables. Case studies within the RNLA can now provide insights on performance of each of the supply methods in a present-day military supply chain context.

Current AM technology (i.e., systems and materials) is quite expensive and process times are relatively long, which affects the performance of each of the supply methods. However, AM costs are expected to drop over the decades to come, along with the process duration. We examine whether and when the choice for a supply method changes as AM technology progresses. RQ4 is raised:

RQ4	**Which supply method must be used for spare parts within RNLA if AM is an option?**
A	How do the four supply methods perform considering current AM technology?
B	How will the performance of each of the supply methods change when AM technology costs and build times are reduced?

2.3 Scope

The scope of the research is limited to a comparison between four supply methods, which do not include dual source dual source combinations of AM and conventional manufacturing sources. We argue that once the investment in 3D designs and/or AM licenses for an AM version of a spare part has been made, it is no longer sensible to order this part at the OEM.

Furthermore, it is important to note that the comparison between supply methods is performed using a mainly economical perspective; the focus lies on investigating the extent to which AM can be financially beneficial to the spare parts supply chain of an organization. We acknowledge that this perspective covers only one of several aspects of AM (e.g. certification, and intellectual property) that need investigating to provide a definitive answer to the questions concerning AM at the RNLA and in general.

Finally, we limit the scope to spare parts for which prior research has shown that the economic potential of AM is greatest. As briefly noted in Chapter 1, this concerns spare parts that have a low demand, have a long leadtime at the regular supply source, are critical for functioning of the asset they belong to, and are associated with high downtime cost of the asset to which the part belongs. Downtime cost, however, is hard to quantify in a military environment, and therefore this aspect will not be included.

2.4 Contribution to science

Chapter 1 indicates that there are a number of studies that evaluate the performance of AM in spare parts supply chains. Not all of these studies present new case study material; some of these studies are mainly numerical experiments (e.g. Song and Zhang, 2018) while others rely on data presented in earlier published research papers (e.g. Liu et al., 2014; Li et al., 2017; Ghadge et al., 2018). This study complements the literature on AM in spare parts supply chains through two case studies with mainly newly collected data in the context of defense.

Several studies have investigated AM versus CM (e.g. Liu et al., 2014), centralized AM versus distributed AM and current AM versus future AM technology (e.g. Khajavi et al., 2014), in terms of spare parts supply chain performance. To the best of our knowledge, the topic of outsourcing AM production versus in-house AM production has not been covered in the existing literature. We consider our comparison between these models to be a key contribution.

The topic of dual source supply models in the context of AM has only recently first received attention (Song and Zhang, 2018). By combining in-house AM and outsourcing AM, we are the first to consider two AM sources with different properties in a dual source model.

2.5 Thesis structure

We answer RQ1 in Chapter 3, where we construct a generic mathematical model. RQ2 is answered in Chapter 4, through explaining how model input variable values can be determined for the three single source supply methods. The same is done for a dual source supply method in Chapter 5, in response to RQ3. In Chapter 6 the generic comparison model and derivations of specific input variable values for each of the supply methods are used in two case studies at the RNLA, through which RQ4 is answered. Conclusions are drawn in Chapter 7.

Chapter 3

Generic model

For a valid comparison in performance of the different supply methods, a generic mathematical model for calculation of costs and service measures serves as a key tool. We thus answer Research Question 1 in this chapter:

RQ1 How can the four considered supply methods be captured in a single generic mathematical model?

The chapter is structured as follows. We first present the general structure of the model in Section 3.1. Assumptions fundamental to the model are stated in Section 3.2. The two main components of the generic model are costs and service level; the former is covered in Section 3.3 while the latter is covered in Section 3.4. A brief description of the inventory system optimization procedure is discussed in Section 3.5. The chapter is then concluded in Section 3.6.

3.1 Generic model structure

The purpose of the generic model is to facilitate the comparison between suitability of the four supply methods for a specific spare part. The comparison is based on total cost and service level, among which a trade-off exists. A schematic representation of the generic model structure is given in Figure 3.1.

First of all, the selected supply method, with its distinct costs and leadtime, strongly affects

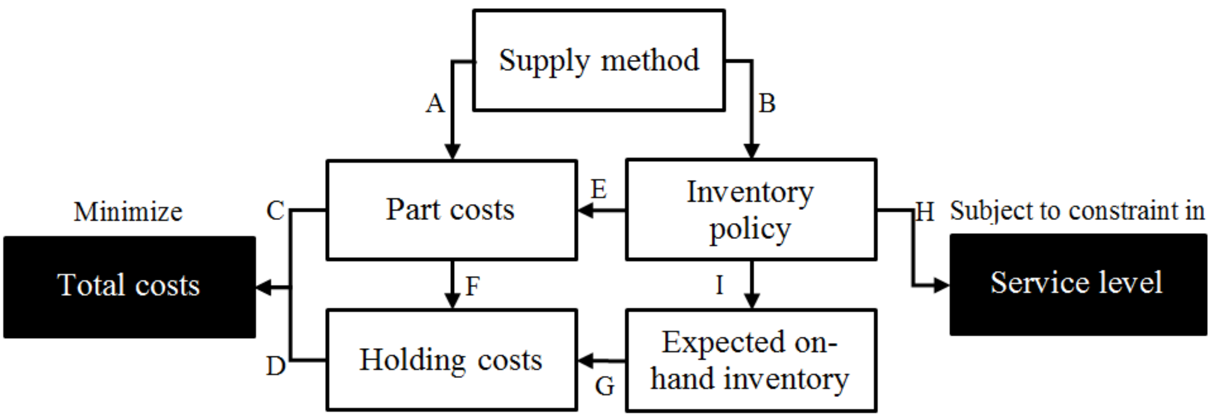


Figure 3.1: Structure of the generic model

(link A) the part costs and (B) the inventory policy. The performance of the supply method is then quantified in terms of costs and service level.

On one hand, the total cost associated with the supply chain of a spare part should be computed. The total cost associated with a spare part is constructed of (C) part costs (defined as the collection of costs incurred in connection with ordering or producing the parts) and (D) holding cost (i.e., the cost of holding inventory). Part costs in our model depend on (E) the order size in the inventory policy. Holding costs are based on the value of inventory, determined by (F) part costs and (G) the expected on-hand inventory level.

On the other hand, performance of the spare part supply chain in terms of service level is computed. Definitions of two different service levels are given in this chapter. The service level is determined directly by (H) the inventory policy chosen. Simultaneously, the inventory on hand – a factor in the total cost calculation – is also determined by (I) the inventory policy, causing the trade-off between cost and service level.

At the RNLA, as in many organizations, a service level objective is set as constraint. It is met through keeping sufficient on-hand inventory, which boosts holding cost. The generic model minimizes this cost while meeting the service level constraint.

This is done for Supply Method 1, 2, 3 and 4, after which cost and service level can be compared.

3.2 Modeling assumptions

In order to construct a generic mathematical model, we need to make some assumptions. Research Question 1A is answered:

RQ1A	Which key assumptions are needed in order to construct a generic model?

In this section key assumptions are presented and motivated, listed by category. To avoid ambiguity in some cases – and because the spare parts we consider are generally kept in stock – we use the terms spare part and stock keeping unit (SKU) interchangeably.

1. **Inventory policy**

   (a) **A single stockpoint:** in terms of the supply chain configuration, we consider a single spare parts stockpoint in the Netherlands that serves the installed base. We can assume this configuration, even though spare parts inventories are in some cases distributed over the Netherlands, because lateral transshipment cost and time are negligible due to the small distances within the country.

   (b) **Continuous-review:** decisions are assumed to be taken in continuous time. This assumption allows us to use continuous-review inventory management theory, which facilitates lower modeling complexity. Furthermore, the continuous-review policy is an accurate representation of the periodic review policy in case of a low demand rate and short review period. The spare parts that we consider at the RNLA have demand rates of at most several items a month and their inventory positions are reviewed every day. We thus conclude that the assumption of a continuous-review system can accurately represent the actual system.

(c) **Backordering:** it is assumed that a demanded spare part is backordered when not in stock, as there are no emergency shipment options that can fulfill the demand.

2. **Demand behaviour**

   (a) **Discrete demand:** the considered items are spare parts, and consequentially it is unrealistic to assume continuous demand.

   (b) **Independently distributed demand:** it is assumed that failure behaviour of one part does not affect failure behaviour of another part. In practice, this may not always be entirely true in the RNLA environment, as failure of parts tends to be partly related to increased system usage during missions. Because their is no data regarding the strength of this effect, and to prevent excessive model complexity, it is not incorporated in the model.

   (c) **Stationary demand:** it is assumed that demand is stationary and is not affected by any seasonality or trends. This assumption is not always valid in the RNLA context, due to the varying frequency and intensity of material usage during missions. This factor is not incorporated in the model. To nonetheless justify the assumption of stationary demand in this study, we attempt to limit the effects of trends by considering spare parts associated to systems that have been in operation for some time. Furthermore, for the data we consider a period of time in which the installed base size remained virtually constant.

   (d) **Poisson demand distribution:** we assume a large installed base of systems, of which part failures occur randomly. Every part failure triggers a demand for a replacement part. In a spare parts context, unplanned, random demands can realistically be modeled as a Poisson process (as stated by, e.g., Basten and van Houtum, 2014).

   (e) **Single demand rate:** only a single demand rate per part is considered. In practice, demand for a part may arise with corrective or preventive maintenance. However, only an aggregate demand rate is available in the RNLA databases, and more detailed information on the origins of spare part demand is not stored.

3. **Spare part characteristics**

   (a) **Non-repairables:** we assume that every single part failure that we observe directly leads to a demanded functioning replacement item, as the spare parts considered in this study are generally non-repairable. Consequently, parts are scrapped after a failure.

   (b) **Non-perishables:** it is assumed that the spare parts do not wear out while inactive. In reality, the materials we consider might degrade over a period of decades. However, we assume relatively high turnover of inventory – within several years – substantiating the non-perishability assumption.

4. **OEM supply source**

(a) **Unlimited supply at the OEM:** it is assumed that the OEM has ample capacity; any number of demanded parts can always be supplied. In practise, shortages at the OEM or total supply disruptions may occur, and might even significantly *increase the potential of AM*. These factors are not incorporated in the model, as the purpose of this study is to investigate the potential of AM as an alternative to the existing OEM supply source under regular circumstances.

(b) **Order quantities at the OEM:** current policy at the RNLA is to determine a fixed order quantity Q for each spare part and to order in batches of Q items. As we aim to accurately represent the situation of OEM supply in Supply Method 1, we mimic this approach. Consequently, we must assume that order quantities at the OEM may be larger than one. This assumption is also required to incorporate the fact that incremental order quantities (i.e., predetermined batch sizes) exist at the OEM for a portion of the spare parts.

(c) **Deterministic OEM leadtimes:** it is assumed that spare parts ordered at the OEM are received a fixed period of time after ordering. In reality, this is not always the case, and the actual leadtime may deviate from the quoted leadtime. We do not take these deviations into account, as the assumption of stochastic leadtime would be highly impractical to combine with the assumptions of stochastic demand and order batching in an exact evaluation (due to an issue named *order crossover*, described by Hadley and Whitin (1963), p. 202). Moreover, there is no data on the variance in leadtime at the RNLA.

5. **AM supply sources**

(a) **Equal quality AM and CM:** regarding AM technology, we assume that parts produced with AM possess the same failure behaviour as parts produced by means of conventional manufacturing methods. We substantiate this assumption by considering that, although current AM parts may occasionally be of lower quality than regular parts, rapid technological development is constantly improving the quality of AM parts.

(b) **A single in-house AM system:** Although several experimental (polymer FDM) AM systems are present at the RNLA, these are not a formal link in the spare parts supply chain. The RNLA does consider deployment of a single AM system there. Decisions on the number of systems that should be acquired are currently not on the agenda. We therefore consider a situation where capacity is limited to one AM system.

(c) **Deterministic in-house AM build times:** It is assumed that the AM build times are deterministic for each specific spare part, as AM machines are generally able to indicate the expected duration of a build job accurately. Note that although AM build times are deterministic, the leadtime in Supply Methods 3 and 4 may vary due to queuing effects.

(d) **One-for-one AM of spare parts:** An advantageous characteristic of AM is the ability to print multiple parts in one build. However, this is only true when all parts are of the same material, and when their sizes allow them to be fit in one build. This is not always true in the case we consider. Furthermore, the build time increases with the number of parts in the build. Based on these arguments, we find it reasonable to assume in our model that production of multiple parts in an AM machine is done in series, and not simultaneously. So, for Supply Methods 2 and 3 (and thus also 4), $Q = 1$. This assumption enables exact evaluation under the highly stochastic leadtimes in the in-house AM situation. It should be noted that, due to this assumption, the actual AM processing rate may be higher than indicated by our model.

(e) **FCFS processing AM jobs:** Jobs at the in-house AM machine are assumed to be processed according to a first-come, first-served (FCFS) sequence. For the purpose of this research – investigating the relative performance of AM compared to CM in the spare parts supply chain – we argue that FCFS is a reasonable assumption.

(f) **External AM provider with ample capacity:** It is assumed that the party to which AM of spare parts is outsourced has ample capacity, as part of their service offer.

(g) **Stochastic leadtimes at external AM provider:** In a survey among external AM providers we have found that leadtimes vary between several days up to a week for polymer parts and between one and three weeks for metal parts. Due to the assumption of one-for-one AM and thus $Q = 1$ for AM supply methods, assuming stochastic leadtimes will not lead to excessive modeling complexity for Supply Method 2. We therefore choose to allow for stochastic leadtimes at the external AM provider.

3.3 Total costs of the generic model

In this section we present a generic method for calculating the cost associated with each of the four supply methods. Supply method-specific cost calculations – such as the cost of in-house AM based on part volume, dimensions and material – are presented in Chapter 4 for single source Supply Methods 1, 2 and 3 and Chapter 5 for dual source Supply Method 4. For now, however, we take a generic approach and answer Research Question 1B:

RQ1B	How can supply method costs be evaluated in the generic model?

This question is answered by first considering two principles that should be taken into account, after which a generic cost function is presented.

3.3.1 Notation

If a variable may have different values for different supply methods, we mark the general variable with superscript M, and the supply method-specific variables with superscripts M1, M2, M3 and M4, indicating supply methods OEM, outsourcing AM, in-house AM, and dual AM, respectively.

3.3.2 Total cost of ownership

Mapping the effect of AM on a spare part supply chain to the fullest extent requires a total cost of ownership (TCO) analysis per SKU. As we assume equal failure behaviour of parts produced with AM and CM, the TCO is limited to part costs and inventory holding costs. Note that part costs here consist of all costs associated with obtaining a spare part, which may include direct and indirect costs.

3.3.3 Value of inventory

At the RNLA, as in many organizations, the inventory holding cost is considered a percentage of the total value of spare parts in inventory — and thus as a function of the cost per unit, or unit cost (u^{M}) per SKU. Therefore, to build a fair comparison of the inventory holding costs for all supply methods, we allocate all costs associated with AM to the unit cost u^{M}. A method for this is given in Chapter 4.

3.3.4 Generic cost function

Taking these two principles into account we formulate a cost function. The total annual cost associated with the spare parts supply chain of a SKU – regardless of the supply method selected – is given by:

$$\text{Total costs} = \text{Part costs} + \text{Holding costs}, \tag{3.1}$$

in which

$$\text{Part costs} = u^{\mathrm{M}} m + f^{\mathrm{M}} \frac{m}{Q}.$$

$$\text{Holding costs} = h u^{\mathrm{M}} E[OH].$$

Here, m represents average annual demand for the SKU, f^{M} the fixed order cost and h the inventory holding cost rate. $E[OH]$ denotes the expected inventory on hand. Especially in long-leadtime contexts, considering $E[OH]$ rather than expected inventory position $E[IP]$ is more accurate for calculating holding costs, as not all items in the inventory position cause holding costs — only the items actually in holding do. Expressions for $E[OH]$ are given in Section 3.4.

3.4 Model inventory system evaluation

Based on the assumptions for the generic model presented in Section 3.2, we now evaluate the inventory system using different service measures. Research Question 1C is answered:

RQ1C	How can the service level of a supply method be evaluated in the generic model?

We first select two different service measures and explain how they aid in evaluating the inventory system. Finally, mathematical expressions are derived.

3.4.1 Generic model inventory policy

Given the assumptions of Section 3.2, the generic model for the four supply methods can be based on a continuous-review (R, Q) policy (e.g. Hillier and Lieberman, 2015); whenever the inventory position of a SKU drops to R (or, equivalently since we assume single demands only, below $R + 1$), an order for Q units is placed to replenish the inventory. For Supply Method 1 (OEM supply) there may be batching ($Q \geq 1$), while for Supply Method 2-4 (outsourcing AM, in-house AM, and dual AM) the assumption of one-for-one AM means that $Q = 1$. In the latter case, the (R, Q) policy is identical to a $(S - 1, S)$ policy (Feeney and Sherbrooke, 1966) or *basestock policy* with $S = R + 1$. As we wish to use the same notation for each of the supply methods in the generic model, we choose to continue with the (R, Q) notation from here on. The decision variables are thus R and Q.

3.4.2 Service measure selection

The RNLA uses a SKU-oriented service level named *fill rate*, denoted by β. The fill rate is equal to the probability that a positive on-hand inventory is observed at the moment a part failure occurs. Although the RNLA currently uses the fill rate, this service measure does not paint a complete picture of inventory management performance. Especially in the case of slow-moving spare parts, the fill rate can negatively bias performance. To illustrate this, let us consider the following example:

> *A costly SKU of which inventory is managed using a policy with $R = -1$ and $Q = 1$, is demanded once in a year ($m = 1$) and has leadtime $L = 0.01$ year; the part can be built with AM in about three days. The fill rate of an item that is not stocked is always zero: $\beta = 0$, which sounds terrible. The expected number of backorders ($E[BO]$) is a commonly used service measure in spare parts management that measures performance quite differently. In this example, there is only one backorder and only during the few days that the item is being printed: $E[BO] = 0.01$, generally not bad.*

Of course above example is quite an extreme one, but it does effectively indicate why it might be valuable to not only consider the fill rate. Particularly in cases with slow-moving demand and short leadtimes – exactly the scenario with AM in this study – the fill rate undervalues actual performance. For this reason, we argue that in addition to the fill rate, also the $E[BO]$ service level should be considered. Therefore, in evaluating performance of inventory systems in this study, we use and compare the two metrics.

3.4.3 Enabling exact evaluation of the service measures

Our aim for the model evaluation is to design one method to evaluate the fill rate and expected number of backorders of all four supply methods, in the most generic possible manner. A truly generic evaluation would therefore allow for the following three elements present in the four supply methods: stochastic demand, stochastic leadtimes and the possibility of order batching.

Order crossover problem

To the best of our knowledge, however, there exists no exact analytic approach that includes these three elements. This is due to the order crossover problem, which makes exact treatment of the demand during leadtime very difficult when both demand and leadtimes are stochastic and $Q > 1$, as described by Hadley and Whitin (1963), p. 202. They further note that an exception exists for situations where demand and leadtime are both generated by a Poisson process, and that for that exception exact evaluation can be done using a Markov analysis. Assuming leadtimes are generated by a Poisson process is inappropriate in our case, though, as queuing effects may produce entirely different leadtime distributions. For systems where leadtimes are distributed generally, there merely exist approximate evaluations (e.g. Hayya et al., 2009).

Circumvention

We can circumvent the above problem and nonetheless perform an exact analysis thanks to several simplifying assumptions we have made in Section 3.2. Due to the assumptions of constant (i.e., deterministic) leadtimes at the OEM and one-for-one AM, not one of the four supply methods actually has a combination of order batching and stochastic leadtimes. As a result, we can make a distinction between inventory systems with one-for-one replenishments and where stochastic leadtimes are allowed (Supply Methods 2-4) and systems with order batching and constant leadtimes (Supply Method 1).

Two distinct types of inventory systems

We can now continue with the expressions for service measures fill rate and expected number of backorders. Additionally, we present the expression for the expected on-hand inventory, needed for the holding costs calculation. In these expressions, we maintain the separation between the two distinct types of systems – with one-for-one replenishments and stochastic leadtimes and systems with order batching and constant leadtimes – to facilitate an exact approach. The calculations we use for the first type of system are obtained from theory on continuous-review base-stock policy models (Van Houtum and Kranenburg, 2015, Section 2.3). For the second system type we base our calculations on an extension to these models (Van Houtum and Kranenburg, 2015, Section 2.10.3).

3.4.4 Evaluation systems with one-for-one AM and stochastic leadtimes

We first cover the probability distribution of the inventory level in steady state, based on which we continue with β, $E[BO]$ and $E[OH]$. The inventory level of a SKU at time t, $IL(t)$, is defined as the on-hand inventory $OH(t)$ minus backorder level $BO(t)$. There cannot be on-hand inventory and backorders at the same time, and thus:

$$OH(t) = (IL(t))^{+},$$
$$BO(t) = (IL(t))^{-},$$

where $x^{+} = \max(0, x)$ and $x^{-} = -\min(0, x)$.

The steady state distribution of the inventory level – and thus also OH and BO – can be deduced from reorder level R and the pipeline inventory. The latter is a random variable denoted by X^{M}, and is specified per supply method. Steady state variables OH and BO are given by:

$$OH = (R + 1 - X^{\mathrm{M}})^{+},$$
$$BO = (X^{\mathrm{M}} - (R + 1))^{+}.$$

Under the assumption of Poisson demand, the fill rate is equal to the probability that that the on-hand inventory is positive, $P\{OH > 0\}$. For systems with one-for-one AM and stochastic leadtimes, $P\{OH > 0\} = P\{X^{\mathrm{M}} < R + 1\}$, and so:

$$\beta = \beta(R) = \sum_{x=0}^{R} P\{X^{\mathrm{M}} = x\}. \tag{3.2}$$

For calculation of expected number of backorders $E[BO]$, we use Eq. 2.6 of Van Houtum and Kranenburg (2015):

$$E[BO] = EBO(R) = \sum_{x=R+2}^{\infty} (x - (R+1))P\{X^{\mathrm{M}} = x\}, \tag{3.3}$$

in which we compute the infinite sum up until a value for x that yields negligible probabilities. Although available, we deliberately do not use the closed-form expression as it does not apply to all four supply methods in this study.

The expected on-hand inventory $E[OH]$ is very similar to the fill rate, but represents the expectation instead of the probability of positive on-hand inventory:

$$E[OH] = EOH(R) = \sum_{x=0}^{R} (R + 1 - x)P\{X^M = x\}. \tag{3.4}$$

3.4.5 Evaluation systems with batching and constant leadtimes

In the case of $Q \geq 1$ and constant leadtimes, so for Supply Method 1, steady state OH and BO cannot be calculated using pipeline inventory X^{M}, because X^{M} can only take values that are multiples of Q. Instead, OH and BO can be calculated based on reorder level R, order size Q and the demand during leadtime. The latter is denoted by random variable D_L^{M} and is Poisson distributed with mean mL^{M} due to the assumption of constant leadtime L^{M}. In expressing OH and BO, random variable U is used. U is a uniformly distributed variable on the integers $\{1, ..., Q\}$ (see Proposition 5.1 of Axsäter, 2015). Steady state variables OH and BO are now given by:

$$OH = (R + U - D_L^{\mathrm{M}})^+,$$
$$BO = (D_L^{\mathrm{M}} - (R + U))^+.$$

The fill rate, or probability of positive on-hand inventory, is now equal to $P\{OH > 0\} = P\{D_L^{\mathrm{M}} < R+U\}$. The latter probability is given by Axsäter (2015) for the situation of Compound Poisson demand. For the situation of regular Poisson demand it can be rewritten to

$$\beta = \beta(R, Q) = \frac{1}{Q} \sum_{y=R+1}^{R+Q} \sum_{x=0}^{y-1} P\{D_L^{\mathrm{M}} = x\}. \tag{3.5}$$

The mathematical expression for the $E[BO]$ under batching and constant leadtimes is similar to the $E[BO]$ expression for the $Q = 1$ case but modified to accommodate the more general $Q \geq 1$. The resulting expression for the $E[BO]$ is given by:

$$E[BO] = EBO(R, Q) = \frac{1}{Q} \sum_{y=R+1}^{R+Q} \sum_{x=y+1}^{\infty} (x - y)P\{D_L^{\mathrm{M}} = x\} \tag{3.6}$$

Similarly, expected on-hand inventory $E[OH]$ is given by:

$$E[OH] = EOH(R, Q) = \frac{1}{Q} \sum_{y=R+1}^{R+Q} \sum_{x=0}^{y-1} (y - x)P\{D_L^{\mathrm{M}} = x\}. \tag{3.7}$$

3.5 Optimization procedure

Using the expressions from Section 3.4 it is possible to calculate costs and service level for the four supply methods for given values for R and Q. In order to determine values for the decision variables, we answer Research Question 1D.

RQ1D	What is a suitable optimization procedure for the generic model?

We start by stating the optimization problem, after which we specify values for the service level constraints and subsequently determine values for Q and R.

3.5.1 Optimization problem

The optimization problem is a minimization of cost function Eq. 3.1 (Total costs $= u^{\mathrm{M}}m + f^{\mathrm{M}}\frac{m}{Q} + hu^{\mathrm{M}}E[OH]$) subject to a fill rate or $E[BO]$ constraint, depending on the service level selected. Because only the last two components of the cost function are affected by decision variables R and Q, the optimization problem can be reduced to:

$$\begin{aligned} &\text{minimize } f^{\mathrm{M}}\frac{m}{Q} + hu^{\mathrm{M}}E[OH] \\ &\text{s.t. } \beta \geq \beta^{\text{obj}}, \qquad Q \in \mathbb{N}_1, \quad R \in \mathbb{N}_0, \end{aligned} \tag{3.8}$$

if we set a fill rate constraint. Alternatively, for an $E[BO]$ constraint:

$$\begin{aligned} &\text{minimize } f^{\mathrm{M}}\frac{m}{Q} + hu^{\mathrm{M}}E[OH] \\ &\text{s.t. } E[BO] \leq EBO^{\text{obj}}, \qquad Q \in \mathbb{N}_1, \quad R \in \mathbb{N}_0. \end{aligned} \tag{3.9}$$

Here, the expression for $E[OH]$ is equal to $EOH(R)$ (Eq. 3.4) or $EOH(R,Q)$ (Eq. 3.7), depending on whether or not batching and stochastic leadtimes are allowed. Similarly, β is equal to $\beta(R)$ (Eq. 3.2) or $\beta(R,Q)$ (Eq. 3.5) and $E[BO]$ is equal to $EBO(R)$ (Eq. 3.3) or $EBO(R,Q)$ (Eq. 3.6). $\mathbb{N}_0$ and $\mathbb{N}_1$ both represent the set of all natural numbers, but differ as the former includes zero while the latter does not: $\mathbb{N}_0 = \{0, 1, 2, ...\}$ and $\mathbb{N}_1 = \{1, 2, ...\}$.

A generally well-performing method to find a solution to the (R,Q) policy optimization problem with stochastic demand is to find optimal order quantity Q under the assumption of deterministic demand, and search for optimal reorder level R after having obtained a value for Q (Axsäter, 2015). We follow this approach.

3.5.2 Service level constraints

Values for service level constraints β^{obj} and EBO^{obj} are set per SKU. For β^{obj}, we adopt the values used by the RNLA: $\beta^{\text{obj}} = 0.99$ for *vital* SKUs and $\beta^{\text{obj}} = 0.95$ for *essential* SKUs (elaboration on the RNLA spare parts classification in Appendix C). These β^{obj} values thus require at least 99% or 95% of demands to be fulfilled directly from stock for vital or essential SKUs, respectively. In order to compare system behaviour under a β^{obj} constraint to behaviour under an EBO^{obj} constraint, similar values need to be chosen for EBO^{obj}. We choose to set $E[BO]^{\text{obj}} = 0.01m$ for vital SKUs and $E[BO]^{\text{obj}} = 0.05m$ for essential SKUs: at most 1% or 5% of demands is being backordered for vital or essential SKUs, respectively. Although the β^{obj} and EBO^{obj} service level constraints differ significantly – and a β^{obj} value cannot be translated to a EBO^{obj} value – using these values does allow us to evaluate the impact of the choice for either a β^{obj} or EBO^{obj} service level constraint.

3.5.3 Order quantity Q

First of all, note that Q is only determined for Sourcing Method 1, and that $Q = 1$ for the other methods. Optimal order quantity Q under the assumption of deterministic demand can be found using the classic EOQ formula and rounding to the nearest integer: $Q = \sqrt{2mf^M/hu^M}, \quad Q \in \mathbb{N}_1$. As we consider a stochastic demand setting, this approach does not necessarily lead to optimal values for Q, but has been described as a generally adequate approximation by Axsäter (2015). For some SKUs an incremental order quantity (IOQ) may exist, which requires rounding to the nearest strictly positive multiple of IOQ.

3.5.4 Reorder level R

After determining Q, the value for optimal reorder level R given Q can be found by setting $R = -1$, and raising R in steps of one until the service level constraint is met. When this happens, the procedure can be stopped immediately and the optimal R (given Q) has been found. This is true because $E[OH]$ and β are non-decreasing (i.e., increasing in or indifferent to increments) in R and $E[BO]$ is non-increasing in R, as we show in Appendix D. We argue that the minimum value of $R = -1$ is intuitive, as it could – in some cases – make sense to only order at the moment a backorder occurs, but it will never be beneficial to order only after multiple backorders have accumulated.

3.6 Conclusion

In this chapter we construct the generic model, suitable for comparing the four different supply methods that we consider. The structure of the generic model is determined, with main factors total costs and service level. For both factors a description of how we compute them is given. To apply the generic model to each of the supply methods, supply method-specific variables need to be given as input. We find that the main variables that are required to be inserted specifically for all supply methods are cost variables u^{M} and f^{M} and one variable for service level computations. Which variable this is differs per supply method: for Supply Method 1, the required variable is demand during leadtime D_L^{M}; for Supply Methods 2, 3 and 4, pipeline inventory X^{M} is used as input for service level computations.

Chapter 4

Single source supply methods

Now that a generic mathematical model for the comparison of the four supply methods has been established, the need arises to determine the values of the input variables for each of the supply methods. Some input variables, for instance spare part unit costs at the OEM (u^{M1}), are independent and can be treated as input parameters. Other variables, like the pipeline inventory distribution when using a limited-capacity in-house AM system (X^{M3}), depend on other non-generic variables and can only be determined after making several assumptions. Specifying the variable values is done per supply method. In this chapter we consider the three single source supply methods, Supply Methods 1, 2 and 3. We answer Research Question 2.

RQ2	**What are the model input variable values for the single source supply methods?**

We cover model input variables of Supply Method 1 in Section 4.1, Supply Method 2 in Section 4.2 and Supply Method 3 in Section 4.3. The variables that are discussed are the Supply Method-specific variables introduced in Chapter 3. These include cost variables u^{M1}, u^{M2}, u^{M3}, u^{M4}, f^{M1}, f^{M2}, f^{M3} and f^{M3}. Furthermore, demand during leadtime D_L^{M} is considered to be an input variable for the generic model, but only for Supply Method 1 (as explained in Section 3.4.3). For Supply Methods 2 and 3, pipeline inventory variables X^{M2} and X^{M3} are to be derived as input for the generic model.

4.1 Supply Method 1: OEM

In order to determine the model input variable values for Supply Method 1, we answer Research Question 2A.

RQ2A	What are the model input variable values for the OEM supply method?

Relevant input variables for which we determine values in this section are unit cost u^{M1} and fixed order cost f^{M1}. Furthermore, we determine the distribution of the demand during leadtime, D_L^{M1}, under Supply Method 1.

4.1.1 Unit cost u^{M1}

The unit cost for spare parts at the OEM supply source can be regarded as a simple input constant. There is an issue with the reliability of this data at the RNLA, worth noting. For the majority of spare parts in the RNLA system, no contract with an OEM exists. As a result, a new price or even a new supplier needs to be found for every order, causing unit cost to fluctuate over time. This effect is difficult to take into account in this study, however, as the RNLA information systems only contain the most recently used unit cost. To assure reliable data in our case study data for unit cost u^{M1} is verified first.

4.1.2 Fixed order cost f^{M1}

The fixed order cost in the situation with OEM supply results from the operations that need to be performed by employees in the purchasing department for issuing an order. RNLA distinguishes between spare parts with an OEM contract and non-contract parts. Based on the assumption that a purchasing employee has to perform a certain estimated amount of time per order, the RNLA estimates the fixed order cost of an order of non-contract parts at €180. For contract parts the RNLA has estimated this cost at €45. Both estimates are confirmed to be realistic by sources within the RNLA (for a list of personal sources, see Appendix E).

4.1.3 Leadtime demand D_L^{M1}

As we assume Poisson demand and constant OEM leadtime L^{M1}, the demand in period $t, t+L$ simply behaves according to a Poisson process with mean mL^{M1}. Its probability density function (PDF) can be calculated using the following recursion:

$$P\{D_L^{\text{M1}} = 0\} = e^{-mL^{\text{M1}}}$$

$$P\{D_L^{\text{M1}} = x+1\} = \frac{mL^{\text{M1}}}{x+1} P\{D_L^{\text{M1}} = x\} \quad \text{for } x \in \mathbb{N}_0 \tag{4.1}$$

Leadtime L^{M1} is defined as the time between the moment that $IP < R+1$ and the spare part(s) are received. It includes internal leadtime and external leadtime. The former is the time it takes employees before an order is created, while the latter is simply the quoted leadtime by the OEM. The internal leadtime is explicitly mentioned here, as it may be longer than one would expect. Internal leadtimes at the RNLA reportedly exceed two months due to understaffed purchasing departments, according to sources within the RNLA.

4.2 Supply Method 2: outsourcing AM

In order to determine the model input variable values for Supply Method 2, we answer Research Question 2B.

RQ2B	What are the model input variable values for the outsourced AM supply method?

Relevant input variables for which we determine values in this section are unit cost u^{M2} and fixed order cost f^{M2}. Furthermore, we determine the demand during leadtime distribution X^{M2} under Supply Method 2.

4.2.1 Unit cost u^{M2}

The unit cost of outsourcing AM, u^{M2}, similarly to unit cost at the OEM, can be obtained by providing the requirements of the AM job to the external AM provider. These job requirements generally include a 3D file, the material type and functional requirements of the to be printed part. The external provider then gives a quotation of the unit cost. This quotation includes all costs that the external AM provider incurs through the job, and a margin for profit.

4.2.2 Fixed order cost f^{M2}

It is very difficult to give a reliable estimate for the fixed order cost of outsourcing AM. For a valid comparison, it would be doubtful to assume that ordering at an external AM provider is free while placing an order at the OEM causes €45 or €180 in order processing costs for contract and non-contract SKUs, respectively. Since we assume one-for-one ordering of parts at an AM provider, however, assuming similar fixed order costs would render the Supply Method 2 extremely expensive. Let us therefore assume that processing orders for AM jobs can be done quite efficient by RNLA personnel compared to placing orders at the OEM. It is assumed that issuing an order at a regular external AM provider takes about one-fourth of the time it takes to order at an OEM, due to a smaller administrative burden. We set $f^{\mathrm{M2}} = €10$, and perform sensitivity analyses on this value in the case studies.

4.2.3 Pipeline inventory X^{M2}

In our model a failed part triggers a new part to be ordered at the external AM provider – and thus to enter the inventory pipeline – according to a Poisson process. On average, the ordered part resides in the pipeline for a time period equal to the expectation of the outsourcing AM leadtime $E[L^{\mathrm{M2}}]$. The ample capacity we assume for the external AM provider resembles an infinite capacity server in a queuing system. The pipeline can thus be considered a $M/G/\infty$ queuing system, for which Palm's theorem (Palm, 1938) states that the pipeline inventory follows a Poisson distribution with mean $mE[L^{\mathrm{M2}}]$. The PDF of X^{M2} can thus be calculated using the recursion from Eq. 4.1.

Regarding outsourcing AM leadtime L^{M2} it is assumed that an efficient internal AM order process will be put in place, eliminating any significant internal leadtimes.

4.3 Supply Method 3: in-house AM

Deploying AM capacity in-house would provide the organization with the ability to circumvent long external leadtimes that come with the OEM supply and would avoid the markup on AM jobs at the third party AM provider. Naturally, this comes at a cost: acquiring an AM system is expensive. Moreover, with in-house AM comes the obstacle of limited capacity. To facilitate proper comparison with the other supply methods, we answer Research Question 2C.

RQ2C	What are the model input variable values for the in-house AM supply method?

Relevant input variables for which we determine values in this section are unit cost u^{M3} and fixed order cost f^{M3}. Furthermore, we determine the demand during leadtime distribution X^{M3} under Supply Method 3.

4.3.1 Unit cost u^{M3}

In order to compute unit cost for in-house AM, u^{M3}, the main AM cost factors are considered. The major cost driver of AM is found to be AM machine cost (incl. purchase price and maintenance), followed by material cost and production labour (Lindemann et al., 2012). The cost buildup with AM machine cost as sole major cost driver is confirmed by more recent studies (Piili et al., 2015; Baumers et al., 2016). For a fair comparison between the different supply methods, the complete costs of a part are included in unit cost u^{M3}. Machine, material and labour costs thus have to be allocated to specific SKUs. We do this based on the AM cost allocation model of Ruffo et al. (2006) (Figure 4.1), which makes the following distinction:

$$\text{In-house AM unit cost } u^{\mathrm{M3}} = \text{Direct cost per build} + \text{Indirect cost per build},$$

We exclude production overhead (i.e., rent, ancillary equipment and energy) and administrative overhead, as these are no major cost drivers and hard to quantify — especially in case of the RNLA.

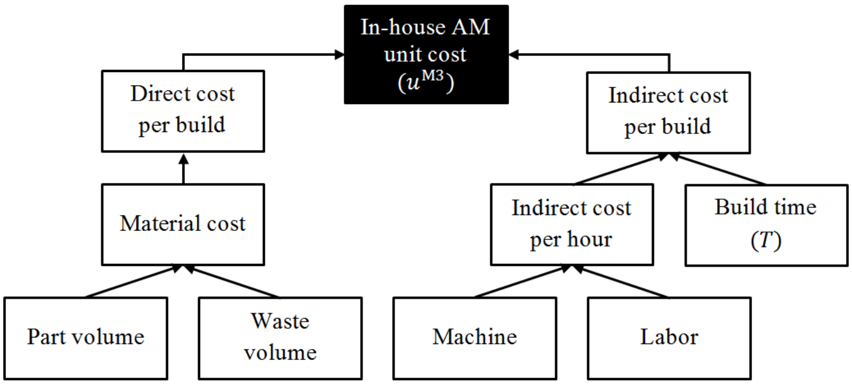


Figure 4.1: AM cost allocation model (Ruffo et al., 2006) adjusted to exclude overhead

Direct cost per build

As stated in Chapter 1, we assume powder bed fusion processes for the case study. This category includes industry-standard processes such as SLS and SLM. In PBF processes, a selection of powder substance in a bed is melted or sintered, leaving the remainder of the powder unprocessed. For a more detailed description of the PBF process, see Appendix F. A portion of the unprocessed powder can often be reused, depending on the material and exact process.

$$\begin{aligned}\text{Direct cost per build} &= \text{Material cost} \\ &= \text{Material price} \times (\text{Volume}^{\text{part}} + \text{Volume}^{\text{waste}})\end{aligned}$$

where material price is in given in €/cm^3 and volumes in cm^3. Waste volume for PBF processes can be computed based on the powder bed volume needed for the build, the part volume and waste factor α, as follows:

$$\text{Volume}^{\text{waste}} = \alpha(\text{Volume}^{\text{bed}} - \text{Volume}^{\text{part}}).$$

Indirect cost per build

The indirect cost per build can be obtained by summing the annual machine and labor costs, and taking into account build time T.

$$\text{Indirect cost per build} = T\frac{\text{Annual machine cost} + \text{Annual labor cost}}{\text{Annual available machine hours} \times \text{Utilization rate}}$$

Annual machine cost can be derived from the purchase price, assuming it depreciates linearly over a given number of years, and annual maintenance costs.

$$\text{Annual machine cost} = \frac{\text{Machine purchase price}}{\text{Useful life in years}} + \text{Annual machine maintenance costs}$$

Annual labor cost is estimated based on the number of full time employees (FTE) needed to handle the machine and pre- and post-processing, which depends strongly on the AM process and machine type.

4.3.2 Fixed order cost f^{M3}

The process of ordering SKUs at external parties – which is costly in terms of RNLA employee time – exists for Supply Method 1 and 2, but not when AM is deployed in-house. Of course there are other relevant labor processes, and associated costs have been included in unit cost u^{M3}. We thus conclude that $f^{\text{M3}} = 0$.

4.3.3 Pipeline inventory X^{M3}

For calculation of inventory X^{M3}, the limited capacity of the AM system is a relevant aspect. Production systems with limited capacity can be modeled with the assumption of unlimited capacity if utilization is low. In our case, however, this assumption is not appropriate, as high capacity utilization is required to make an in-house AM system justifiable economically. We therefore decide that the limited capacity needs to be modeled as such, with a job queue. As a result, we need information not only on the SKU considered but also on the other SKUs in the system.

Build job time expectation and variation

In order to do calculations for X^{M3} information on all SKUs that are supplied by the AM machines is required. Our single-item approach does not facilitate this. We therefore take a small sample of the set of SKUs that are serviced on the AM machine, and compute expected print time $E[T_{set}]$, variance $V[T_{set}]$ and coefficient of variation $cv[T_{set}] = \frac{V[T_{set}]}{E[T_{set}]^2}$. Note that we require the expectation of T over all *build jobs* – and not SKUs – and that we therefore factor in demand rate m. We consider SKUs $i = \{1, ..., |I|\}$ in sample set I.

$$E[T_{set}] = \sum_{i \in I} \frac{m_i}{\sum_{i \in I} m_i} T_i, \tag{4.2}$$

$$V[T_{set}] = \frac{\sum_{i \in I} m_i (T_i - E[T_{set}])^2}{(\sum_{i \in I} m_i) - 1} \tag{4.3}$$

These metrics are used in the analysis of the queue needed to derive pipeline inventory X^{M3} in this section and X^{M4} in Chapter 5.

Exact analysis
The probability distribution of pipeline inventory X^{M3} for in-house AM can be found through exact analysis of the finite multi-item capacity production-inventory system (van Harten and Sleptchenko, 2000; Sleptchenko et al., 2002; Sleptchenko, 2002), which is a complex and computationally expensive procedure. Furthermore, we do not have information on all SKUs in the system, but merely have estimates derived from a sample.

Approximation method selection
A practical though accurate alternative used by Díaz and Fu (1997) is to plug in $M/G/1$ throughput times in the $M/G/\infty$ model, which assumes FCFS processing. They use a mean-value analysis to obtain the first two moments of X^{M3}, which are subsequently used to fit a Negative Binomial (NB) distribution to X^{M3} for each SKU i. They find the method to be sufficiently accurate to approximate the actual system behaviour. We choose to adopt this method and to validate it for the purpose of our study. A step-wise procedure of the Díaz and Fu (1997) method is given in Appendix G.

Approximation method validation
A full description of the validation of the approximation for X^{M3} is provided in Appendix H. To validate whether we can correctly assume the Díaz and Fu (1997) approximation method for X^{M3} to be appropriate, we first consider the purpose of the approximation in this study. That is to compute fill rate β and expected number of backorders $E[BO]$ under one-for-one AM and stochastic leadtimes (Section 3.4). Let us denote the approximation of X^{M3} by $\overline{X^{\mathrm{M3}}}$ and values of β and $E[BO]$ computed using $\overline{X^{\mathrm{M3}}}$ by $\overline{\beta}$ and $\overline{E[BO]}$, respectively.

For validation, we thus check to what extent the values of $\overline{\beta}$ and $\overline{E[BO]}$ match the values of β and $E[BO]$ computed using the actual X^{M3}, which we find using a long-term simulation. An experimental dataset of 20 SKUs with different demand rates and AM process times is composed. We compare $\overline{\beta}$ with β and $\overline{E[BO]}$ with $E[BO]$ for a small sample, and observe that $\overline{\beta}$ and β are virtually identical, regardless of changes in utilization and variability (average relative error $\delta^{\mathrm{avg}} = 8.2 \times 10^{-4}$, maximum relative error $\delta^{\mathrm{max}} = 2.1 \times 10^{-3}$). Differences between $\overline{E[BO]}$ with $E[BO]$ are more substantial ($\delta^{\mathrm{avg}} = 0.071$, $\delta^{\mathrm{max}} = 0.25$), but the approximation is considered sufficiently accurate for the purpose of this study, especially since the quite large relative error is mainly caused by a single outlier. This outlier indicates that the approximation is relatively inaccurate for situations where both system utilization and print time variability are high, which we keep in mind.

4.4 Conclusion

In this chapter we present which exact values we use for the input variables specified in the generic model, for single source Supply Methods 1, 2 and 3. Especially for Supply Method 3, this requires a collection of calculations. Attention is paid to unit cost u^{M3} and pipeline inventory X^{M3} in particular. The former is computed based on an existing cost-allocation method (Ruffo et al., 2006), while the latter leverages a pipeline inventory approximation proposed by Díaz and Fu (1997). Finally, we validate the use of the approximation for this study.

Chapter 5

A dual AM source supply method

This chapter focuses on Supply Method 4: a combination of in-house AM and outsourced AM. This so-called dual AM supply method provides the benefits of in-house AM but offers an alternative source to avoid excessive queues or even an overflowing system. In order to use the generic model of Chapter 3 for calculating costs and service levels of a dual AM source supply method, Research Question 3 is answered.

RQ3	**What are the model input variable values for a dual AM source supply method?**

Several prior studies consider an AM option as contingency source in a dual supply model. Knofius et al. (2017), for example, investigate a spare parts supply chain with both CM and AM sources, supplying similar SKUs but with different failure rates. Song and Zhang (2018) cover a similar situation but focus on allocating SKUs to the sources. In an extension of their model dual sourcing is allowed; demand is primarily satisfied by an CM-supplied inventory but is overflowed to the AM source when stock-outs occur. Westerweel et al. (2018b), in a study at the RNLA, consider a periodic-review spare parts inventory control system with a CM and an AM source.

Our dual source scenario differs from these prior studies on several aspects. First of all, both of the supply options in our dual source model use AM. The difference between the two sources lies in leadtime and cost. In-house AM is assumed to always come with a shorter process time (queuing time not included) than the leadtime of outsourcing AM, and lower per-job costs. Outsourcing AM takes more time and is associated with higher per-job costs, but queuing effects can be neglected due to ample capacity. For proper comparison to the other scenarios we again assume FCFS processing.

Before we can derive values for the model input variables, specification of decision rules in the supply method is needed. That is, how do we determine when to use in-house AM and when to use the external AM source? And, can we use an optimal decision rule or do we need to find a good alternative? We cover this subject in Section 5.1. Model input variable values for a dual AM source method are derived in Section 5.2

5.1 Dual sourcing decision rules

The operational decision when to choose which AM source is key to the entire dual source supply method. To specify the structure of our dual source supply method, we therefore answer Research Question 3A.

RQ3A	What is a good rule for deciding when to use in-house AM and outsourcing AM in a dual source supply method?

We consider a review on multiple-supplier inventory models in supply chain management by Minner (2003), wherein dual source models are categorized based on demand and leadtime characteristics and the number of stocking points. Our dual AM model can be characterized as a single-stage stochastic leadtime model due to the queuing effects at the in-house AM source. Because of the Poisson demand rate, the queue and the assumption of high capacity utilization, variance of the waiting time is generally high. For a decision rule to be effective, it should thus factor in the expected waiting time in the queue at the moment when a demand comes in.

5.1.1 Optimal decision-making

Aside from expected waiting time at the in-house AM, the following other factors should be taken into account to make optimal sourcing decisions every time demand occurs: in-house and external AM costs, external leadtime, holding cost rate and the service level status and objective. An optimal decision rule would consider all factors and decide – based on a trade-off between leadtime costs and taking into account the service level objective – which source to use. To determine the exact in-house AM leadtime, it should be known exactly which SKUs are being built, in queue and in which sequence. This can simply not be done within the scope of this research. We therefore aim to design an efficient decision making alternative that captures the essence of the optimal decision rule.

5.1.2 An efficient and effective decision rule

One option that could be considered is to select in-house AM as supply method when the in-house AM machine is available, and outsource whenever it is not. When in-house build times and outsource leadtimes are similar, this could work. However, we expect the former to be several times faster than the latter, and therefore argue that waiting for the in-house AM machine to become available results in shorter overall average leadtimes.

The alternative decision rule we propose is based on the expected waiting time at the in-house AM system. If the system (queue and in service) contains strictly less than K items, the new demand is placed at the end of the queue. When the system contains K or more items, any new demand is outsourced.

We set K based on expected in-house build time $E[T]$ and expected external leadtime $E[L^{\text{ex}}]$, so that a job is processed using the source that is expected to take the smallest amount of time. Thus,

$$K = \frac{E[L^{\text{ex}}]}{E[T]}, \quad K \in \mathbb{N}_1 \tag{5.1}$$

rounding to the nearest integer.

Essentially, this allocates jobs to in-house or external AM based on expected waiting time in queue. As a result, it is expected to yield decent decisions, and therefore adequately serves the purpose of this study. Moreover, modeling complexity of this decision rule is acceptable.

There is an important disadvantage to this decision rule, which should be noted. While the rule optimizes the service level, it does not minimize costs; any cost differences between the two sources are not taken into account. When in-house AM is expected to take only marginally longer than outsourcing, this could result in sub-optimal decisions. Yet, we choose not to take this aspect into account, as it would make service levels very difficult to evaluate.

A second notable inaccuracy of the decision rule is in the use of expected in-house build time $E[T]$. By using this variable, the decision rule does not take into account that the job currently in the server might already be partly completed. When $E[T]$ is relatively small compared to $E[L^{\text{ex}}]$ – which we expect to be the case in this research – the effect of this inaccuracy is small.

5.2 Input variable values Supply Method 4

Based on the sourcing decision rule proposed in Section 5.1, we can derive values for the input variables in the generic mathematical model. Research Question 3B is answered:

RQ3B	How can model input variable values for a dual AM supply source method be derived?

We first consider the cost variables f^{M4} and u^{M4} and then cover pipeline inventory X^{M4}.

5.2.1 Fixed order cost f^{M4}

Fixed order cost variable f^{M4} can be calculated by taking a weighted average over f^{M2} and f^{M3}, such that:

$$f^{\text{M4}} = p_K f^{\text{M2}} + (1 - p_K) f^{\text{M3}},$$

where p_K is the probability that an item is supplied by outsource AM and $(1 - p_K)$ naturally the probability a part is built in-house.

5.2.2 Unit cost u^{M4}

Calculating unit cost variable u^{m4} is done in a similar manner, but taking into account one additional complexity. That is, when a portion p_K of the total demand is outsourced, initial capacity utilization of the in-house AM machine (ρ) drops by $p_K\rho$. Therefore the indirect cost per build are allocated to fewer build jobs, multiplying the indirect cost per build by $\frac{1}{1-p_K}$. As a result,

$$u^{\text{M4}} = p_K u^{\text{M2}} + (1 - p_K)(\text{Direct cost per build} + \frac{\text{Indirect cost per build}}{(1 - p_K)}).$$

5.2.3 Outsourcing probability p_K

For the value of p_K, we turn to theory on $M/G/1/K$ queuing systems. A $M/G/1/K$ queue is characterized by exponentially distributed inter-arrival times, generally distributed process times, a single server and a maximum queuing system capacity of K. K is therefore identical to the sourcing threshold presented in Section 5.1.2. We use the work of MacGregor Smith (2011) on $M/G/1/K$ performance modelling for computing several properties of our system, starting with p_K. In queuing theory, p_K is referred to as the blocking probability, which is equal to the portion of demand that is outsourced in our dual AM model. The value of p_K can be calculated as a function of K, capacity utilization ρ and squared coefficient of variation of the printing process $cv[T]^2$. According to an approximation given by MacGregor Smith (2011):

$$p_K = \frac{\rho^{\left(\frac{cv[T]^2\sqrt{\rho\exp(-cv[T]^2)}-\sqrt{\rho\exp(-cv[T]^2)}+2K}{2+cv[T]^2\sqrt{\rho\exp(-cv[T]^2)}-\sqrt{\rho\exp(-cv[T]^2)}}\right)}(\rho-1)}{\rho^{\left(2\frac{cv[T]^2\sqrt{\rho\exp(-cv[T]^2)}-\sqrt{\rho\exp(-cv[T]^2)}+K+1}{2+cv[T]^2\sqrt{\rho\exp(-cv[T]^2)}-\sqrt{\rho\exp(-cv[T]^2)}}\right)}-1} \tag{5.2}$$

It should be emphasized that this is an approximation, although it has been proven to be a fairly accurate one. For more on this we refer to MacGregor Smith (2011).

5.2.4 Pipeline inventory X^{M4}

Per-SKU pipeline inventory distribution X^{M4} is essential for calculation of the different performance measures. The PDF of X^{M4} depends on both internal AM pipeline X^{in} and external AM pipeline X^{ex}. In this section we derive both PDFs and then explain how we use them to construct X^{M4}.

In-house AM pipeline inventory X^{in}

We first approximate the PDF of X^{in}_{set}, the pipeline inventory of an entire set of SKUs that is supplied by the same AM machine. Probability $P\{X^{\text{in}}_{set} = x\}$ where $0 \leq x < K$, $x \in \mathbb{N}$ can be approximated accurately using the relations between p_K, p_0 and p_n in $M/G/1/K$ queuing systems. Here, p_0 denotes the probability of an empty system and is given by (MacGregor Smith, 2011):

$$p_0 = \frac{(\rho-1)}{\rho^{\left(2\frac{cv[T]^2\sqrt{\rho\exp(-cv[T]^2)}-\sqrt{\rho\exp(-cv[T]^2)}+K+1}{2+cv[T]^2\sqrt{\rho\exp(-cv[T]^2)}-\sqrt{\rho\exp(-cv[T]^2)}}\right)}-1}. \tag{5.3}$$

p_n denotes the probability of a total of n items in the $M/G/1/K$ system, as an aggregate of all SKUs, given by:

$$p_n = p_0\rho^n \tag{5.4}$$

The latter formula is not exact when the service time distribution is other than exponential, but this can be effectively remedied according to MacGregor Smith (2011) by adjusting the probability mass for the values of p_n so that the mass $1 - p_0 - p_K$ is distributed according to Eq. 5.4. Using this information on the total number of items in the queuing system, demand rate m and per-SKU utilization rates $r = m * T$, the per-SKU X^{in} can be calculated. Based on conditional probabilities, $P\{X = n\}$ is found to be given by:

$$P\{X^{\text{in}} = n\} = \begin{cases} p_0 + \sum_{x=1}^{K} p_x(1-\frac{r}{\rho})(1-\frac{m}{M})^{x-1}, & \text{for } n = 0 \\ \displaystyle\sum_{x=0}^{K-n} p_{(n+x)}\left[\frac{r}{\rho}(\frac{m}{M})^{n-1}(1-\frac{m}{M})^{x}\binom{n+x-1}{x}\right. \\ \qquad\left. + (1-\frac{r}{\rho})(\frac{m}{M})^{n}(1-\frac{m}{M})^{x-1}\binom{n+x-1}{n}\right], & \text{for } n \in \mathbb{N}_1 \end{cases} \tag{5.5}$$

For a derivation the reader is referred to Appendix J.

External AM pipeline inventory X^{ex}
X^{ex} can be derived as follows. The rate at which demands arrive at the external source is demand rate m multiplied by blocking probability p_K. It is known that the overflow behaves as a Poisson process which is alternately turned on for an exponentially distributed time and then turned off for another exponentially distributed time, which is named the *interrupted* Poisson process (Kuczura, 1973). For simplicity, and because the effect of this approximation is expected to be only slight due to ample capacity at the external AM source, we assume a standard Poisson process rather than an interrupted Poisson process. We later validate this approximation. Consequently, we can compute X^{ex} in a similar way as the situation with only AM outsourcing, but with a lower arrival rate. Thus, X^{ex} is Poisson distributed with mean $p_K mT$.

Joining X^{in} and X^{ex}
Let us start by noting X^{M4} can only be approximated. Exact derivation would require X^{in} and X^{ex} to be independent, which they are not; orders in the outsourcing AM pipeline are likely to co-occur with a full in-house queuing system because of the overflow process. The strength of this dependence depends on the difference in in-house and outsource AM process times. Given that an in-house AM job takes hours up to at most a few days and an outsourced job is likely to take several weeks, the correlation between the number of items in the in-house queue and the outsourced AM pipeline is weak. For this reason, we argue that the convolution $X^{\text{M4}}(n) = \sum_{k=0}^{n} X^{\text{in}}(k) X^{\text{ex}}(n-k)$ can be used regardless of the dependence.

Approximation method validation
A full description of the approximation method validation, including the dataset used, is provided in Appendix I.

In deriving X^{M4} for the dual AM supply method three approximations are used: the MacGregor Smith (2011) $M/G/1/K$ approximation for X^{in}, the assumption of a Poisson arrival process instead of an interrupted Poisson process for computation of X^{ex} and the convolution of the not entirely independent X^{in} and X^{ex}. As a consequence, the overall accuracy of the X^{M4} must be validated before use. Similar to the validation method of the in-house AM pipeline inventory in Chapter 4, we consider the fact that we use X^{M4} to compute service measures β and $E[BO]$ and subsequently verify whether the approximation of X^{M4} yields sufficiently accurate values of these service levels.

Two main factors that affect the queuing system are sourcing threshold K and AM build time variability. We therefore argue that the approximation accuracy should be tested under varying values for K and $cv[T_{set}]$, the coefficient of variation of build times of the set of SKUs that is supplied by the AM system. It is found that the approximation yields accurate values for fill rate β, under all conditions ($\delta^{\text{avg}} = 1.7 \times 10^{-3}$, $\delta^{\text{max}} = 5.1 \times 10^{-3}$). The accuracy of values for $E[BO]$ is not convincing, especially under high build time variability ($\delta^{\text{avg}} = 0.13$, $\delta^{\text{max}} = 0.41$). We therefore decide *not to use* this approximation for calculation of the $E[BO]$ service level in this study. The $E[BO]$ service level can therefore only be used for Supply Methods 1, 2 and 3. Consequently, Supply Method 4 is only evaluated using fill rate β.

5.3 Conclusion

In this chapter the we set out to determine values for generic model input variables f^{M4}, u^{M4} and X^{M4}. In order to do this however, the dual AM source model first needs to be specified; a decision rule needs to be designed. We list the aspects that an optimal decision rule would take into account, and observe that this optimal decision rule has a high degree of complexity. It is concluded that, for the purpose of this research, an alternative and more efficient decision rule suffices. The decision rule we design essentially allocates jobs to the supply source that has the shortest expected leadtime at that moment in time, based on the queue length and composition. For the calculation of pipeline inventory X^{M4} under the chosen decision rule, we use an existing approximation based on $M/G/1/K$ queuing systems (MacGregor Smith, 2011) combined with another approximation. The overall approximation accuracy is then validated. It is found that the approximation is very accurate for fill rate β calculations, but not sufficiently accurate to compute expected number of backorders $E[BO]$. We conclude that we use the approximation but refrain from using it for computations of $E[BO]$.

Chapter 6

Case study: supply decisions at the RNLA

We can now investigate whether AM can be an economically beneficial addition or replacement for spare part supply chains with its current costs and technical possibilities by testing the developed comparison model in a real life context. We pose Research Question 4, which we answer by means of two case studies.

RQ4	**Which supply method must be used for spare parts within RNLA if AM is an option?**

In the case studies we perform an analysis on a small set of spare parts, for which data is collected. The topic of data collection is briefly described in Section 6.1. We then present two separate case studies: one in which we consider polymer AM and the second considering metal AM. Both cases are considered as either of them are believed by the RNLA to have great potential. Nonetheless they are considered separately as related technologies, costs and analytic results are quite diverging. RQ4 is answered by first considering present-day AM technologies in RQ4A and subsequently investigating how the situation might change if AM costs and build times are further reduced, in RQ4B.

RQ4A	How do the four supply methods perform considering current AM technology?
RQ4B	How will the performance of each of the supply methods change when AM technology costs and build times are reduced?

Both RQ4A and RQ4B are answered separately for polymer AM and metal AM cases.

A general method for the case studies is given in Section 6.2. Case study 1, polymer AM, is covered in Section 6.3 and Case study 2, metal AM, in Section 6.4. In Section 6.5 results of both case studies are joined in order to come to an answer to RQ4A and RQ4B.

6.1 Data collection

6.1.1 Spare part selection

Although the RNLA has several dozens of military systems for which AM might prove a valuable spare parts supply chain solution, we choose to focus on one system in particular. The selected system for the case study is the Fennek reconnaissance and security vehicle, of which the RNLA owns 365 in total. The Fennek is a suitable case study subject as the RNLA has drawings of its parts, which facilitates the process of creating 3D files for AM. Furthermore, the vehicle has been in use at the RNLA already since 2007 with a large fleet, yielding useful information on the failure behaviour of its parts.

We consider parts that have been deemed potentially interesting for AM in earlier studies at the RNLA. We thoroughly review these parts to create a selection for this research. The analysis starts with 44 spare parts from studies by Melman (2018), Westerweel et al. (2018b) and a cooperative experiment between the RNLA and AM specialist DiManEx BV. It must be noted that these prior studies used different selection methods, ranging from top-down to user-based approaches.

Three filters are applied, based on data completeness, numerical spare part attributes and technical feasibility. We first filter out parts that have missing or unreliable values for OEM unit cost u^{M1} or annual demand rate m in the RNLA SAP database. Then, parts with $u^{\mathrm{M1}} < 20$, $m > 50$ or that are not critical are eliminated, as high-cost and slow-moving SKUs have higher economical potential for AM (Knofius et al., 2017). A third filter is applied based on AM feasibility, for which the SKUs are studied manually and consultation of several experts in the field of AM and metal AM is obtained (for a list of consulted personal sources, we refer to Appendix E). It is required that the parts can be produced with currently available AM technology, as we aim to provide insight in the present-day potential of spare parts supply chain optimization with AM. After filtering, nine distinct SKUs remain. Of these, three are suitable for polymer AM and six for metal AM.

6.1.2 General input data

Aside from information on the SKUs, some general figures are needed as input for both the polymer and the metal AM case. First of all, build time T is needed for every SKU. T depends on the AM machine used, build material, part dimensions, volume, orientation and warm-up time. We take these factors into account, and estimate values for T based on the different system specifications and under advisement of an external AM expert.

Cost and leadtime information of outsourcing AM is based on quotations by Belgian AM provider Materialise. Quotations are based on 3D files, AM process and build material. Several of the 3D files used as input for the quotations were designed in the prior experiment with the RNLA and DiManEx BV, while the others we construct ourselves based on own measurements.

The cost of labor for operations associated with in-house AM is also required in the overall cost calculation. We assume the salary of a full time employee (FTE) of rank sergeant level 14 (annual gross salary: €32,000) as this is the rank of RNLA personnel currently experimenting with AM on missions. Although we study a different setting, it is a assumed that the rank of personnel needed is similar.

6.2 General case study method

Before polymer and metal AM are considered separately, a general method for the case study is developed. We perform the following steps:

1. *Set service level constraints* To compare the performance of the different supply methods for each of the SKUs, we first set the service level constraints. We start with the fill rate objectives as prescribed by the RNLA, as covered in Section 3.5: $\beta^{\text{obj}} = 0.99$ for vital SKUs and $\beta^{\text{obj}} = 0.95$ for essential SKUs.

2. *Set capacity utilization* The situation we want to investigate has high capacity utilization ρ, as a high ρ drives down indirect build cost and is required to study whether AM can bring about cost reductions. The set of SKUs we consider is limited, and a system that solely serves these SKUs will have a very low ρ. We therefore assume that the system serves a large group of so-called virtual SKUs as well. The characteristics ($E[T]_{set}$ and cv^{T}_{set}) of the set of virtual SKUs are assumed to be identical to the SKUs of which we have data. The numbers are based on a utilization $\rho = 0.90$ of the practical maximum number of machine hours available per year.

3. *Determine reorder level* The developed model is used to compute the required minimum reorder level R for each of the SKUs under Supply Method 1, 2, 3 and 4. Total costs per SKU are then calculated based on these reorder levels according to the generic model.

4. *Analyze inventory levels* Expected inventory on hand $E[OH]$ is analyzed for each of the supply methods, to obtain insights in the potential of AM in reducing inventory levels.

5. *Substitute service level constraint* Subsequently the supply methods are analyzed under under a service level constraint. As described in Section 3.5, we set $EBO^{\text{obj}} = 0.01m$ for vital SKUs and $EBO^{\text{obj}} = 0.05m$ for essential SKUs, as this is similar – but definitely not the same – as a β^{obj} service level constraints. In this analysis, Supply Method 4 is excluded from this part of the analysis as the approximation of pipeline inventory X^{M4} did not prove to be sufficiently accurate to compute $E[BO]$ (see Section 5.2.4).

6. *Increase capacity utilization* To test whether Supply Method 4 truly aids in preventing the in-house AM system queue from becoming excessive, the different supply methods are investigated under an increased aggregate capacity utilization of $\rho = 0.99$.

7. *Investigate reduced AM costs and build times* To gain insights in how progress in AM technology may change future supply chains – and to answer RQ4B – we analyze the effect of decreases in AM costs and build times. This topic is studied more extensively for the metal AM case, as high costs and long build times are most prominent there.

8. *Sensitivity analysis fixed order cost* Finally, there are two input variables for which the selected values carry uncertainty and are expected to significantly affect results. These are fixed order cost variables f^{M1} and f^{M2}. We perform a sensitivity analysis to evaluate to what extent variation in f^{M1} and f^{M2} affects total costs of Supply Methods 1 and 2.

6.3 Case study 1: polymer AM at the RNLA

The spare parts considered in the polymer case study are depicted in Figure 6.1 and include a reservoir cap (SKU 1), a camera support (SKU 2) and an air vent (SKU 3). The first two

(a) SKU 1 (3D rendering) *(b) SKU 2 (3D rendering)* *(c) SKU 3 (3D rendering)*

Figure 6.1: The SKUs considered for the polymer AM case study

are special cases. Once the reservoir cap is lost, the RNLA is forced to acquire an entire new reservoir. And, when a camera support breaks, the RNLA must send both support and camera back to the OEM for a costly replacement.

6.3.1 Case-specific input data

The AM technology that is selected for this case study is SLS. A major advantage of SLS over FDM or SLA is the fact that support material is not needed. This dramatically reduces post processing and thus labor, making it particularly interesting for the RNLA. Furthermore, polymer SLS systems are becoming increasingly cost-effective. The system we consider in this case is the Formlabs Fuse1, one of these new-generation low-cost polymer SLS machines, and therefore interesting for this case study. The total machine price, which includes a cleaning system, amounts to € 17,700. We assume linear depreciation over 5 years, based on prior research on polymer SLS costs (Atzeni et al., 2010). We assume 5,000 machine operation hours a year (about 60% of the total number of hours in a year) in line with other studies on polymer AM (Ruffo et al., 2006; Atzeni et al., 2010). We argue that one FTE can operate and maintain the machine, as SLS does not require significant post-processing. The build material we consider is Nylon 12 (poly-amide or PA12), which is known for high toughness, and has proven to be suitable for several parts in earlier RNLA experiments. PA12 costs 0.066€/cm^3 (3DChimera, 2019) and has a recommended waste factor of $\alpha = 0.50$ (Formlabs, 2019). Finally, the leadtime of outsourcing polymer AM is 5 days, as currently offered by local AM providers. Although our model allows a stochastic AM leadtime, we choose to fix it for a fair comparison with the equally deterministic OEM leadtime.

6.3.2 Results

First of all, note that per-SKU case study results are fully documented in Appendix K. The supply methods are first compared under aggregate capacity utilization $\rho = 0.90$ and subject to a per-SKU fill rate constraint. Based on the limited set of polymer SKUs considered, the expected build time of a job that we use to compute queuing effects is estimated at $E[T_{set}] = 2.76$ hours, and $cv[T_{set}] = 0.126$.

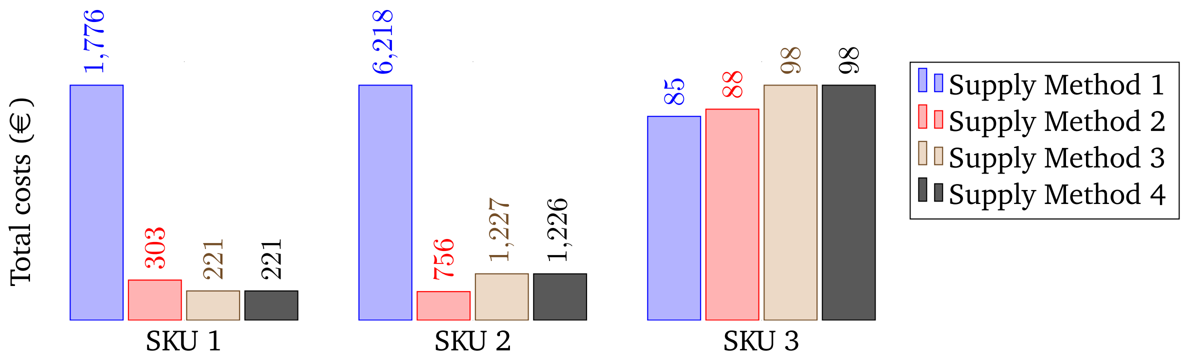


Figure 6.2: The total costs per supply method for each polymer AM SKU, under aggregate system utilization $\rho = 0.90$ and a fill rate constraint. Cost figures are based on annual part and holding costs and rounded to the nearest integer.

Total costs

Total costs per SKU per supply method are presented in 6.2. One may observe that Supply Method 1 is exceptionally costly for SKU 1 and SKU 2, while different supply methods perform more similarly for SKU 3. This can be explained by the fact that SKU 1 and SKU 2 are both special cases: failure of the SKU leads to replacement of the entire sub-assembly to which the SKU belongs. In these cases, it appears that supply methods with AM provide great benefit. In a regular case, such as SKU 3, the three AM supply methods are found to be relatively costly. Outsourcing AM is found to be the cheapest alternative with only 2.6% higher annual total costs than regular OEM supply. Virtually no difference exists between Supply Methods 3 and 4, as there occurs almost no outsourcing in the dual source method ($K = 25,\ p_K = 8 \times 10^{-4}$).

Cost buildup

Although polymer AM proves to bring cost reductions only in special cases for the SKUs considered, supply methods with AM are found to affect the total cost buildup also for a regular case such as SKU 3. Here, the portion of total costs attributed to holding costs drops significantly compared to Supply Method 1 (27%) to 7% under Supply Method 2, and 5% under both Supply Methods 3 and 4. With current AM costs, however, this reduction in holding costs is balanced out by relatively high part costs. The cost buildup of the unit cost of in-house AM (u^{M3}) is interesting to elaborate on, as it reveals the cost drivers of AM. We find that for the SKUs in the polymer AM case study, on average 41% of unit cost is comprised of direct costs (i.e., build material) and the other 59% of indirect costs (i.e., machine costs and labor).

Inventory reductions

These reduced holding costs are a direct consequence of shorter leadtimes associated with AM sources. Shorter leadtimes cause fill rate objectives to be attained using a lower reorder level, resulting in a lower expected inventory on hand $E[OH]$, as demonstrated in Figure 6.3. Significant reductions in $E[OH]$ compared to Supply Method 1, between -73% and -90%, can be achieved using Supply Method 2, 3 and 4.

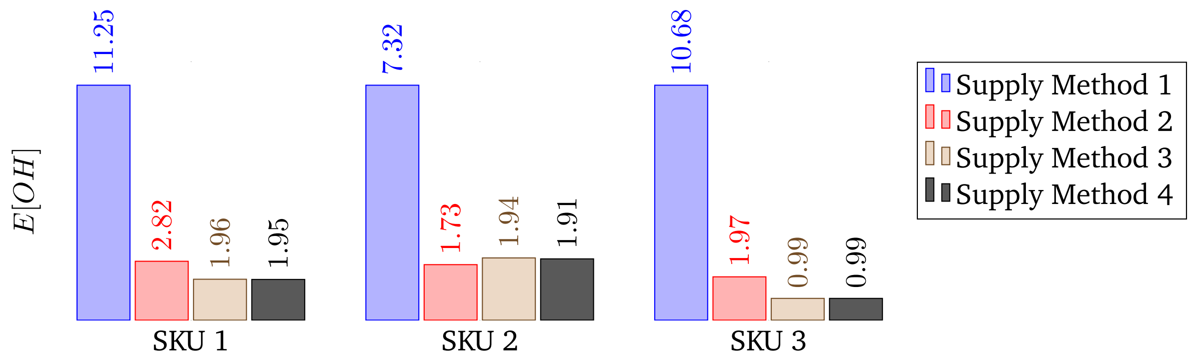


Figure 6.3: Expected inventory on hand $E[OH]$ for all supply methods for each polymer AM SKU, under aggregate system utilization $\rho = 0.90$ and a fill rate constraint.

Supply method performance under $E[BO]$ constraint

To illustrate the difference between a fill rate and $E[BO]$ constraint, we now exchange the former ($\beta^{\text{obj}} = 0.99$ for vital or $\beta^{\text{obj}} = 0.95$ for essential SKUs) for the latter ($EBO^{\text{obj}} = 0.01m$ for vital or $EBO^{\text{obj}} = 0.05m$ for essential SKUs). We find that an interesting decrease in reorder levels takes place. Reorder levels of all SKUs now drop to $R = -1$ when using in-house AM and dual AM source supply methods. This naturally results in $E[OH] = 0$. The fact that the service level constraint is met while $R = -1$ is quite compelling; it means that no spare parts inventory needs to be held when AM is deployed in-house, if one considers the above $E[BO]$ service level constraint. It must be noted that, although the selected reorder level may drop to $R = -1$, the total cost comparison between the different supply methods does not change significantly. High AM part costs still dominate and Supply Method 1 remains the most cost-effective option.

Effectiveness dual AM supply

The initial function of the outsourcing option in Supply Method 4 is to unload the in-house AM system when high capacity utilization is causing a long queue. In the $\rho = 0.90$ case, and having returned to a fill rate constraint, we observe that the outsourcing option is virtually never used, and that Supply Method 3 and Supply Method 4 are almost identical in results. Recall that, as described in Chapter 5, a job is outsourced when the expected in-house leadtime is longer than leadtime at the external AM provider. We expect Supply Method 4 to distinguish itself under higher aggregate capacity utilization and set $\rho = 0.99$ to observe if this is true.

The first observation is that when increasing $\rho = 0.90$ to $\rho = 0.99$, with the same sourcing threshold $K = 25$, the percentage of outsourced demand increases with a factor 20 to 0.016. In the $\rho = 0.99$ scenario differences between Supply Methods 3 and 4 are interesting. We observe that required reorder levels of Supply Method 3 increase significantly, while reorder levels of Supply Method 4 remain very low. For SKU 1, 2 and 3, the new reorder level under Supply Method 4 is $R = 1$.

Decreasing AM costs and build times

Investigating the effect of progressing AM technology in terms of costs and build times is – in the polymer case – only interesting for SKU 3, as this is no special case. We briefly analyze how

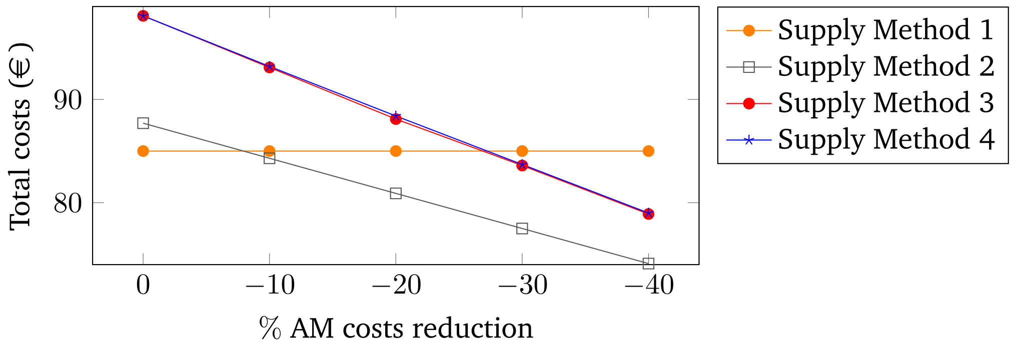


Figure 6.4: Effect of decreasing AM costs on the total costs of SKU 3 under Supply Methods 1, 2, 3 and 4. Results are based on the assumption that AM outsourcing costs decrease with half the rate of AM technology.

equal reductions in all costs related to outsourcing AM and AM technology (i.e., AM machines and build material) affect the total costs of SKU 3, and perform a more extensive analysis of AM costs and build time reductions for metal AM in Section 6.4. It must be noted that the costs of outsourcing AM are not likely to decrease linearly with AM technology cost. We observe that a 10% reduction in AM technology cost yields a 5% reduction in in-house AM unit cost u^{M3}. This $2:1$ ratio is also used to determine the cost reduction of outsourcing AM relative to the cost reduction of AM technology, in further analyses of AM costs reductions. Ultimately, for the polymer AM case of SKU 3, we find that deploying in-house AM can lead to cost reductions when AM costs reduce with roughly 27% from their current level (Figure 6.4). Outsourcing polymer AM may become the most cost-effective option under a merely 7% AM costs reduction.

Sensitivity analysis fixed order cost

A detailed description of the sensitivity analysis of fixed order cost variables f^{M1} and f^{M2} is given in Appendix L. We observe that, for polymer SKUs, the total costs of Supply Method 1 are on average not sensitive to changes in f^{M1}. However, when total annual costs are relatively low, changes in f^{M1} do show a significant effect on the total costs of Supply Method 1. This is the case for SKU 3, for which halving and doubling f^{M1} lead to -13% and $+19\%$ changes in total costs, respectively. Such adjustments in total costs would significantly affect conclusions regarding the suitability of AM supply methods for SKU 3.

Changes in fixed order cost for Supply Method 2, f^{M2}, are found to strongly affect the total costs of Supply Method 2 as well. Of the polymer SKUs, however, only for SKU 3 would these changes have a significant effect on the comparison between the four supply methods. We conclude this sensitivity analysis by noting that findings for SKU 3 should be considered with some reservation.

6.4 Case study 2: metal AM at the RNLA

The SKUs we consider for the metal AM case study include a t-joint, two large threaded pins, a support hook, a dowel pin and an inspection hole cover. Based on the small set of metal SKUs considered, the expected build time of a job used to compute queuing effects is estimated at

$E[T_{set}] = 10.43$ hours, and $cv[T_{set}] = 0.132$.

6.4.1 Case-specific input data

For this case study we select the direct metal laser sintering process: one of the standard processes in metal AM. The machine selected is the Additive Industries MetalFAB1, a high-end industrial DMLS system. The MetalFAB1 is a modular system and its productivity depends strongly on the selected modules (Additive Industries, 2019). As we aim to use the system in a one-for-one production scenario, we select the most low-volume production option, which is the MetalFAB1 Process & Application Development configuration. This version is estimated to attain 85% productivity, which equals 7,500 hours a year. Machine price is €875,000 and is assumed to depreciate linearly over 7 years. A metal AM system requires significantly more labor than a polymer system. Due to high automation of this specific system, however, we assume that two FTEs can fully operate and maintain the machine. We consider two different types of build material. Material prices are based on AM-power (2017). The quite costly but strong titanium alloy Ti6Al4V (3.2€$/\text{cm}^3$) is selected for parts with higher functional requirements, aluminium alloy AlSi10Mg (0.86€$/\text{cm}^3$)) is assumed for parts for which material strength requirements are less demanding. Ti6Al4V can be reused without significant property changes for at least 11 builds (Cordova et al., 2019). AlSi10Mg can be reused for a minimum of 18 builds (Vock et al., 2019). We deduce waste factors $\alpha_{\text{Ti6Al4V}} = \frac{1}{11}$ and $\alpha_{\text{AlSi10Mg}} = \frac{1}{18}$. Finally, the leadtime of outsourcing metal AM is fixed at 10 days, as currently offered by local AM providers.

6.4.2 Results

Note that per-SKU case study results are included in Appendix K.

Total costs

For all six SKUs we consider for the metal AM case, we find that Supply Method 1 is favoured based on total costs; total costs skyrocket under AM Supply Methods 2, 3 and 4 (Figure 6.5). An interesting observation is the fact that in five out of six cases outsourcing metal AM is the most costly option. And that, even when high ρ causes indirect build cost to be allocated to a high number of build jobs, costs of in-house AM do not even approach OEM costs. Finally, we again see virtually no difference between the costs of in-house AM and dual AM source supply, as a result of minuscule blocking probability $p_K = 2.2 \times 10^{-3}$.

Cost buildup

We now study the cost buildup of all six SKUs in the metal AM case. It is found that – compared to polymer AM – the share of total costs attributed to part costs is even higher. Taking an average over the cost buildup of SKU 4-9, we find that the part costs percentage of total costs increases from 85% for Supply Method 1 to 95% for Supply Method 2 and 97% for both Supply Methods 3 and 4. These high part costs can be attributed to high indirect unit cost u^{M3} and u^{M4}: 79% of unit cost is comprised of indirect costs (i.e., machine and labor costs), while only 21% can be attributed to direct costs (i.e., build material).

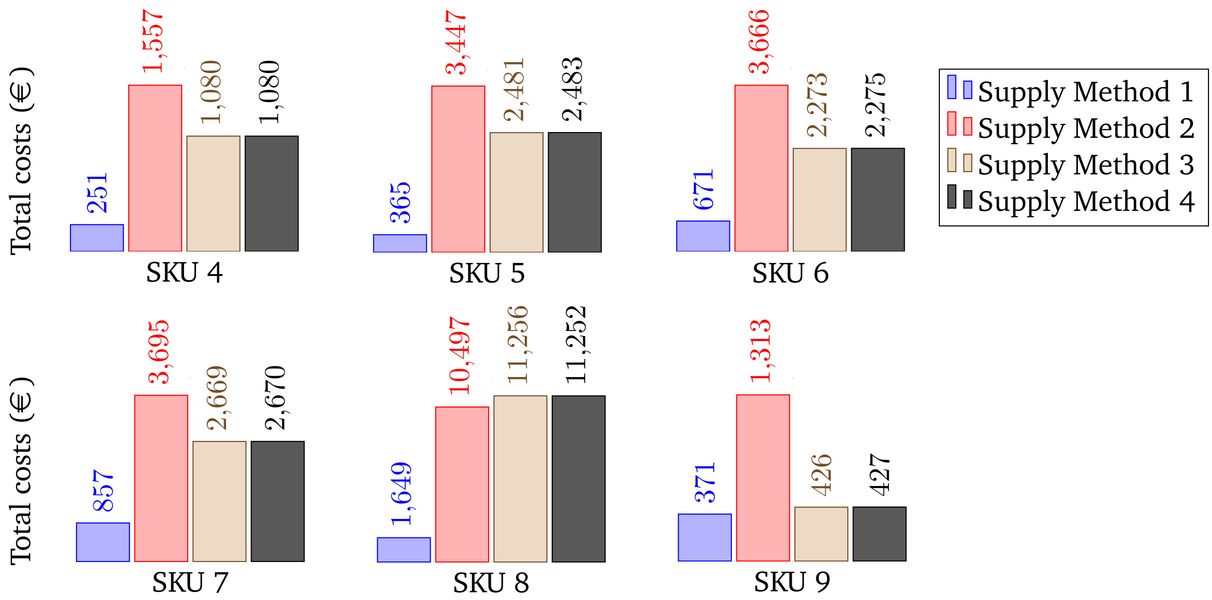


Figure 6.5: The total costs per supply method for each metal AM SKU, under aggregate system utilization $\rho = 0.90$ and a fill rate constraint.

Inventory reductions

When considering the extend to which AM supply methods can achieve a reduction in inventory levels, the same effects as with polymer AM exist: reorder levels R and expected on-hand inventory $E[OH]$ drop (Figure 6.6).

Here, extra attention is paid to the decrease in $E[OH]$ when the external AM supply source is added to the in-house AM supply method; we contrast Supply Methods 3 and 4. While on average only 0.22% of demand is outsourced ($p_K = 2.2 \times 10^{-3}$), a reduction of 0.95% in $E[OH]$ is obtained by adding the outsource option.

Supply method performance under $E[BO]$ constraint

We follow the exact same approach in exchanging fill rate constraints for $E[BO]$ constraints as we did in the polymer AM section. It is observed that, identically to the polymer AM SKUs, reorder level R drops to $R = -1$ for all SKUs under an $E[BO]$ constraint for Supply Method 3 and 4. On-hand inventory appears no longer to be needed when in-house AM is available.

Effectiveness dual AM supply

Having returned to a fill rate constraint, we investigate the effectiveness of the dual AM supply option in Supply Method 4 under capacity utilization $\rho = 0.90$ and $\rho = 0.99$. The result of the increase in capacity utilization can be seen in Figure 4 in Appendix M. Under $\rho = 0.90$, we observe that sourcing threshold $K = 20$ and $p_K = 2.2 \times 10^{-3}$. When $\rho = 0.99$, the portion of demand that is outsourced increases tenfold to 0.021. Similar to our observation in the polymer AM case, we again see that reorder levels R and $E[OH]$ increase significantly when capacity utilization is raised from $\rho = 0.90$ to $\rho = 0.99$, while R and $E[OH]$ remain low for Supply Method 4. We thus find that the second source in the dual AM supply method effectively reduces the need for higher inventory levels in cases of high in-house system capacity utilization.

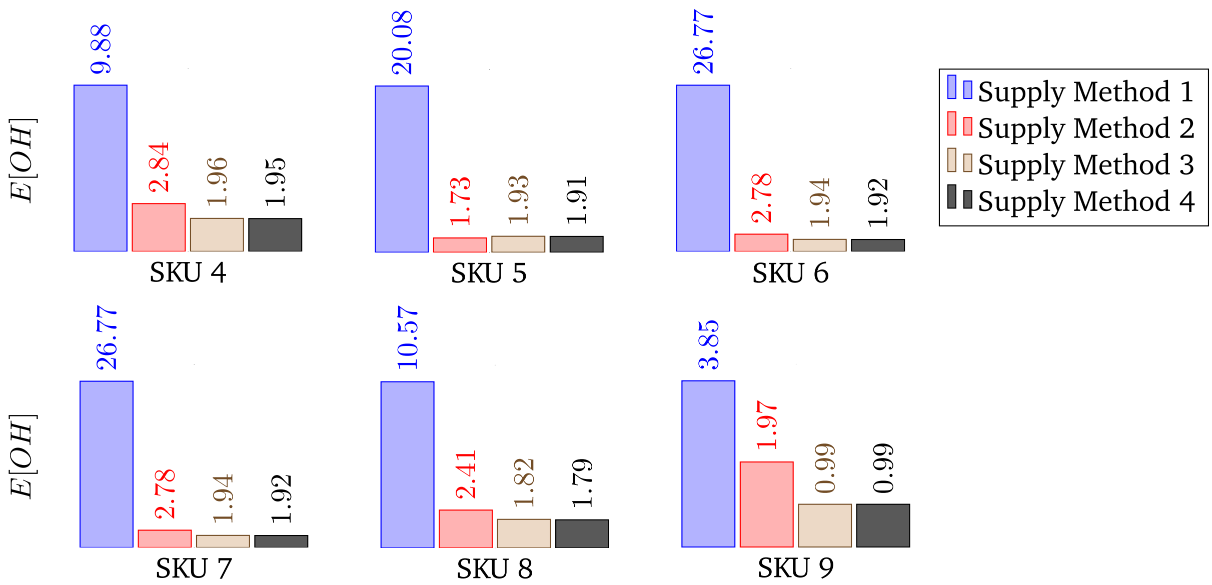


Figure 6.6: Expected inventory on hand $E[OH]$ for all supply methods for each metal AM SKU, under aggregate system utilization $\rho = 0.90$ and a fill rate constraint.

Decreasing AM costs and build times

From Figure 6.5 we can conclude that metal AM with its current costs is simply too expensive to be a regular link in the spare parts supply chain. We now investigate the degree to which metal AM costs and build times need to become more cost-effective before they can be seen as a potentially valuable addition to the regular RNLA spare parts supply chain. For this analysis we take the aggregate total costs over SKUs 4-9, and present the results in Figure 6.7.

It can be observed very clearly that reasonable reductions in AM technology costs or build time will not make the it economically attractive to use metal AM as replacement for the current supply method; neither large reductions in AM costs nor build time achieve economic feasibility. We find that solely when both AM costs and build time decrease by roughly 70%, metal AM may become a cost-effective replacement for the current OEM supply method.

Sensitivity analysis fixed order costs

As described in more detail in Appendix L, we observe that fixed order cost variables f^{M1} and f^{M2} slightly affect the total costs of Supply Methods 1 and 2. This limited effect, however, does not have significant impact on any of the other findings in the metal AM case study.

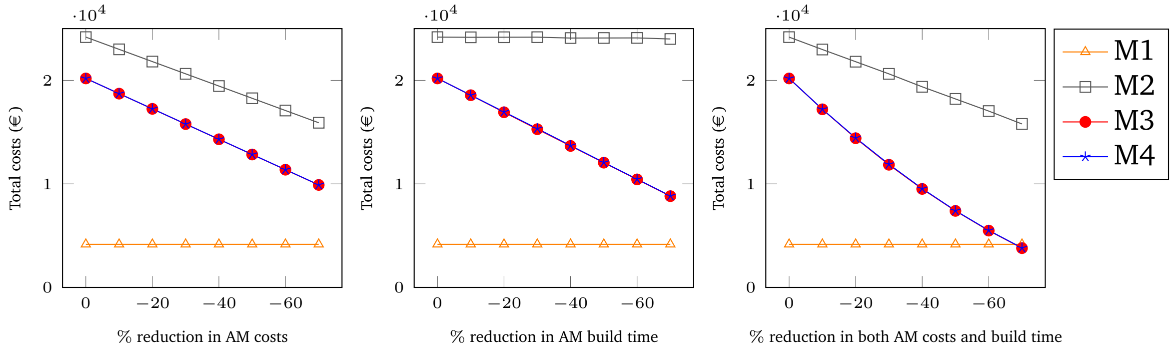


Figure 6.7: Effect of a future reduction in AM costs (left), build time (center) and both (right) on the aggregate total costs of SKUs 4-9 under Supply Methods 1, 2, 3 and 4. Results are based on the assumption that AM outsourcing costs decrease with half the rate of AM technology.

6.5 Conclusion case studies

In the case study analysis of the nine SKUs, key observations are that at this point in time AM supply methods can achieve cost reductions only in special cases. When small in-house or external AM build jobs provide a solution to the failure of a sub-part – that would otherwise lead to the purchase of an entire new part – this can significantly cut spending. This ability to quickly produce customized items appears to be the main value of AM in its current stage. For a central role in the regular RNLA spare parts supply chain, AM proves to remain overly expensive. This is clear for polymer AM and very evident for metal AM.

Whether the same conclusions are expected to be drawn in the future – under reduced AM costs and build times – depends strongly on the material considered. Supply Method 2 is found to become economical for polymer SKUs after only a single-digit cost reduction, while Supply Methods 3 and 4 require more significant cost reductions. Nonetheless, the idea of outsourcing AM of slow-moving polymer parts is certainly worth reviewing for the RNLA. This cannot be said for metal parts. No reasonable reduction in metal AM costs nor build time will render Supply Methods 2, 3 and 4 economical for the RNLA, as far as the SKUs in this case study at the RNLA are concerned.

Chapter 7

Conclusions and recommendations

7.1 Conclusions

The objective of this study has been to answer the question whether a supply method based on AM could be a cost-effective option in spare parts supply chains. The main research question has been:

Main RQ	**Which supply method must be used for spare parts if AM is an option?**

We have attempted to answer this general question by considering the RNLA environment in particular, and in this section we comment on the generalizability of findings.

The question had been triggered by the coalescence of several developments: increasingly costly slow-moving spare parts inventories pose a problem to organizations such as the RNLA; AM has proven to be a valuable technology for the RNLA as a supply method for specific customized spare parts in remote locations; applications of AM technology have widened significantly and associated costs have declined. Consequently, the impression had been created that also in the domestic RNLA spare parts supply chain an AM supply method could be a valuable link.

In order to come to an answer, a model has been constructed to compare several supply methods regarding both costs and service level performance. The supply methods considered in this comparison are regular OEM supply, outsourcing AM, in-house AM and a dual AM source method that combines in-house with external AM. The comparison model has been designed to include all relevant cost components associated with the supply chain of a spare part. The trade-off between, on one hand, long leadtimes and low part (OEM supply) costs and, on the other hand, short leadtimes and high part costs (the different AM supply methods) is at the heart of the comparison model.

The comparison model has been used as a basis for two case studies at the RNLA. In the first case study, the economic potential of polymer AM has been investigated for three distinct spare parts. In the second case study, we have considered metal AM and investigated its potential for six parts. Case study conclusions are that the use of AM supply methods dramatically reduces the need for inventory. This is in line with large potential inventory cost reductions found in prior studies on AM in spare parts supply chains by Khajavi et al. (2014) and Ghadge et al. (2018). These studies do not, however, weigh inventory cost reductions against increases in AM part costs. We do make the comparison and find that – for the spare parts and environment that we consider – the inventory reduction cannot offset high part costs associated with AM; neither outsourcing AM, in-house AM nor a dual AM source method can be a cost-effective supply method for the considered spare parts. This conclusion is based on the costs and capabilities of current AM technology. As AM costs are expected to continue declining, case study results indicate that polymer AM could prove to become a true alternative for the regular OEM supply method in the near future. For metal AM, the cost difference between the regular OEM supply and the AM supply methods is found to be so substantial, that combined AM cost and build time reductions of 70% are needed to achieve cost-effectiveness of AM. The requirement of a significant reduction in metal AM production costs to reach break-even is in agreement with Westerweel et al. (2018a), although they conclude that cost reductions between 40% and 55% are needed for the parts in their case study. This difference is believed to depend on the spare parts selected; they consider parts that are quite costly to manufacture conventionally relative to the parts considered in our case study.

The extent to which this study can be generalized beyond the RNLA environment is arguable. Clear-cut conclusions have been drawn regarding AM within the RNLA, and specifically for the type of spare parts considered in the case study. The developed comparison model can be applied to other spare parts within the RNLA as well. However, in some respects the model has been specified to the RNLA in particular, and requires adjustments before application in different contexts. We have, for instance, not taken into account that AM parts can achieve cost reductions while functioning, as this is not relevant for the parts considered at the RNLA. This aspect is crucial when making a cost analysis of AM in the air industry, where weight reductions are among the key advantages of AM (Huang et al., 2016). We argue that generalizability of the model and case study results is restricted, and that context-specific factors should be considered carefully in any AM cost analysis.

7.2 Limitations

To enable the cost comparison of different supply methods, a number of assumptions have been made, which could be regarded as limitations. Two major issues in current AM applications have largely been ignored in this study: licenses of the OEM that allow AM of parts, and certification for part use. Although these are essential aspects of AM in its current phase, we deliberately disregard them in this cost study, as they involve a very wide range of fields: from legal and regulatory to quality control and materials science. These issues are an even larger burden on the application of AM for organizations where air safety is concerned, which was concluded from exploratory conversations with the Royal Netherlands Air Force, which considered AM for parts of the Chinook helicopter.

Another research limitation is the selection of spare parts considered in the case study; the set of parts considered in the case study is limited in size and individual parts are of low complexity. The initial aim has been to compose a large and varied set of spare parts to examine as a basis for conclusions, which was impeded by two main factors. Firstly, during the part selection process many parts were deemed technically unsuitable for AM, for various reasons. This limitation does, however, provide valuable insights in the actual applicability of current

AM technology. Secondly, incomplete or unreliable data on the spare parts caused many parts – that would otherwise have been interesting AM case subjects – to be eliminated from the set. The number of spare parts that could be considered for the case study has thus been strongly diminished. Despite the small set of spare parts in the case study, however, multiple valuable insights have been obtained throughout the research, based on which we compose a list of recommendations.

7.3 Recommendations

First of all, several recommendations can be deduced from this study's limitations, starting with the topics of licensing and certification. These topics were not thoroughly considered in this study, as their extent well exceeds the maximum possible comprehensiveness for a master thesis. However, in order to further widen the spectrum of fields in which AM can have positive impact, licensing as well as certification are critical topics for future research. Based on the second limitation, the case study's small number of spare parts and their low complexity, we recommend similar case studies with a larger and more varied set of parts. The current case study indicates that the inventory reductions that can be achieved through AM do not offset the large increase in part costs, for the considered parts. However, for complex spare parts more costly to manufacture in the conventional way, the increase in part costs would be expected to be less dramatic. In these cases, the inventory reductions that AM achieve could counterbalance – or even outweigh – the increase in part costs. An interesting future study would therefore be to apply the cost comparison model to this type of spare parts.

Several other recommendations can be made based on the case study. It has been shown that – for the spare parts in the case study – inventory reductions with AM are significant, but that reduced holding costs do not outweigh increased part costs. As stated, this might differ for more complex parts due to a lower increase in part costs, but conclusions might also be different in situations where the reduction in holding costs is greater. For the RNLA, these situations include remote operations, where storing spare parts is significantly more expensive than in the Netherlands, and it has been shown that AM can achieve significant reductions (Westerweel et al., 2018b). Consequently, we argue that experimentation with AM applications in these environments should definitely be continued. For these special environments, large-scale AM-propelled inventory reductions do have the potential to offset the high costs that come with AM.

In addition to special environments, AM can also bring about cost reductions for special cases in the regular domestic environment. The case study suggests that the technology *does* hold great promise for special cases. For instance, parts that cannot be ordered separately at the OEM – but have to be bought as part of a larger assembly – prove to be excellent opportunities for AM to demonstrate its value. The RNLA is advised to further investigate for which special cases AM could be a solution, and how the technology can be leveraged to its full potential in these cases. Examples of other special cases that are worth revision are last-time buys, obsolescence or temporary supply disruptions.

Based on the data collection process throughout this study, it is argued that identification of special SKUs for which AM could bring about cost reductions, can best be done using a bottom-up approach. Several prior studies describe top-down approaches for selecting promising business cases for AM from large sets of data. Due to the current quality of digital data at the RNLA, however, effective identification of AM business cases solely based on data is virtually impossible. Nevertheless, the ability to perform such top-down analyses could effectively aid the RNLA in creating value from data in the future. As a result, the organization is advised to improve the quality of its data.

For our second to last recommendation, we focus on the cooperation between the RNLA and various external AM specialist parties. Our case study indicates that for polymer materials – for which cost-reductions through AM appear to be more reasonable than for metal AM – the option of outsourcing AM activities shows greater potential than in-house deployment. This finding is in line with the fact that the RNLA is a service organization rather than a production company. Although experimenting with new technologies is a valuable activity for the RNLA, actual production does not belong to the list of RNLA core tasks. Additionally, by taking on external AM providers to aid in AM activities, their knowledge and expertise can be leveraged. This is an important advantage of close cooperation with external AM providers, and should be harnessed.

The last recommendation we make concerns the comparison model that has been developed. The model effectively provides insight in how an AM option with short leadtimes affects the required inventory levels for meeting a certain service level. Moreover, it allows multiple AM supply methods to be compared, among which a dual source method. Although the latter does not demonstrate its true value in the case study performed, it could effectively limit or shorten queues for overloaded systems (i.e., where capacity utilization is greater than one) or when the relative difference between the in-house and external leadtime is smaller. This second scenario is interesting, as it could apply to situations in which external AM providers offer next-day delivery. For such situations, further research regarding the performance of the proposed decision rule – and perhaps different dual source decision rules – could be appealing. These scenarios are among many that would be interesting for future application of the comparison model. Ultimately, the model will allow an AM cost analysis to be performed in a variety of environments and spare parts, in order to identify promising future AM applications.

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Appendices

A List of abbreviations

Abbreviation	In full
AM	Additive manufacturing
CM	Conventional manufacturing
DMLS	Direct metal laser sintering
EBM	Electron beam melting
FCFS	First-come, first-served
FDM	Fused deposit modeling
$M/G/1$	Queuing system with Poisson arrivals, generally distributed service times and a single server
$M/G/1/K$	$M/G/1$ system with a finite system capacity K
$M/M/C$	Queuing system with Poisson arrivals, exponentially distributed service times and C servers
NATO	North Atlantic Treaty Organization
NB	Negative binomial
OEM	Original equipment manufacturer
PBF	Powder bed fusion
PDF	Probability density function
RNLA	Royal Netherlands Army
RNLAF	Royal Netherlands Air Force
RQ	Research question
SHS	Selective heat sintering
SKU	Stock keeping unit
SLA	Stereolithography
TCO	Total cost of ownership

Table 1: A list of abbreviations

B Overview of variables

Table 2: An overview of variables

Variable	Unit	Description
a	time units	Interarrival time demand
A	items	Number of items in the queue of a queuing system
B	items	Number of items in service in a queuing system
BO	items	Backorders
$cv[\,]$	time	Coefficient of variation
D_L	items	Demand during leadtime
$E[\,]$	-	Expected value
EBO^{obj}	items	E[BO] maximum objective
f	€	fixed order cost
h	-	Annual holding cost rate
I	-	Set of SKUs
i	-	SKU identifier
IL	items	Inventory level
IP	items	Inventory position
K	items	Max number of items in a finite-buffer queuing system
L	time units	Leadtime
M	-	Supply Method
M	items	Aggregate demand rate
m	items	Annual demand rate
OH	items	On-hand inventory
$P\{\,\}$	-	Probability
p_n	-	Probability of n items in a queuing system
Q	items	Order size
r	-	SKU-specific system capacity utlization
R	items	Reorder level
s	-	Number of servers in a queuing system
S	items	Basestock level
t	-	Arbitrary moment in time
T	time units	Build time
u	€	Unit order cost
U	-	Uniformly distributed integer variable
$V[\,]$	-	Variance
W	time units	Waiting time
X	items	Pipeline inventory
α	-	Waste factor PBF material
β	-	Fill rate
β^{obj}	-	Fill rate minimum objective
δ	-	Relative error
μ	items per time unit	Processing rate AM system
ρ	-	Aggregate system capacity utilization

C Spare part classification at the RNLA

The RNLA classifies their spare part assortment. Several inventory management decisions are based on this classification. The RNLA uses several different classification methods for spare parts, including the VED model and the 20-classes model. Additionally, the RNLA groups spare parts based on leadtime, which includes the total internal and external leadtime.

In the VED model, spare parts are assigned classification *vital, essential, desirable* or *non-stock*, based on failure probability and importance for operation. Parts labeled *vital* have a high failure probability and are, logically, vital for system availability and operations. Parts classified as *essential* have a medium failure probability and are essential for system availability and operations. Part categories *vital* and *essential* are kept in stock at the RNLA. Parts labeled *desirable* have a low failure probability and barely affect system availability and operations. These parts are stocked in some cases, depending on the other classification methods. For parts with label *non-stock*, no central inventory is kept.

Spare parts are also classified based on unit cost at the OEM (u^{M1}) and demand frequency. This happens in the 20-classes model, shown in Table 3, which contains all classification criteria. Classifications *A0* to *E3* are assigned to spare parts according to these criteria. The model furthermore distinguishes between consumables and repairable parts. New parts are assigned to a separate class, as no meaningful demand data is available for these parts.

The last spare part characteristic the RNLA considers to classify spare parts is the total leadtime, the time period between demand occurrence and inventory replenishment. It is calculated as the sum of the external (OEM) leadtime and the time needed internally to process orders, or internal leadtime. The RNLA distinguishes between parts with a short leadtime and a long leadtime. This distinction, however, depends on the VED classification, as shown in Table 4.

Service level objectives β_i^{obj} are set as follows. For every single SKU, the RNLA specifies β_i^{obj} based on the spare part classifications. For non-repairable spare parts labeled, $\beta_i^{\mathrm{obj}} = 0.99$. For *vital* non-repairables, $\beta_i^{\mathrm{obj}} = 0.95$. There is one exception: for *essential* non-mover SKUs (type D1-D3 in Table 3) with short leadtime (cf. Table 4) no inventory is held and thus $\beta_i^{\mathrm{obj}} = 0$.

u^{M1}€ 5000	A3	B3	C3	D3	E3
€ 100< u^{M1} ≤€ 5000	A2	B2	C2	D2	E2
u^{M1} ≤€ 100	A1	B1	C1	D1	E1
Repairable	A0	B0	C0	D0	E0
Demand frequency	High	Middle	Low	Non-mover	New

Table 3: The 20-classes model

VED class	Short leadtime	Long leadtime
Vital	≤ 1 year	> 1 year
Essential	≤ 6 months	> 6 months
Desirable	≤ 2 months	> 2 months

Table 4: Leadtime classification

D Proof

Here we provide proof that $E[OH]$ and fill rate β are non-decreasing in reorder level R, while $E[BO]$ is non-increasing in R. For each of the three metrics, we first provide proof for systems with one-for-one AM and stochastic leadtimes and then cover systems with batching and constant leadtimes.

D.1 $E[OH]$ non-decreasing in R

Systems with one-for-one AM and stochastic leadtimes

Let us restate the general equation from Eq. 3.4:

$$E[OH] = EOH(R) = \sum_{x=0}^{R}(R+1-x)P\{X^M = x\}.$$

Inserting increasing values for R into this equation leads to:

$$EOH(R) = \begin{cases} 0 & \text{for } R=-1 \\ P\{X^M=0\} & \text{for } R=0 \\ 2P\{X^M=0\}+P\{X^M=1\} & \text{for } R=1 \\ \vdots & \vdots \\ (n+1)P\{X^M=0\} & \\ \ +(n+1-1)P\{X^M=1\}+\cdots+(n+1-n)P\{X^M=n\} & \text{for } R=n \end{cases}$$

As probabilities clearly cannot take on negative values, but can be equal to zero, the value of $E[OH]$ increases by at least zero when R increases, and is thus non-decreasing in R.

Systems with batching and constant leadtimes

We restate the general equation from Eq. 3.7:

$$E[OH] = EOH(R,Q) = \frac{1}{Q}\sum_{y=R+1}^{R+Q}\sum_{x=0}^{y-1}(y-x)P\{D_L^{\mathrm{M}} = x\}.$$

The second summation can be written in full as:

$$\sum_{x=0}^{y-1}(y-x)P\{D_L^{\mathrm{M}}=x\} = yP\{D_L^{M1}=0\}+(y-1)P\{D_L^{M1}=1\}+\cdots + (y-(y-1))P\{D_L^{M1}=y-1\}$$

This summation increases in y. The value of y is set in the first summation of Eq. 3.7. As a result, for a fixed Q and increasing the value of R, the value of $EOH(R,Q)$ develops as follows:

$$EOH(R,Q) = \begin{cases} \frac{1}{Q}\sum_{y=0}^{Q-1}\sum_{x=0}^{y-1}(y-x)P\{D_L^{\mathrm{M}}=x\} & \text{for } R=-1 \\ \frac{1}{Q}\sum_{y=1}^{Q}\sum_{x=0}^{y-1}(y-x)P\{D_L^{\mathrm{M}}=x\} & \text{for } R=0 \\ \frac{1}{Q}\sum_{y=2}^{1+Q}\sum_{x=0}^{y-1}(y-x)P\{D_L^{\mathrm{M}}=x\} & \text{for } R=1 \\ \vdots & \vdots \\ \frac{1}{Q}\sum_{y=n+1}^{n+Q}\sum_{x=0}^{y-1}(y-x)P\{D_L^{\mathrm{M}}=x\} & \text{for } R=n \end{cases}$$

It can be seen that the value of y over which is summed increases in R, and with that the value of $EOH(R,Q)$ increases or remains constant.

D.2 β non-decreasing in R

Systems with one-for-one AM and stochastic leadtimes

From Eq. 3.2:

$$\beta = \beta(R) = \sum_{x=0}^{R} P\{X^{\mathrm{M}} = x\},$$

one can clearly observe that for an increase in R from $R = n$ to $R = n+1$, the total sum of probabilities (which are non-negative) increases by $P\{X^M = n+1\}$. As this is true for every value on the domain of R ($-1 \geq R$) it can be said that β is never decreasing in R.

Systems with batching and constant leadtimes

We restate Eq. 3.5:

$$\beta = \beta(R,Q) = \frac{1}{Q} \sum_{y=R+1}^{R+Q} \sum_{x=0}^{y-1} P\{D_L^{\mathrm{M}} = x\},$$

and observe that proof that $E[OH]$ is non-decreasing in R can be applied in an identical way.

D.3 $E[BO]$ non-increasing in R

Systems with one-for-one AM and stochastic leadtimes

We restate Eq. 3.3:

$$E[BO] = EBO(R) = \sum_{x=R+2}^{\infty} (x - (R+1))P\{X^{\mathrm{M}} = x\},$$

and observe that $(x-(R+1))P\{X^M = x\} \geq 0$ on the sum domain. With an increase of R, the sum domain always decreases. Thus, $E[BO]$ cannot increase for an increase of R.

Systems with batching and constant leadtimes

In Eq. 3.6:

$$E[BO] = EBO(R,Q) = \frac{1}{Q} \sum_{y=R+1}^{R+Q} \sum_{x=y+1}^{\infty} (x-y)P\{D_L^{\mathrm{M}} = x\}$$

it can again be observed that $(x-y)P\{D_L^{M1} = x\} \geq 0$. Consequently, when y increases in the second summation, the total value of the second summation cannot increase. Finally, an increase in the value of R in the first summation always causes y to increase. As a result, $E[BO]$ can be said to be non-increasing in R.

E Personal sources

In this appendix, we list the personal sources and organizations who provided useful input for this thesis, through interviews or other forms of communication. Sources are categorized by the subject for which their input was important.

The RNLA organization

[Removed for confidentiality]

RNLA spare parts supply chain

[Removed for confidentiality]

AM at the Royal Netherlands Army

[Removed for confidentiality]

AM at the Royal Netherlands Air Force

[Removed for confidentiality]

Additive Manufacturing

[Removed for confidentiality]

AM systems

[Removed for confidentiality]

F Powder bed fusion processes

A brief description of powder bed fusion (PBF) processes is provided here. The description is based on an overview of AM processes by Loughborough University (2019).

The PBF process category includes the following commonly used printing techniques: direct metal laser sintering (DMLS), electron beam melting (EBM), selective heat sintering (SHS), selective laser melting (SLM) and selective laser sintering (SLS). A generic schematic representation of the PBF process is provided in Figure 1. A laser or electronic beam is used to melt and fuse material powder together. All PBF processes involve the spreading of powder over previous layers, either using a ruller or a blade. A reservoir below of or aside the bed provides new powder material supply. After every layer, the build platform lowers and a new powder layer is added.

In SLS, powder (metal, polymer or composites) is sintered together layer by layer. DMLS describes the same process, but solely for metal materials. SHS differs from other processes by way of using a heated thermal print head to fuse powder material together. Instead of a laser, EBM uses a high-energy electron beam to fuse metal powder particles.

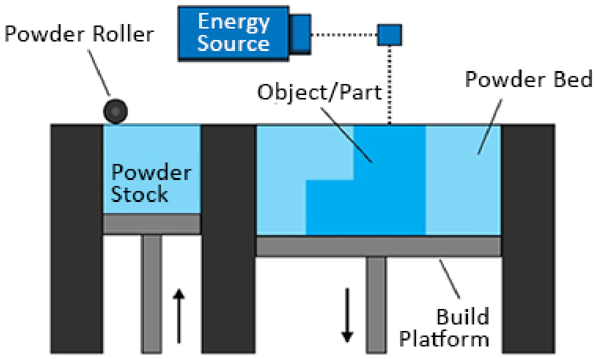


Figure 1: The PBF process (Loughborough University, 2019)

G Approximation method for Supply Method 3 pipeline inventory X^{M3}

In this appendix, the procedure of fitting X on the negative binomial (NB) distribution is elaborated upon (Section G.1), based on Díaz and Fu (1997). Using Adan and Resing (2002), the procedure was verified and several corrections were made (Section G.2).

G.1 Procedure

First of all, a multi-item approach is taken, where the subscript i indicates that the variable belongs to SKU i. The total set of SKUs is denoted by I.

In order to fit the distribution of pipeline inventory X_i, the number of items of SKU i in the AM machine and queue, on a NB distribution the values for the first two moments of X_i are required. To compute the first moment, $E[X_i]$, we distinguish between two components of items in the system: those in the queue, $E[A_i]$, and those being processed in the AM machine, $E[B_i]$:

$$E[X_i] = E[A_i] + E[B_i].$$

We start with input parameters for each SKU $i \in I$: arrival rate m_i, service time T_i and per-SKU capacity utilization $r_i = m_i E[T_i]$, The aggregate arrival rate is $M = \sum_{i \in I} m_i$. Aggregate expected service time $E[T] = \sum_{i \in I} \frac{m_i}{M} E[T_i]$, expected squared service time $E[T^2] = \sum_{i \in I} \frac{m_i}{M} E[T_i]^2$ and $E[T^3] = \sum_i \frac{m_i}{M} E[T_i]^3$. For a stable system, it is required that $ME[T] \leq 1$. Note the assumptions of Poisson arrivals, FCFS service and a single server. The per-SKU number of items in the AM system is equal to $E[B_i] = r_i$. The per SKU number of items in queue is calculated using Little's formula:

$$E[A_i] = m_i E[W],$$

wherein $E[W]$, the expected waiting time per item is equal to:

$$E[W] = \frac{cv[a]^2 + cv[T]^2}{2} \frac{E[T]\rho}{1 - \rho}. \tag{1}$$

Here, squared coefficient of variation in inter-arrival times $cv[a]^2 = 1$, due to the assumption of Poisson arrivals. Furthermore, $cv[a]^2$ represents the squared coefficient of variation in service times. Eq. 1 can be deducted from Kingman (1961), who states that $E[W^{M/G/k}] = \frac{1}{2}(cv_S^2 + 1)E[W^{M/M/c}]$. Note that, due to the nature of $M/G/1$ queues and the assumption of FCFS service, $E[W_i] = E[W], \forall i \in I$. This is also true for the variance $V[W_i] = V[W], \forall i \in I$.

The second moment of X_i is variance $V[X_i]$. It is constructed of the variance in number of items per SKU in queue, $V[A_i]$, and the variance of the number of items being processed in the AM machine, $V[B_i]$. Because these variables are correlated – a positive number of items in the queue is only possible when the AM system is active – the $V[X_i]$ is computed as follows:

$$\begin{aligned} V[X_i] &= V[A_i] + V[B_i] - \text{covariance}[A_i, B_i] \\ &= V[A_i] + V[B_i] + 2(\frac{r_i}{\rho} E[A_i] - E[A_i]E[B_i]). \end{aligned} \tag{2}$$

To calculate $V[A_i]$, we perform the following steps. We first derive $V[W]$ based on Adan and

Resing (2002):

$$V[W] = E[W^2] - (E[W])^2, \tag{3}$$

wherein $E[W]$ is already known and $E[W^2]$ can be calculated as follows:

$$E[W^2] = 2(E[W])^2 + \frac{\rho E[R^{st,2}]}{1-\rho}. \tag{4}$$

In Eq. 4, $E[R^{st,2}]$, the expected squared residual service time, is rewritten in line with Adan and Resing (2002):

$$E[R^{st,2}] = \frac{E[T^3]}{3E[T]}, \tag{5}$$

enabling us to construct the following short equation for $V[W]$:

$$V[W] = E[W]^2 + \frac{\rho E[T^3]}{3(1-\rho)E[T]}. \tag{6}$$

We then use the obtained value for $V[W]$ to calculate $cv_W^2 = V[W]/E[W]^2$ and subsequently cv_{Ai}^2 through

$$cv_{Ai}^2 = 1/E[A_i] + cv_W^2.$$

Variance of the number of items in queue can then easily be deducted through $V[A_i] = cv_{Ai}^2 * (E[A_i])^2$. The variance of per SKU number in the machine is given by $V[B_i] = E[R_i^2] - (E[B_i])^2$, in which $E[R_i^2] = r_i$, giving

$$V[B_i] = r_i - (r_i)^2.$$

Through filling in Eq. 2 we obtain the variance of the number of items in the system per SKU.

We can now approximate the distribution of X_i by fitting a negative binomial distribution to the first and second moments of X_i. The negative binomial distribution has the following probability mass function:

$$P(X_i = x) = \binom{r_i + x - 1}{x} p_i^x (1-p_i)_i^r \quad \text{for} x = 0, 1, 2, ...,$$

where r_i and p_i are positive parameters and $0 < p_i < 1$ such that:

$$E[X_i] = r_i(1-p_i)/p_i,$$

$$V[X_i] = r_i(1-p_i)/p_i^2.$$

G.2 Corrections Díaz and Fu (1997)

Expected waiting time $E[W]$ of an item in a multi-class $M/G/k$ model with s servers is given by Díaz and Fu (1997) as

$$E[W] = \left[\frac{cv[a]^2 + cv[a]^2}{2}\right]\left[\frac{E[T](s\rho)^2}{ss!(1-\rho)^2}\right]\left[\frac{(s\rho)^2}{s!(1-\rho} + \sum_{n=1}^{s-1}\frac{(s\rho)^n}{n!}\right].$$

However, the corrected expression is

$$E[W] = \left[\frac{cv[a]^2 + cv[a]^2}{2}\right]\left[\frac{E[T](s\rho)^2}{ss!(1-\rho)^2}\right]\left[\frac{(s\rho)^{\mathbf{s}}}{s!(1-\rho} + \sum_{n=1}^{s-1}\frac{(s\rho)^n}{n!}\right]^{\mathbf{-1}}.$$

For the case of $s = 1$, which we consider, the corrected expression leads to

$$E[W] = \frac{cv[a]^2 + cv[a]^2}{2}\frac{E[T]\rho}{1-\rho}. \tag{7}$$

This expression can also be derived using Adan and Resing (2002). They define random variable R^T as residual service time, written as $E[R^T] = \frac{cv[a]^2+cv[a]^2}{2}E[T]$. Inserting this in their expression for $E[W] = \frac{\rho E[R^T]}{1-\rho}$, leads to Eq. 7.

Furthermore, waiting time variance $V[W]$ of an $M/G/1$ system has been expressed by Díaz and Fu (1997) as

$$V[W] = \frac{ME[T^3]}{3(1-\rho)} + \frac{M^2E[T^2]^2}{2(1-\rho)^2} + \frac{ME[T]E[T^2]}{(1-\rho)} + E[T^2] - E[T+W]^2 - cv_S^2E[T]^2.$$

Using this expression can lead to negative values for $V[W]$, and does not correspond with the expression derived using Adan and Resing (2002) in Equations 3-6:

$$V[W] = E[W]^2 + \frac{\rho E[T^3]}{3(1-\rho)E[T]}.$$

As a last remark on the procedure described by Díaz and Fu (1997), we note that the aggregated square coefficient of the waiting time is given by $cv[W]^2 = V[W]E[W]^2$. This should be corrected to

$$cv[W]^2 = \frac{V[W]}{E[W]^2}.$$

H Validation of approximation method for Supply Method 3 pipeline inventory X^{M3}

In this appendix we validate the use of the Díaz and Fu (1997) approximation method for the in-house AM pipeline inventory X^{M3} through a simulation experiment. We first discuss the experiment setup, continue with a description of the data used and conclude with an analysis of the experiment results.

Experiment setup

To validate whether we can correctly assume the approximation method for X^{M3} to be appropriate, we first consider the purpose of the approximation in this study. That is to compute the fill rate β and expected number of backorders $E[BO]$ under one-for-one AM and stochastic lead-times (Section 3.4). Let us denote the approximation of X^{M3} by $\overline{X^{\text{M3}}}$ and values of β and $E[BO]$ computed using $\overline{X^{\text{M3}}}$ by $\overline{\beta_i}$ and $\overline{E[BO]}$, respectively. To validate the use of the approximation, we thus check the extent to which the values of $\overline{\beta}$ and $\overline{E[BO]}$ match the values of β and $E[BO]$ computed using the actual X^{M3}, which we find using a long-term simulation.

To be certain that the approximation is appropriate in a variety of circumstances, we vary the capacity utilization ρ and AM process time variability in our experiment. We choose to vary these two variables as they are the main factors that affect the formation of a queue. We first investigate the approximation accuracy for situations where AM system capacity utilization ρ is varied and the coefficient of variation of the process time is fixed ($cv[T_{set}] = 1$). We choose to study the $\rho = 0.7$, $\rho = 0.8$ and $\rho = 0.9$, as we argue that only relatively high capacity utilization levels can be justified economically. The ρ level is varied by adjusting the number of days that the AM system is available, denoted by $days$. We then study the approximation accuracy under three different levels of AM process time variability while maintaining a fixed system capacity utilization ($\rho = 0.9$). The approximation is tested under very low variability ($cv[T_{set}] = 0.05$), medium variability ($cv[T_{set}] = 1.0$) and relatively high variability ($cv[T_{set}] = 1.5$). We choose to implement the simulation using Java software because it offers a lot of freedom in design.

Simulation specifications

For clarification of the simulation proces, we take a multi-item approach and introduce subscript i to indicate SKU i and I for the entire set of SKUs.

In practice the simulation works as follows. For each of the SKUs in I we set inventory level $IL = 1$ and reorder level $R = 0$. Although the situation we assume has continuous review, the simulation requires a time increment to be set. Given that we consider demand rates of at most several dozens per year, and assuming that a print job takes at least an hour, we argue that a time increment of one hour is reasonable. Now, every hour demand for each SKU i in I arrives with probability m_i divided by the number of hours a day and days a year. The number of hours a day the system is available, $hours$, is set to 8. If demand arrives and the reorder level is reached, an order is immediately placed in the AM system job queue. When the AM system empties, the next job is taken from queue and initiated. For the simulation we use deterministic AM process times T_i. Every hour the number of items of each SKU in the pipeline (queue + AM system) is registered and used to compute a long-term PDF of X_i. The time period over which the simulation is set to run is required to be long enough for the average state of the system to converge to the steady state, but still acceptable in computation time. We choose to set the simulation time period to 10000 years – equivalent to several hours computation time on a TU/e desktop – to find an accurate estimation of X_i.

Experiment data

For the experiment three sets of SKUs are created with characteristics that we consider in this study, most importantly low demand rates and short in-house AM process times. We construct a set I of 20 different SKUs. AM process times are constant and range over $T_i = [2/(days \times hours), ..., 40/(days \times hours)]$ years. Demand is Poisson distributed and demand rates $m_i = [1, ..., 25]$ items per year. The three experimental datasets are composed such that their $cv[T_{set}]$ are exactly $cv[T_{set}] = [0.05, 1.0, 1.5]$ in set 1 (Table 5), set 2 (Table 6) and set 3 (Table 7). Furthermore, the three sets are designed to have exactly the same system capacity utilization ρ.

i	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
m_i	1	1	1	1	2	3	4	9	6	7	8	9	10	11	12	13	14	15	20	25
$T/(days \times hours)$	9	9	9	9	9	8	8	8	8	8	8	8	9	9	9	9	8	9	8	8

Table 5: Test dataset 1 ($cv[T_{set}] = 0.05$) for the validation experiment

i	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
m_i	1	1	1	1	2	3	4	9	6	7	8	9	10	11	12	13	14	15	20	25
$T_i/(days \times hours)$	40	40	35	21	21	21	20	23	20	20	15	15	10	6	4	3	2	2	2	2

Table 6: Test dataset 2 ($cv[T_{set}] = 1.0$) for the validation experiment

i	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
m_i	1	1	1	1	2	3	4	9	6	7	8	9	10	11	12	13	14	15	20	25
$T_i/(days \times hours)$	40	38	36	36	8	8	2	2	2	2	2	2	2	2	2	2	2	2	6	36

Table 7: Test dataset 3 ($cv[T_{set}] = 1.5$) for the validation experiment

Results

For every SKU $i \in I$, we now have an approximation of pipeline inventory $\overline{X_i}$ found by using the Díaz and Fu (1997) method and an accurate estimation of X_i obtained through the simulation. We now compare $\overline{\beta_i}$ with β_i and $\overline{E[BO_i]}$ with $E[BO_i]$, and start with the fill rates. Let us set our minimum fill rate objective $\beta_i^{\text{obj}} = 0.95$. For brevity, we consider a small sample of the SKUs (i=1, i=10). In each of the test cases, reorder level R_i is set so that β_i^{obj} is met. We perform a similar experiment for $E[BO_i]$. A maximum $E[BO]$ objective is set to $EBO_i^{\text{obj}} = 0.05$, and reorder levels R_i are set to meet this objective. Results of both experiments are shown in Table H. It can be observed that the approximated value $\overline{\beta_i}$ is virtually identical to simulated value β_i, regardless of changes in utilization and variability. The average relative difference is found to be $\delta^{\text{avg}} = 8.2 \times 10^{-4}$ with maximum relative difference $\delta^{\text{max}} = 2.1 \times 10^{-3}$. Larger relative differences exist between $\overline{E[BO_i]}$ and $E[BO_i]$, especially when $\rho_I = 0.9$. Nonetheless, it can be argued that the approximation error is sufficiently small – taking into account there the rather large relative error is mainly caused by a single outlier – for accurate calculation of both service measures ($\delta^{\text{avg}} = 0.071$, $\delta^{\max} = 0.25$).

SKU i	ρ_I	$cv[T]$	$R_i^{\beta_i \text{obj}}$	$\overline{\beta_i}(R_i)$	$\beta_i(R_i)$	$R_i^{EBO_i \text{obj}}$	$\overline{EBO_i}(R_i)$	$EBO_i(R_i)$
1	0.7	0.05	0	0.991	0.991	-1	9.09×10^{-3}	8.62×10^{-3}
1	0.7	1.0	0	0.971	0.972	-1	2.89×10^{-2}	2.86×10^{-2}
1	0.7	1.5	0	0.966	0.967	-1	3.49×10^{-2}	3.48×10^{-2}
1	0.8	1.0	0	0.961	0.961	-1	3.95×10^{-2}	3.99×10^{-2}
1	0.9	1.0	1	0.997	0.996	0	6.57×10^{-3}	7.29×10^{-3}
10	0.7	0.05	1	0.998	0.998	0	4.48×10^{-3}	4.84×10^{-3}
10	0.7	1.0	2	0.990	0.990	0	2.00×10^{-2}	2.16×10^{-2}
10	0.7	1.5	2	0.987	0.988	0	2.71×10^{-2}	2.60×10^{-2}
10	0.8	1.0	1	0.977	0.975	0	4.81×10^{-2}	5.32×10^{-2}
10	0.9	1.0	2	0.979	0.977	2	2.23×10^{-2}	2.99×10^{-2}

Table 8: Results of an experimental comparison between service measures based on approximated and simulated X^{M3}

I Validation of approximation method for Supply Method 4 pipeline inventory X^{M4}

In this validation experiment for Supply Method 4 pipeline inventory X^{M4}, we take the exact same approach as in the validation experiment for X^{M3}. Now, we fix system utilization ρ and test approximation quality for different levels of sourcing threshold K and different degrees of variability. The dataset from Appendix H is used. Again, reorder level R is determined under both a fill rate constraint ($\beta^{\mathrm{obj}} = 0.95$) and an $E[BO]$ constraint ($EBO^{\mathrm{obj}} = 0.05$). Experiment results are shown in Table I. Based on these results, we conclude that the approximation quality is more than sufficient for fill rate calculations ($\delta^{\mathrm{avg}} = 1.7 \times 10^{-3}$, $\delta^{\mathrm{max}} = 5.1 \times^{1} 0^{-3}$). We further conclude that the approximate values for $E[BO]$ deviate to much from their simulated values ($\delta^{\mathrm{avg}} = 0.13$, $\delta^{\mathrm{max}} = 0.41$), and that we can not reliably use the approximation for X^{M3} to compute $E[BO]$ in our study.

SKU i	K	$cv[T_{set}]$	$R_i^{\beta_i obj}$	$\overline{\beta_i}(R_i)$	$\beta_i(R_i)$	$R_i^{EBO_i obj}$	$\overline{EBO_i}(R_i)$	$EBO_i(R_i)$
1	2	1.0	0	0.959	0.960	-1	4.15×10^{-2}	4.08×10^{-2}
1	5	0.05	0	0.982	0.984	-1	1.78×10^{-2}	1.60×10^{-2}
1	5	1.0	0	0.961	0.961	-1	3.93×10^{-2}	3.94×10^{-2}
1	5	1.5	0	0.960	0.959	-1	4.08×10^{-2}	4.25×10^{-2}
1	10	1.0	0	0.955	0.955	-1	4.57×10^{-2}	4.56×10^{-2}
10	2	1.0	1	0.987	0.985	0	2.63×10^{-2}	3.02×10^{-2}
10	5	0.05	1	0.994	0.994	0	1.15×10^{-2}	1.32×10^{-2}
10	5	1.0	1	0.987	0.984	0	2.68×10^{-2}	3.32×10^{-2}
10	5	1.5	1	0.993	0.988	0	1.45×10^{-2}	2.45×10^{-2}
10	10	1.0	1	0.976	0.973	1	6.30×10^{-3}	9.17×10^{-3}

Table 9: Results of an experimental comparison between service measures based on approximated and simulated X^{M4}

J Derivation of per-SKU pipeline inventory distribution

In this section the PDF of per-SKU pipeline inventory, X_i, is derived from the PDF of the overall number of items in the pipeline.

Let us start with a brief description of the situation. We consider set I containing a total of $|I|$ SKUs. Requests for AM jobs of specific SKU i occur with rate m_i, following a Poisson distribution. These jobs are processed at a single AM server, which processes SKU i with rate $\mu_i = 1/T_i$ (i.i.d). An unbounded queue may arise in front of the server. The number of items of SKU i in the queuing system (server + queue) is per-SKU pipeline inventory X_i. The total number of items in the queuing system – regardless of SKU type – is denoted by $Y = \sum_{i \in I} X_i$.

Our method of deriving X_i from Y is based on the assumption that the following two conditional probabilities are known:

- p_i^S, the probability that the item in the server is of SKU i, if there is an item in the server;
- p_i^Q, the probability that an item in queue is of SKU i, if there is exactly one item in the queue;

In our single-server system with Poisson arrivals and generally distributed service times, the probability that an item in the server is of SKU i is equal to the $p_i^S = \frac{r}{\rho}$, the relative utilization. The probability that an arbitrary item in queue is of SKU i solely depends on the relative arrival rate, and is thus given by $p_i^Q = \frac{m_i}{M}$. We denote the complementary probabilities by $\hat{p}_i^S = 1 - p_i^S$ and $\hat{p}_i^Q = 1 - p_i^Q$.

Using p_i^S, p_i^Q, $\hat{p}_i^S$ and $\hat{p}_i^Q$, we can derive the distributions of X_i from the distribution of Y. Let us start with the case of $P\{X_i = 0\}$. $P\{X_i = 0\}$ is equal to the probability that the entire queuing system is empty plus all probabilities that there are n items in the queuing system, none of which are of SKU i. Formally, this probability is given by

$$P\{X_i = 0\} = p_0 + \sum_{x=1}^{\infty} p_x (\hat{p}_i^S)(\hat{p}_i^Q)^{x-1}.$$

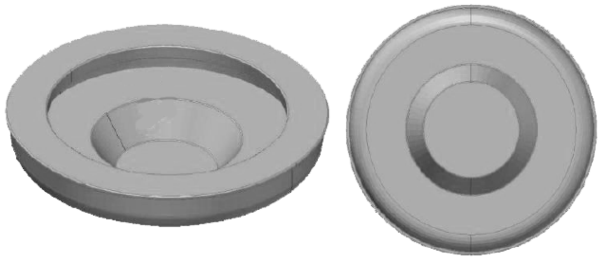
The probabilities that X_i takes on a positive value are somewhat more complex. For example, the chance that there are two items of SKU i in the queuing system is equal to the sum of the following probabilities: that there are exactly two items in the queuing system, both of which are SKU i (one in the server and one in the queue); that there are three items in the queuing system, of which one in the server and exactly one out of two in the queue; that there are three items in the queuing system, of which none in the server and two out of two in the queue. Continuing this sequence of conditional probabilities and generalizing it for $P\{X_i = n\}$ leads to the following equation:

$$P\{X_i = n\} = \sum_{x=0}^{\infty} p_{(n+x)} \Bigg[p_i^S (p_i^Q)^{n-1} (\overline{p}_i^Q)^x \binom{n+x-1}{x} + \overline{p}_i^S (p_i^Q)^n (\overline{p}_i^Q)^{x-1} \binom{n+x-1}{n} \Bigg], \qquad \text{for } n \geq 1, \quad n \in \mathbb{N}_1$$

with which we can determine the pipeline inventory distribution for each specific SKU.

K SKU-specific case study input data and results

General SKU input data



3D rendering, side and top view (DiManEx BV)

Part name	Reservoir cap
Ann. dem. (m)	13
OEM unit ccost (u^{M1})	121.62*
OEM fixed order cost (f^{M1})	45
OEM leadt. L^{M1}	260
IOQ	1
Fillr. obj. (β^{obj})	.99

Input case study AM

Photo of reservoir cap on reservoir (DiManEx BV)

Dimensions (mm)	$22.1 \times 22.1 \times 5.4$
Volume (cm^3)	0.6
AM build material	PA12
AM machine	Fuse1 (SLS)
Build time (T)	1.50
Outsource AM leadtime (L^{M2}) (days)	5

Results case study AM ($\rho = 0.90$, fill rate constraint)

	Method 1 (OEM)	Method 2 (Out)	Method 3 (In)	Method 4 (Dual)
Total costs	1776.32	302.69	220.75	220.78
Part costs	1639.56	299.00	217.46	217.53
Holding costs	136.76	3.67	3.29	3.26
Unit cost (u)	121.62	13.00	16.73	16.72
Reorder level (R)	15	2	1	1
Order quantity (Q)	10	1	1	1
Expected inventory on-hand ($E[OH]$)	11.245	2.822	1.963	1.946

*Comments: when a reservoir cap is lost by military personnel, the RNLA is forced to buy the entire reservoir at the OEM. Separate caps cannot be bought.

Table 10: Case study details: SKU 1

General SKU input data

3D rendering (DiManEx BV)

Part name	Camera support
Ann. demand (m)	20
OEM unit cost (u^{M1})	294.50*
OEM fixed order cost (f^{M1})	45
OEM leadtime f^{M1}	150
IOQ	1
β^{obj})	.95

Input case study AM

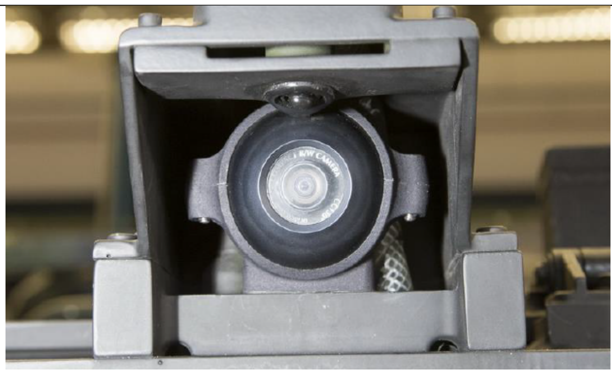


Photo of camera support and camera (DiManEx BV)

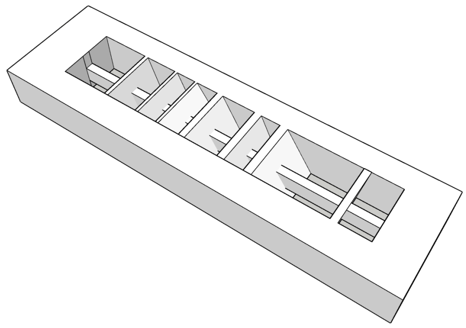
Dimensions (mm)	$80.8 \times 56.5 \times 36.2$
Volume (cm^3)	17.1
AM build material	PA12
AM machine	Fuse1 (SLS)
Build time (T)	3.50
Outsource AM leadtime (days)	5

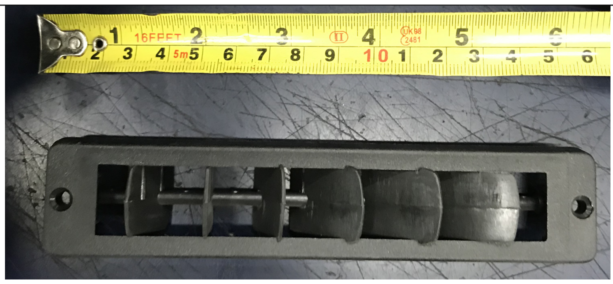
Results case study AM ($\rho = 0.90$, fill rate constraint)

	M1	M2	M3	M4
Total costs	6218.06	756.37	1226.80	1226.26
Part costs	6002.50	751.60	1215.04	1214.67
Holding costs	215.56	4.77	11.76	11.60
Unit cost (u)	294.50	27.58	60.75	60.73
Reorder level (R)	11	1	1	1
Order quantity (Q)	8	1	1	1
Expected inventory on-hand ($E[OH]$)	7.320	1.729	1.936	1.910

*Comments: the camera support occasionally breaks when the Fennek vehicle drives into objects. A separate new support cannot be bought at the OEM. The RNLA is forced to sent the entire camera unit back to the OEM, and pays a high price to receive a replacement.

Table 11: Case study details: SKU 2

General SKU input data		
 3D rendering, sketch, top view	Part name	Air vent
	Annual demand (m)	2
	OEM unit cost (u^{M1})	21.34
	OEM fixed order cost	180
	OEM leadtime f^{M1}	150
	IOQ	1
	Fillrate objective (β^{obj})	.99

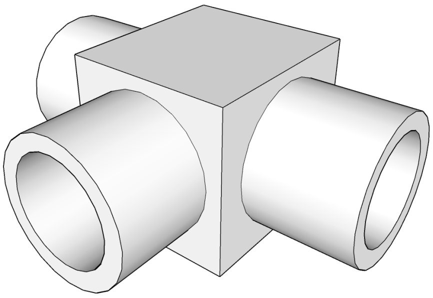
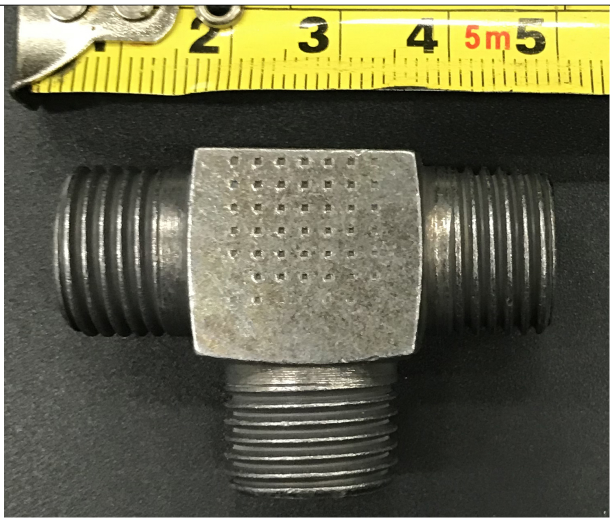
Input case study AM		
 Photo original part	Dimensions (mm)	$48 \times 175 \times 19$
	Volume (cm^3)	60.4
	AM build material	PA12
	AM machine	Fuse1 (SLS)
	Build time (T)	3.50
	Outsource AM leadtime (L^{M2}) (days)	5

Results case study AM ($\rho = 0.90$, fill rate constraint)

	Method 1 (OEM)	Method 2 (Out)	Method 3 (In)	Method 4 (Dual)
Total costs	85.45	87.68	98.10	98.08
Part costs	62.68	81.60	93.46	93.45
Holding costs	22.79	6.08	4.65	4.63
Unit cost (u)	21.34	30.80	46.73	46.72
Reorder level (R)	2	1	0	0
Order quantity (Q)	18	1	1	1
Expected inventory on-hand ($E[OH]$)	10.679	1.972	0.994	0.991

*Comments:

Table 12: Case study details: SKU 3

General SKU input data		
 3D rendering, sketch	Part name	T-joint
	Annual demand	6
	OEM unit cost	32.98
	OEM fixed order cost	45
	OEM leadtime	190
	IOQ	1
	Fillrate objective (β^{obj})	.99
Input case study AM		
 Photo original part	Dimensions (mm)	$43 \times 32 \times 19$
	Volume (cm^3)	10.6
	AM build material	Ti6Al4V
	AM machine	MetalFAB1 (DMLS)
	Build time (T)	5.00
	Outsource AM leadtime (L^{M2}) (days)	10

Results case study AM ($\rho = 0.90$, fill rate constraint)				
	M1	M2	M3	M4
Total costs	251.23	1557.37	1079.50	1080.30
Part costs	218.65	1489.80	1045.39	1046.38
Holding costs	32.58	67.57	34.11	33.92
Unit cost (u)	32.98	238.30	174.23	174.37
Reorder level (R)	6	2	1	1
Order quantity (Q)	13	1	1	1
Expected inventory on-hand ($E[OH]$)	9.879	2.836	1.958	1.945
*Comments:				

Table 13: Case study details: SKU 4

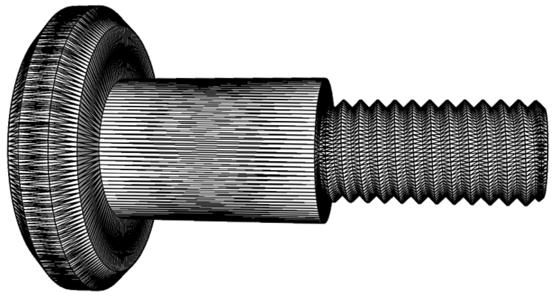
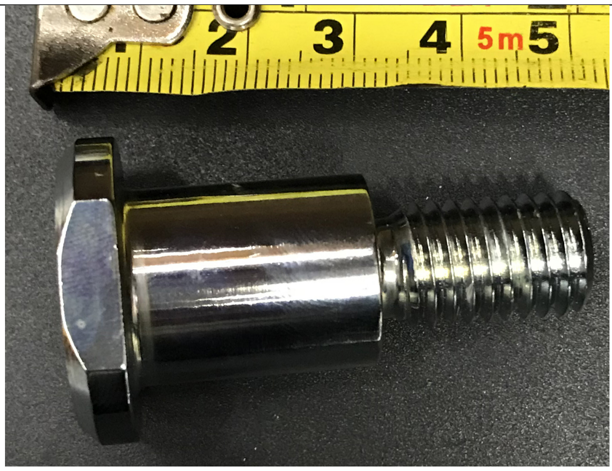
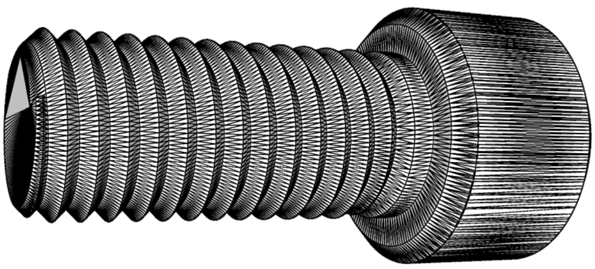
General SKU input data				
 3D rendering, sketch	Part name	Pin, chest		
	Annual demand (m)	10		
	OEM unit cost (u^{M1})	26.61		
	OEM fixed order cost	180		
	OEM leadtime f^{M1}	346		
	IOQ	10		
	Fillrate objective (β^{obj})	.95		
Input case study AM				
 Photo original part	Dimensions (mm)	$34.6 \times 34.8 \times 58$		
	Volume (cm^3)	14.7		
	AM build material	Ti6Al4V		
	AM machine	MetalFAB1 (DMLS)		
	Build time (T)	7.00		
	Outsource AM leadtime (L^{M2}) (days)	10		
Results case study AM ($\rho = 0.90$, fill rate constraint)				
	M1	M2	M3	M4
Total costs	364.54	3446.79	2481.69	2483.34
Part costs	311.10	3389.90	2434.77	2436.89
Holding costs	53.44	56.88	46.92	46.45
Unit cost (u)	26.61	328.99	243.48	243.67
Reorder level (R)	9	1	1	1
Order quantity (Q)	40	1	1	1
Expected inventory on-hand ($E[OH]$)	20.083	1.730	1.927	1.906
*Comments:				

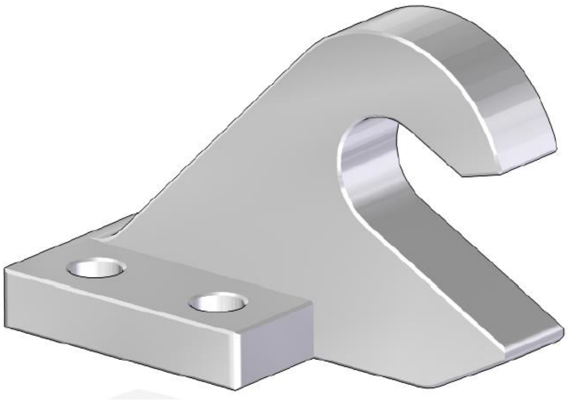
Table 14: Case study details: SKU 5

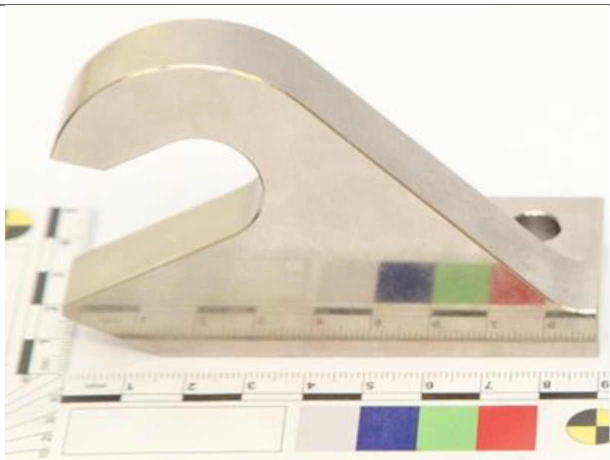
General SKU input data		
 3D rendering, sketch	Part name	Pin, internal
	Annual demand (m)	8
	OEM unit cost (u^{M1})	60.13
	OEM fixed order cost	180
	OEM leadtime f^{M1}	216
	IOQ	50
	Fillrate objective (β^{obj})	.99

Input case study AM		
 Photo original part	Dimensions (mm)	$31.2 \times 31.2 \times 64$
	Volume (cm^3)	25.3
	AM build material	Ti6Al4V
	AM machine	MetalFAB1 (DMLS)
	Build time (T)	7.00
	Outsource AM leadtime (L^{M2}) (days)	10

Results case study AM ($\rho = 0.90$, fill rate constraint)				
	M1	M2	M3	M4
Total costs	670.83	3666.32	2273.05	2275.59
Part costs	509.84	3545.84	2219.17	2222.12
Holding costs	160.98	120.48	53.86	53.46
Unit cost (u)	60.13	433.23	277.40	277.75
Reorder level (R)	6	2	1	1
Order quantity (Q)	50	1	1	1
Expected inventory on-hand ($E[OH]$)	26.773	2.781	1.942	1.925
*Comments:				

Table 15: Case study details: SKU 6

General SKU input data		
 3D rendering (DiManEx BV)	Part name	Support plate, left
	Annual demand (m)	8
	OEM unit cost (u^{M1})	87.07
	OEM fixed order cost	180
	OEM leadtime f^{M1}	150
	IOQ	1
	Fillrate objective (β^{obj})	.95

Input case study AM		
 Photo original part (DiManEx BV)	Dimensions (mm)	$90.8 \times 35 \times 59.8$
	Volume (cm^3)	52.4
	AM build material	AlSi10Mg
	AM machine	MetalFAB1 (DMLS)
	Build time (T)	10.00
	Outsource AM leadtime (L^{M2}) (days)	10

Results case study AM ($\rho = 0.90$, fill rate constraint)				
	M1	M2	M3	M4
Total costs	857.13	3695.35	2668.64	2670.39
Part costs	776.56	3616.56	2605.50	2607.75
Holding costs	80.57	78.79	63.13	62.64
Unit cost (u)	87.07	442.07	325.69	325.95
Reorder level (R)	3	1	1	1
Order quantity (Q)	18	1	1	1
Expected inventory on-hand ($E[OH]$)	9.254	1.782	1.939	1.922
*Comments:				

Table 16: Case study details: SKU 7

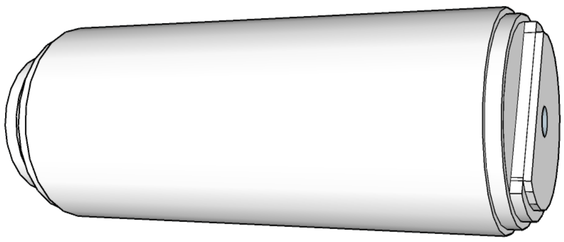
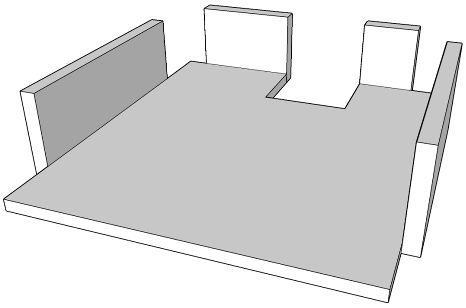
<table>
<tr><th colspan="5">General SKU input data</th></tr>
<tr><td rowspan="7">
3D rendering, sketch</td><td colspan="2">Part name</td><td colspan="2">Dowel pin</td></tr>
<tr><td colspan="2">Annual demand (m)</td><td colspan="2">21.50</td></tr>
<tr><td colspan="2">OEM unit cost (u^{M1})</td><td colspan="2">70.58</td></tr>
<tr><td colspan="2">OEM fixed order cost</td><td colspan="2">45</td></tr>
<tr><td colspan="2">OEM leadtime f^{M1}</td><td colspan="2">178</td></tr>
<tr><td colspan="2">IOQ</td><td colspan="2">1</td></tr>
<tr><td colspan="2">Fillrate objective (β^{obj})</td><td colspan="2">.95</td></tr>
<tr><th colspan="5">Input case study AM</th></tr>
<tr><td rowspan="6">
Photo original part</td><td colspan="2">Dimensions (mm)</td><td colspan="2">$24 \times 91.8 \times 24$</td></tr>
<tr><td colspan="2">Volume (cm^3)</td><td colspan="2">30.7</td></tr>
<tr><td colspan="2">AM build material</td><td colspan="2">Ti6Al4V</td></tr>
<tr><td colspan="2">AM machine</td><td colspan="2">MetalFAB1 (DMLS)</td></tr>
<tr><td colspan="2">Build time (T)</td><td colspan="2">15.00</td></tr>
<tr><td colspan="2">Outsource AM leadtime (L^{M2}) (days)</td><td colspan="2">10</td></tr>
<tr><th colspan="5">Results case study AM ($\rho = 0.90$, fill rate constraint)</th></tr>
<tr><td></td><td>Method 1 (OEM)</td><td>Method 2 (Out)</td><td>Method 3 (In)</td><td>Method 4 (Dual)</td></tr>
<tr><td>Total costs</td><td>1649.02</td><td>10497.62</td><td>11256.9</td><td>11252.87</td></tr>
<tr><td>Part costs</td><td>1574.38</td><td>10383.43</td><td>11162.28</td><td>11160.55</td></tr>
<tr><td>Holding costs</td><td>74.64</td><td>114.19</td><td>94.62</td><td>92.32</td></tr>
<tr><td>Unit cost (u)</td><td>70.58</td><td>472.95</td><td>519.18</td><td>519.07</td></tr>
<tr><td>Reorder level (R)</td><td>12</td><td>2</td><td>1</td><td>1</td></tr>
<tr><td>Order quantity (Q)</td><td>17</td><td>1</td><td>1</td><td>1</td></tr>
<tr><td>Expected inventory on-hand ($E[OH]$)</td><td>10.575</td><td>2.415</td><td>1.823</td><td>1.779</td></tr>
<tr><td colspan="5">*Comments:</td></tr>
</table>

Table 17: Case study details: SKU 8

General SKU input data		
 3D rendering, sketch	Part name	Cover, inspection hole
	Annual demand (m)	1
	OEM unit cost (u^{M1})	235.28
	OEM fixed order cost	180
	OEM leadtime f^{M1}	236
	IOQ	1
	Fillrate objective (β^{obj})	.99

Input case study AM		
 Photo original part, taken in prior research	Dimensions (mm)	$124 \times 129 \times 34$
	Volume (cm^3)	124
	AM build material	AlSi10Mg
	AM machine	MetalFAB1 (DMLS)
	Build time (T)	10
	Outsource AM leadtime (L^{M2}) (days)	10

Results case study AM ($\rho = 0.90$, fill rate constraint)	M1	M2	M3	M4
Total costs	370.79	1312.64	425.69	427.35
Part costs	280.28	1098.02	387.26	388.84
Holding costs	90.70	214.62	38.43	38.50
Unit cost (u)	235.28	1088.02	387.26	388.82
Reorder level (R)	2	1	0	0
Order quantity (Q)	4	1	1	1
Expected inventory on-hand ($E[OH]$)	3.855	1.973	0.992	0.990
*Comments:				

Table 18: Case study details: SKU 9

L Sensitivity analysis fixed order cost

In this appendix we describe a sensitivity analysis of fixed order cost variables f^{M1} and f^{M2}, for SKUs of both the polymer and metal case studies. The reason that these two variables in particular are selected for a sensitivity analysis is the expectation that they significantly affect main research results combined with the uncertainty in their input values. For Supply Method 1, we set $f^{\mathrm{M1}} = €\,45$ for SKUs for which the RNLA has an OEM contract and $f^{\mathrm{M1}} = €\,180$ for non-contract SKUs, based on the values used at the RNLA. There exists no quantitative substantiation of these values at the RNLA, however. Furthermore, we assumed that $f^{\mathrm{M2}} = €\,10$ for Supply Method 2, based on the assumption that outsourcing an AM order to an external AM provider would come with a significantly smaller administrative burden than issuing an order at the OEM. Clearly there is some uncertainty in this assumption.

In this sensitivity analysis we investigate to what extent a decrease or increase in the values of f^{M1} and f^{M2} affects the total cost associated with Supply Methods 1 and 2. The base case that we consider has system capacity utilization $\rho = 0.90$ and a fill rate constraint. Table 19 shows how a 50% reduction and 100% increase in f^{M1} affects the total costs of Supply Method 1. Table 20 considers f^{M2} and the total costs of Supply Method 2. In our analysis we distinguish between polymer (SKUs 1-3) and metal (SKUs 4-9) spare parts. The average effect of multiplication of f^{M1} by 0.5 on the total costs of Supply Method 1 is found to be -5.5% (polymer SKUs) and -3.6% (metal SKUs). Multiplication of f^{M1} by 2.0 leads to an average total costs increase of 7.4% (polymer SKUs) and 6.8% (metal SKUs) for Supply Method 1. Especially for SKUs with relatively low total costs, the sensitivity of the total costs to f^{M1} is relatively high.

For Supply Method 2, the effect of multiplying f^{M2} by 0.5 on the total costs of Supply Method 2 is found to be -15.4% (polymer SKUs) and -1.2% (metal SKUs). Multiplying f^{M2} by 2.0 leads to an increase in total cost by on average 30.7% (polymer SKUs) and 2.3% (metal SKUs) for Supply Method 2. Again, SKUs with relatively low values for total costs are affected strongest by variation in f^{M2}.

For both Supply Methods 1 and 2, implications of the above variations in f^{M1} and f^{M2} for the total costs comparison are demonstrated in Figure 2 (polymer SKUs) and Figure 3 (metal SKUs). It can be concluded for that only for SKU 3, sensitivity of the total costs to f^{M1} and f^{M2} significantly affects the cost comparison between the different supply methods.

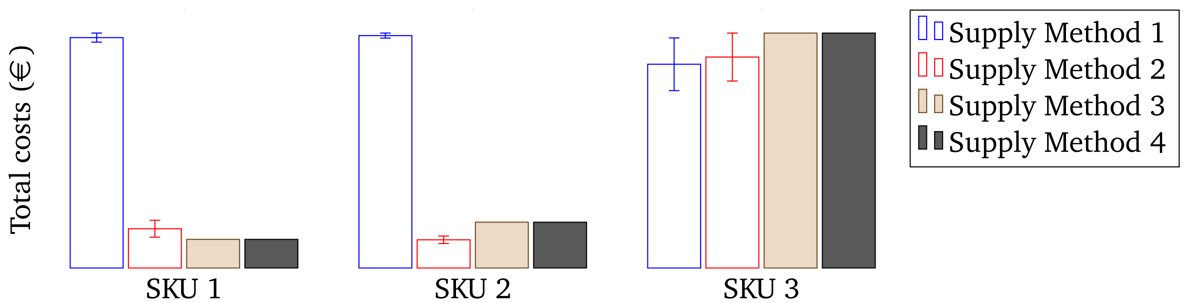


Figure 2: The total costs per supply method for each polymer AM SKU, under aggregate system utilization $\rho = 0.90$ and a fill rate constraint. Error bars for Supply Methods 1 and 2 indicate deviations in total costs for cases in which f^{M1} and f^{M2} are multiplied by factors 0.5 and 2.0.

SKU	f^{M1} multiplier					
	0.5		1.0		2.0	
	TC (€)	TC (%)	TC (€)	TC (%)	TC (€)	TC (%)
1	1741	98%	1776	100%	1814	102%
2	6151	99%	6218	100%	6284	101%
3	74	87%	85	100%	102	119%
4	239	95%	251	100%	265	106%
5	336	92%	365	100%	402	110%
6	656	98%	671	100%	700	104%
7	819	96%	857	100%	923	108%
8	1622	98%	1649	100%	1690	103%
9	368	99%	371	100%	409	110%

Table 19: The effect of a variation in f^{M1} on the total costs (TC) of Supply Method 1. For each case wherein f^{M1} is multiplied by a factor (0.5, 1.0 and 2.0) total costs are shown both in terms of absolute value and relative to the base case.

SKU	f^{M2} multiplier					
	0.5		1.0		2.0	
	TC (€)	TC (%)	TC (€)	TC (%)	TC (€)	TC (%)
1	238	79%	303	100%	433	143%
2	656	87%	756	100%	956	126%
3	78	89%	88	100%	108	123%
4	1527	98%	1557	100%	1617	104%
5	3397	99%	3447	100%	3547	103%
6	3626	99%	3666	100%	3746	102%
7	3655	99%	3695	100%	3775	102%
8	10390	99%	10498	100%	10713	102%
9	1308	100%	1313	100%	1323	101%

Table 20: The effect of a variation in f^{M2} on the total costs (TC) of Supply Method 2. For each case wherein f^{M1} is multiplied by a factor (0.5, 1.0 and 2.0) total costs are shown both in terms of absolute value and relative to the base case.

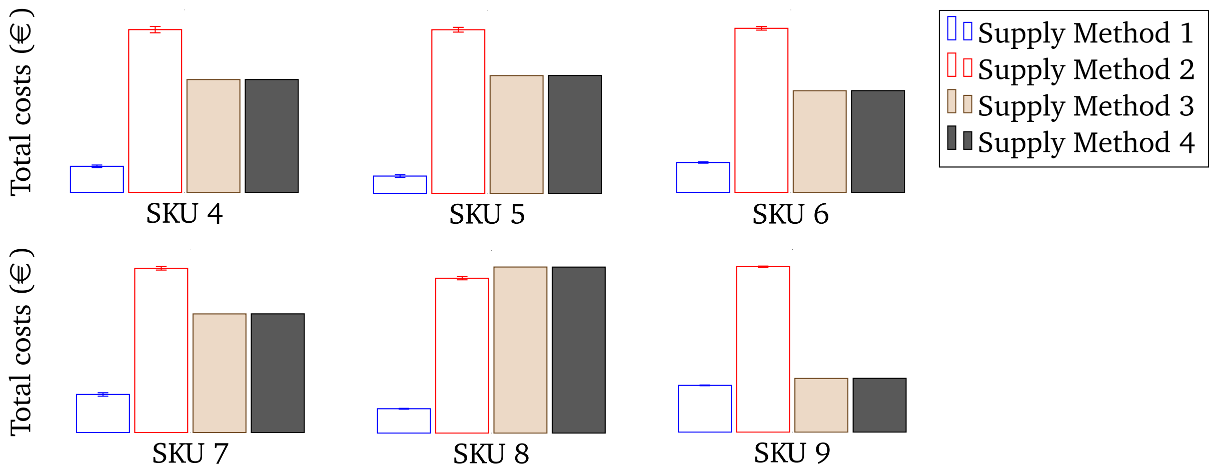


Figure 3: The total costs per supply method for each metal AM SKU, under aggregate system utilization $\rho = 0.90$ and a fill rate constraint. Error bars for Supply Methods 1 and 2 indicate deviations in total costs for cases in which f^{M1} and f^{M2} are multiplied by factors 0.5 and 2.0.

M Effectiveness of dual AM supply

In this appendix we provide more detail on the effect of the second source in the dual AM method, particularly when system capacity utilization is raised from $\rho = 0.90$ to $\rho = 0.99$. As shown in Figure 4, higher capacity utilization causes higher expected on-hand inventory levels under single source Supply Method 3. When a second source is added in Supply Method 4, however, this need for higher $E[OH]$ is generally relieved.

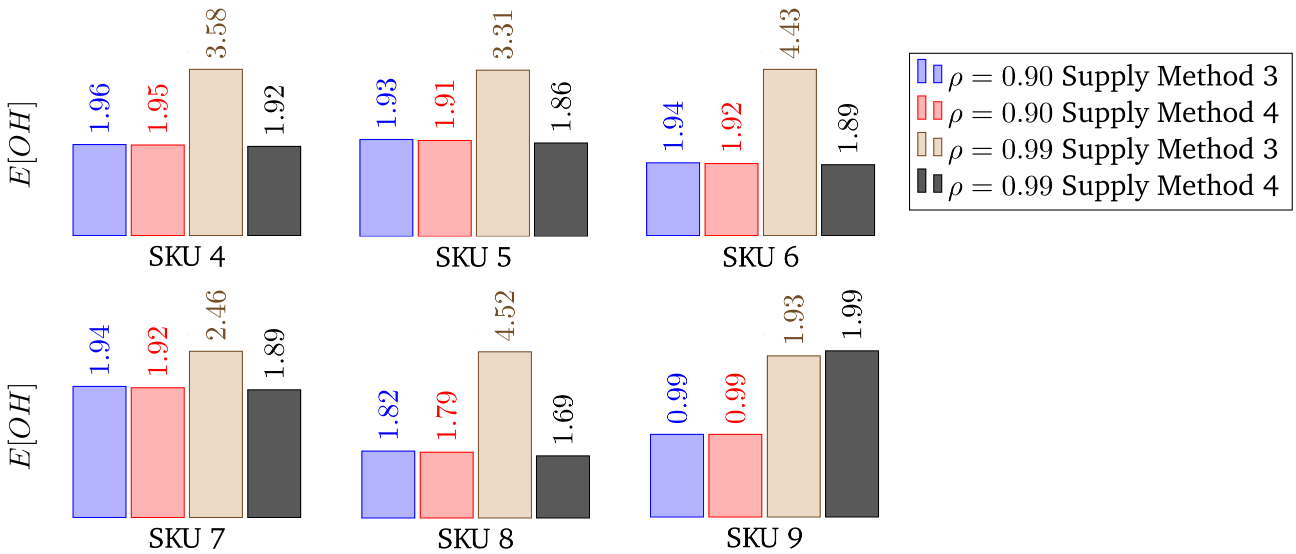


Figure 4: Expected inventory on hand $E[OH]$ for Supply Methods 3 and 4 for each metal AM SKU, under both aggregate system utilization $\rho = 0.90$ and $\rho = 0.90$