MASTER

The impact of ADI quality on spare parts inventory control with additive manufacturing

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Master Thesis

The Impact of ADI Quality on Spare Parts Inventory Control with Additive Manufacturing

In partial fulfillment of the requirements for the degree of Master of Science in Operations Management and Logistics

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Abstract

Condition Monitoring (CM) increases the available data on possible future demand. This challenges companies to incorporate the collected Advance Demand Information (ADI) in their inventory management. In combination with recent developments in Additive Manufacturing (AM), it is possible for manufacturers to produce spare parts on demand instead of keeping large amounts of stock. In this thesis, we investigate to what extent the combination of ADI and AM can result in inventory and cost reductions in the spare parts supply chain. A Markov Decision Process is designed and implemented to provide insights in the use of ADI and to compare an inventory system using AM to an inventory system based on conventional production of spare parts. Through a numerical study, we show that the use of (im)perfect ADI can yield substantial cost savings and reduction in inventory in both contexts, dependent on the quality and timing of the ADI. Furthermore, we find that only in settings where both failure rates and production costs are equal or when production costs are lower, the failure rate is slightly higher and backorder costs are high, the additive manufacturing based system can outperform the traditional manufacturing system. We conclude that the production costs and reliability of AM parts are key factors that influence the future potential of AM.

Summary

Introduction

Increased use of Condition Monitoring (CM) results in a large amount of data about the condition of capital goods. The data can be analysed to predict failures in advance using a prediction technique. In case of a predicted failure, the prediction tool issues a warning signal (demand signal) before the actual failure, which can be seen as Advance Demand Information (ADI). ADI can be used for optimising spare parts inventory, as it enables proactive behaviour instead of reactive behaviour. However, the obtained ADI is typically imperfect due to: 1) false positives (warnings without failures), 2) false negatives (failures without warnings) and 3) uncertainty about the exact timing of the failure. Consequently, manufacturers are still required to keep some level of inventory, but they want to keep this level as low as possible.

To further reduce the level of inventory, a technology called Additive Manufacturing (AM) can be used. AM is a technology that builds 3D objects by adding layer-upon-layer of material, such as plastic or metal. The objects are based on a digital 3D model. In the recent years, AM has become more and more popular and is seen as a game-changer in the spare parts production, as it enables on-demand printing of spare parts with much shorter supply lead times. Currently, additive technologies are mainly used in the automotive and aerospace industry.

This master thesis is initiated to research the potential benefits of using ADI in combination with Additive Manufacturing. Previous literature mainly discusses the use of ADI in the context of consumer orders or in the context of traditional manufacturing. Furthermore, as AM is indicated as a potential game-changer in the spare parts production, we want to investigate whether AM can realise this potential in practice, compared to an inventory control system using traditional manufacturing (TM).

We therefore formulate the main research question:

What are the characteristics that (im)perfect ADI and Additive Manufacturing must have to be valuable in a spare parts inventory control system compared to an inventory system using TM?

Research Design

To answer the main research question, a discrete-time Markov Decision Process (MDP) has been designed and implemented. An MDP is a model for decision making under uncertainty, as it considers short-term rewards as well as opportunities for future decision making. The objective is to generate the optimal inventory control policy, such that the long-run production, holding and backorder costs are minimised. This optimal inventory policy is found by using a method called value iteration. Value iteration is an algorithm that converges to the optimal values when time goes to infinity. The algorithm has an upper bound on the error, which is set to 10^{-6}. Considerable effort has been made to verify and to validate the outcomes of the model. For example, a Markov-chain has been manually formulated and solved to check whether the outputs of the Markov-chain and the model are identical. Also, mathematical derivations have been formulated to ensure a solid mathematical foundation of the MDP.

A test bed has been designed using realistic values. The values have been collected via prior literature and studies and interviews with experts in the field of inventory control and AM. For the test bed, we assume that TM has a longer supply lead time than AM. Also, we assume that the quality of printed parts is inferior to regular parts, which increases the probability that printed parts fail more often. Different cost values for printed parts are considered, which range from 0.5-4 times the cost of traditional manufactured parts. Likewise, different values for the demand lead time are considered to analyse settings where the demand lead time is either shorter, equal or longer than the supply lead time. The obtained values are validated by multiple experts in the field of inventory control and AM. The experts have been consulted individually to ensure the validity of the collected values, i.e., to prevent that the experts influence each other on what they consider to be realistic values.

Results

A numerical experiment has been performed to provide insights on the value of incorporating (im)perfect ADI in an inventory control system, either using AM or TM. The total cost in the different imperfect ADI configurations are compared to the setting with perfect ADI. The results in the AM context show that for higher failure rates, it is more desirable to have fewer false negatives than having fewer false positives. As the failure rate decreases, it becomes more important to predict failures correctly. Also, the value that can be gained by using (im)perfect ADI, increases for lower failure rates.

First, we tested a setting where the demand and supply lead time are equal to each other. Then, we increased the demand lead time, such that is longer than the supply lead time. We find that increasing the demand lead time does not result in large cost savings. This is a result from the fact that in the initial setting we already have a demand lead time that is equal to the supply lead time. Consequently, the predicted demand can already be satisfied JIT. Further increasing the demand lead time does therefore not result in much value to be gained, because it is possible to react to ADI anyway.

For the TM context, we find that large value can be gained by using (im)perfect ADI. This is especially valid for settings where the backorder costs are low. In the case where backorder costs are high, the demand information is relatively less useful, as we find that keeping inventory diminishes the effect of an increasing precision. The uncertainty that corresponds to the imperfectness of the ADI and the fact that the supply lead time is longer than the demand lead time, requires that some extra safety stock is kept.

Also, we find that in this context, increasing the demand lead time does results in extensive cost savings. First, we tested a setting where the supply lead time was longer than the demand lead time. Then, we extended the demand lead time, such that it became equal to the supply lead time. Consequently, it is possible to satisfy predicted demand JIT and large cost savings can be achieved. Also, using the extended demand lead time, larger cost savings can be achieved by incorporating (im)perfect ADI compared to the initial shorter demand lead time.

The comparison between the AM and TM context shows in general, that the system based on traditional manufacturing outperforms the system based on additive manufacturing. The system using AM results in lower total cost only in specific settings, such when failure rates and production costs are equal or when production costs are lower, the failure rate is slightly higher and backorder costs are high. Increasing the demand lead time resulted in even better outcomes for the TM context, except for the setting where the failures rates and production costs are equal, as in this setting AM still outperforms TM.

Conclusion

This thesis has shown that a significant amount of cost savings can be achieved by incorporating (im)perfect ADI. This is valid for both a system that is based on traditional manufacturing as well as on additive manufacturing. Extending the demand lead time resulted only in the TM context in large cost savings, as JIT delivery became possible. Having a demand lead time that is longer than the supply lead time does not result in large value to be gained, as it is possible to react to ADI anyway. Furthermore, this study has quantified the difference between a system using either traditional or additive manufacturing. Only in settings where both failure rates and production costs are equal or when production costs are lower, the reliability is slightly worse and backorder costs are high, the additive manufacturing based system can outperform the traditional manufacturing system. Concluding, the production costs and reliability of AM parts are key factors that influence the future potential of AM.

Limitations and Future Research

Future research on the assumptions that have been made in this research might be interesting. For example, instead of considering a deterministic and identical demand lead time for all parts, the effect of a stochastic or non-identical demand lead time can be investigated. This increases the mathematical level of the model, but probably does not result in many new insights. Another interesting future research direction is to develop a heuristic that takes into account the characteristics of (im)perfect ADI. For example, traditional base-stock policies based on predicted demand cannot be used for the model, due to imperfect demand signals. The heuristic can be used for solving larger problem instances.

Preface

This master thesis is the result of the project that was conducted in order to complete the master Operations Management & Logistics at the Eindhoven University of Technology. It marks the end of my time as a student.

First of all, I would like to thank my mentor and first supervisor of the university, Rob Basten. I am grateful for his available time to answer my questions, provide new insights and feedback to help to finish this project. Furthermore, I would like to thank my second supervisor, Tarkan Tan, for his valuable input and feedback on my thesis.

Dirk Deurloo
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Contents

List of Figures

List of Tables

1 Introduction

Manufacturers use capital goods for the production of their products or for delivering their services. These capital goods are highly utilised and under almost continuous stress. Therefore, these goods require maintenance to keep them in a state in which they can perform their function (Van Houtum and Kranenburg, 2015). The goal is to prevent equipment from failing, as for example down-time costs are high. In order to achieve this, Condition Monitoring (CM) is often used. Using this method, a lot of data is collected about the condition of all equipment. The data can be analysed to predict failures in advance using a prediction technique (Topan et al., 2018). In case of a predicted failure, the prediction tool issues a warning signal (demand signal) before the actual failure, which can be seen as Advance Demand Information (ADI). ADI can be used for optimising spare parts inventory, as it enables proactive behaviour instead of reactive behaviour. In other words, if the start of the failure process can be identified early enough (expected time to failure is longer than the supply lead time), there is no need to stock a part (Louit et al., 2011). However, the obtained ADI is typically imperfect because of the following reasons: 1) false positives (warnings without failures), 2) false negatives (failures without warnings) and 3) uncertainty about the exact timing of the failure (Topan et al., 2018). This last kind of demand can be seen as random demand, which cannot be predicted. To deal with this random demand, it is still needed to keep some level of inventory, but manufacturers want to keep this level low as possible as too much unnecessary inventory results in high cost.

A new technology called Additive Manufacturing (AM), or 3D printing, could resolve the problem of too much inventory. This technology has become more and more popular over the last years and is a game-changer in the spare parts production, as it enables on-demand printing of parts with much shorter supply lead times (Segzdaite, 2019). Consequently, it is possible to eliminate inventory and only produce spare parts when they are needed. An example is the U.S. Navy, which has installed a 3D printer on one of its warships. They can use the printer for manufacturing specific parts that are needed in case of a failure, instead of replacing, for example, a complete door (3DPrintingIndustry.com, 2018). However, there are also some disadvantages of using AM, such as the high development costs compared to traditionally manufactured parts, which decreases the attractiveness of always using AM (Westerweel et al., 2018b). Another disadvantage is the potential inferior quality of printed parts. Deloitte (2019) states that currently only a few materials can be used for manufacturing, while satisfying industry quality standards. There are also some size restrictions in the use of AM, only parts that are smaller than the printer's casing size can be produced (Attaran, 2017). This results in situations where large parts need to be produced in separate segments, but this increases production time. Still, many researchers agree on the fact that Additive Manufacturing is the future (DHL, 2016; PWC, 2017).

There is an increasing number of papers being published on how AM can be used in, for example, spare parts inventory control or maintenance policies. The same is valid for papers about incorporating perfect ADI in inventory control, while papers considering imperfect ADI are rare. A more detailed discussion of related papers is provided in Section 2. This thesis aims to quantify how and by how much inventory levels and costs can be reduced by using AM and (im)perfect ADI compared to a traditional inventory control system using (im)perfect ADI. In order to quantify the effect, a Markov Decision Process will be formulated and optimised using the value-iteration method. The MDP is inspired by the work of Topan et al. (2018) and Westerweel et al. (2018a). This thesis can be placed in the context of relatively inexpensive, plastic (polymer) parts, such as gears, gauges and housings for sensitive electronics. It can also be placed in the context of laboratories and medical equipment. For example, parts of a washing centrifuge for blood group serology or parts of X-ray equipment are manufactured by using additive technologies (GmbH, 2020).

This thesis is organised as follows. In Chapter 2, literature related to Additive Manufacturing in the spare parts supply chain and Advance Demand Information is discussed. In Chapter 3, the problem description for the thesis is introduced and the corresponding research questions are formulated. Also, the methodology of how to answer the research questions is discussed. In Chapter 4, the model description and the corresponding mathematical model are provided. Furthermore, the verification and validation efforts of the model are presented. In Chapter 5, the test bed is presented. Chapter 6 provides the results of the numerical experiment for both the AM and TM context. The last chapter, Chapter 7, provides the main conclusions, managerial insights and suggestions for future research.

Academic Relevance

This thesis differs from the reviewed literature in Section 2, in that it is, to the author's best knowledge, the first that considers (im)perfect ADI in a context with additive manufacturing. As Sections 2.3 and 2.4 show, most of the papers consider inventory systems that use traditional manufacturing, for example Topan et al. (2018), which is used as inspiration how to incorporate (im)perfect ADI. Therefore, this thesis provides insights in the use of ADI in the context of additive manufacturing. Also, as we make a comparison between a traditional and an additive manufacturing system, we provide insights in the differences (in performance) between these type of inventory systems. The use of an additive manufacturing system is inspired by the work of Westerweel et al. (2018a). Furthermore, both Topan et al. (2018) and Westerweel et al. (2018a), are used as motivation for the MDP that has been formulated in this thesis.

Additionally, Topan et al. (2018) assume a lost-sales inventory model, while in this thesis a backordering inventory model is used. In other words, Topan et al. (2018) assume that all unmet demand is satisfied by either an emergency shipment or that it is lost to a competitor. In the context of this thesis, it is not realistic to use that assumption. For example, the car manufacturer Porsche uses additive technologies to produce spare parts for its classic cars. Classic car owners want the parts of the Original Equipment Manufacturer (OEM) and are not able to switch to another car manufacturer. Therefore, it is reasonable to assume a backordering policy.

Last, Westerweel et al. (2018a) assume a zero lead time for the (emergency) printing source. However, in this thesis, it is assumed that not only the regular supply source has a positive lead time ($L > 0$), but also the additive supply source. It is reasonable to assume a positive lead time, as it cannot be expected that all parts can be printed during an overnight printing job. Furthermore, it can also be the case that a printed part has to come from a central warehouse, which implies that it takes a certain amount of time before it is delivered at the location where the part is required. In the example of Porsche, it is reasonable to assume that only at large factories a printer is available for printing spare parts. So, when a part is required at a local store, it takes a certain amount of time before the part is delivered at that local store. Therefore, it is reasonable to assume a (small) positive lead time for the additive supply source.
Another key difference is that Westerweel et al. (2018a) do not use any kind of (im)perfect ADI. While, in this thesis, it is the aim to investigate the value of (im)perfect ADI in an inventory control systems using either TM or AM.

2 Literature Review

In this chapter, relevant literature regarding Additive Manufacturing and Advance Demand Information is discussed (see Figure 1). The papers mentioned in the Venn diagram are considered to be the most important papers for this thesis. First, Additive Manufacturing is discussed and its applications in practice. Then, we discuss how AM is used in a dual sourcing strategy. Furthermore, two different forms of ADI are discussed: perfect and imperfect. In the end, some papers regarding Markov Decisions Problems (MDP) are discussed.

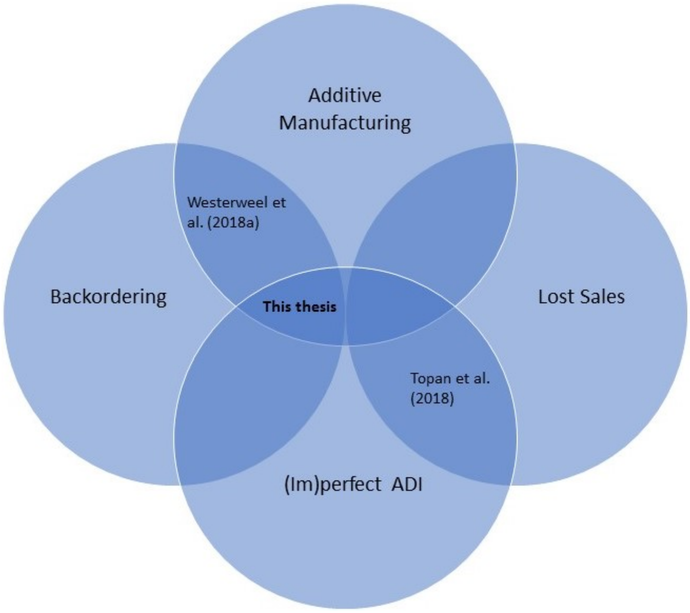


Figure 1: *Venn diagram with overview of different literature directions*

2.1 Additive Manufacturing

Additive Manufacturing, or 3D printing, is the construction of an object by adding materials layer by layer based on a digital 3D model (Huang et al., 2013). The development of AM technologies started in the 1980s. Large progress has been made since then and it is believed that AM will be a game-changer in many industries. AM naturally affects the production industry, as it does not require tools and changeover times. Furthermore, as it only uses the necessary amount of material to produce, it minimises material waste. Another industry in which the use of AM is growing, is the healthcare industry. Based on, for example, tomography and imaging, it is possible to produce high complex, patient-specific constructs. The healthcare industry is the third largest user of AM technologies and the use is expected to grow even more (Liaw and Guvendiren, 2017). Also, in the retail sector the use of AM is growing. For example, Nike and Adidas use AM for customised end products, such as footballs and shoes (Weller et al., 2015).

Major AM processes are fused deposit modelling, inkjet printing, laminated object manufacturing, laser engineered net shaping, stereolithography, selective laser sintering and three-dimensional printing (Huang et al., 2013). Initially, mainly polymers were the considered materials in AM technology, but recently more materials are being used to produce functional parts. Still, more research is needed to ensure that AM can compete with traditional manufacturing, as AM technologies are, for example, unable to produce large-sized objects (Prakash et al., 2018). Despite some drawbacks, already many manufacturers are using AM technologies for the production of (spare) parts. For example, in the automotive industry, Ford uses 3D printed brake components for one of their cars. Another example is Porsche that uses 3D printing for some specific parts of their engines. Also, in the aviation industry 3D printing is a popular production method. British Airways has installed 3D printers around the world to make it possible to produce parts on demand (Boissonneault, 2019).

2.2 Additive Manufacturing in the Spare Parts Supply Chain

An industry in which AM can have a significant effect is the spare parts industry. The number of papers that investigate the effect AM technologies can have on the supply chain has increased massively in the last years (Gao et al., 2015). A dual source supply chain is often used to deal with potential interruptions in the supply process. By using two suppliers, a manufacturer uses supplier diversification to reduce risks and uncertainty (Ahiska et al., 2013). Another reason why manufacturers often uses a dual sourcing strategy is that one of the two suppliers offers a faster (expedited) delivery at a higher cost compared to the other supplier. So, as argued by Minner (2003), the optimal choice in an environment with multiple suppliers has to trade-off the aspects of direct costs and supplier services.

Holmström et al. (2010) propose two different approaches to implement AM in the spare parts supply chain. The first approach is centralised AM, in which spare parts are centralised in a single location per region. This should improve the availability of spare parts and reduce holding cost, but the downside is the increase in response time. The other approach is distributed AM, in which there are many locations where spare parts can be manufactured and stored. This is especially help full for isolated systems, such that parts can be produced on demand. Holmström et al. (2010) conclude that currently on demand and centralised production of spare parts is the better approach. However, if AM does develop as expected, the distributed approach becomes more feasible.

Knofius et al. (2020) consider the situation with traditional and additive manufacturing for spare parts, a so called dual sourcing option. They assume a different failure behaviour of parts produced by the two methods. Their numerical experiments shows that a dual sourcing option is superior compared to single sourcing. The savings can go up to 10%, even when the costs of an AM part are three times higher than a traditional manufactured part. The main conclusion of the paper of Knofius et al. (2020) is that dual sourcing strategies are important for discovering all of the benefits of AM technologies. Song and Zhang (2019) continue to investigate the situation in which both traditional and additive manufacturing are available. Their model decides on which part to stock and which part to print. Song and Zhang (2019) find that as the unit cost of printing decreases and the lead time of 3D printing decreases, the utilisation of the AM technology increases. Furthermore, they conclude that putting parts on stock and printing parts on demand are complementary for achieving cost minimisation.

Another situation in which a number of papers have investigated the effect of AM is in military and humanitarian missions. For example, Westerweel et al. (2018a) study how the Dutch army can use remote-location printing to deal with spare parts shortages that occur between replenishments. They assume that printed parts are less reliable than regular parts and that printed parts are only temporary replacements until a regular part has arrived. Westerweel et al. (2018a) show that the optimal policy is relatively simple and has a single threshold deciding when to print or when to wait until the next replenishment. They conclude that the policy results in large operational cost savings and increased availability of assets. Den Boer et al. (2020) conduct a qualitative study on the impact of AM on responsiveness, efficiency and sustainability on the supply chain during military missions. They conclude that AM can reduce lead times, waste, inventory and improves readiness and sustainability of parts for armed forces during missions abroad.

2.3 Perfect Advance Demand Information

An early paper that considers advance warnings of customers for their demands is the paper of Hariharan and Zipkin (1995). They analyse constant and stochastic lead times, as well as single-stage systems and multi-stage systems. Hariharan and Zipkin (1995) conclude that all lead time information must be available in some central point in the supply chain where all the decisions are made, as policies benefit of coordination. However, they also indicate that their models need to be tested in more realistic scenarios with more (demand) uncertainty.

Instead of a continuous review policy, Gallego and Özer (2001) consider a periodic review system. They analyse stochastic inventory systems with either a positive set-up cost for each order or a zero set-up cost. In the case of a positive set-up cost, state-dependent (s, S) policies are optimal for finite-horizon problems. The state of the system is dependent on a modified inventory position. In case of a zero set-up cost, a state-dependent base-stock policy is found to be optimal. The optimal policy is an increasing function of observed demands beyond a certain protection period. Gallego and Özer (2003) extends the problem to a multi-echelon system. They show that the original multi-echelon problem can be decomposed into single location periodic-review problems. Again, they used the modified inventory position as proposed in Gallego and Özer (2001) for further reducing the dimension of each location. Gallego and Özer (2003) show that state-dependent, echelon base-stock policies are optimal, especially in case of stationary problems. Another extension of the paper of Gallego and Özer (2001) is discussed in the paper of Wang and Toktay (2008). They discuss the same model, but now flexible (early) delivery is allowed. Wang and Toktay (2008) show that by introducing flexible delivery, large cost savings can be achieved. Furthermore, they found that the benefits of flexibility increases when there are larger degrees of ADI available. A striking finding in their paper is that the benefit of increasing the demand lead time by one period is larger than decreasing the supply lead time by one period. Previous studies that did not consider flexible delivery argued that the effect of decreasing the demand lead time or the supply lead time is equivalent.

Louit et al. (2011) consider a spare parts inventory control model based on the condition (remaining life time) of an item. They argue that inventories can be reduced as parts can be ordered at the moment a potential failure is identified. In their numerical experiment, they show that an expedited order is more beneficial than early delivery of the spare part in case of a failure. Instead of considering a single-component configuration, Lin et al. (2017) consider an arbitrary number of machines. They show that a state-dependent policy may lead to costs savings of on average 20% compared to a state-independent policy. Furthermore, Lin et al. (2017) show that some parameters (e.g. number of machines or lead time) have a large influence on the costs savings. Another important conclusion is that not using available degradation information may result in additional costs of more than 25%.

2.4 Imperfect Advance Demand Information

In the paper of Topan et al. (2018), a clear explanation on what is imperfect ADI is given. As mentioned in Section 1, they argue that ADI is imperfect because of the following three reasons: 1) false positives (warnings without failures, also known as the precision), 2) uncertainty about exact timing of the failure and 3) false negatives (failures without warning, also known as the sensitivity).

Topan et al. (2018) consider a lost-sales inventory model with imperfect ADI in a spare parts case as well as in machine sales case. Condition monitoring is used for collecting the ADI. A numerical study showed that imperfect ADI can result in significant cost savings, but that the quality of the information is dependent for the amount of savings. It is desirable to have less false negatives than false positives. The benefit of ADI increases even further when it is allowed to return excess stock, especially in the case of false ADI.

Tan et al. (2007) are analysing inventory policies incorporating imperfect ADI, where the ADI is collected on customers demands. Their numerical experiment shows that the optimal ordering policy is a state-dependent order-up-to type. The optimal order level is an increasing function of the ADI size. Furthermore, Tan et al. (2007) propose a function for the upper bound of the order-up-to level, which is also depending on the ADI size.

Tan et al. (2009) consider a multi-period inventory problem with two different demand classes having different priorities (class 1 and class 2). To deal with the different priorities, they developed a rationing policy utilising ADI. Numerical tests show that the value of ADI increases when the demand variance is higher, relative importance of class-1 demand is higher and when there is sufficient demand of class-2 at the first period. Tan et al. (2009) conclude that despite ADI is often imperfect, the benefits of using imperfect ADI can be sufficiently large.

3 Research Design

In this chapter, the project description is formulated. In Section 3.2, the main research question and the corresponding sub-questions are formulated. Each of the research question is more elaborated on directly after the question itself. Last, the scope of the thesis is provided.

3.1 Project Description

In this master thesis, we study a single-item, single-location spare parts inventory problem by utilising (im)perfect Advance Demand Information with an option to produce via Traditional (TM) or Additive Manufacturing (AM). Condition monitoring is used for collecting information in order to produce a demand signal (ADI). We assume that the timing of the ADI is known and fixed. In other words, the demand lead time is deterministic and identical for all parts.

As mentioned in Chapter 1, there are multiple demand types. The first type are so-called true positives (TP), a demand signal that turns out to be true with probability p. The second demand type are so-called false positives (FP), the demand for which we obtain a demand signal but will eventually not occur with probability $1 - p$. This could result in a situation where it is decided to produce a part based on the ADI. In the end, however, the demand will not occur and we have a part on stock. This part could be used for another future demand, but in any case, some inventory cost needs to be paid.

How sure we can be about the number of true positives is dependent on the precision of the condition monitoring tool. The precision (p) is defined as the number of true positives divided by the sum of true and false positives. Hence, the precision can be formulated as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

The third and last demand type are false negatives (FN). This is demand for which no demand signal is obtained but still occurs. So, only a specific fraction of demand can be predicted, which is called the sensitivity (q). Hence, the sensitivity can be formulated as:

$$\text{Sensitivity} = \frac{\text{predicted demand}}{\text{predicted demand} + \text{random demand}}$$

3.2 Research Questions

The main research question of this thesis is:

What are the characteristics that (im)perfect ADI and AM must have to be valuable in a spare parts inventory control system compared to an inventory system using TM?

To answer the main research question, the following research questions are formulated:

1. **How to model a spare parts inventory control system with ADI?**
To answer this research question, we develop a Markov Decision Process (MDP). An MDP is used, as this kind of model is helpful in decision making in situations where outcomes are partly random and partly under the control of a decision maker. The defined MDP is used for both the traditional and the additive manufacturing context. Westerweel et al. (2018a) consider the use of AM at remote locations. Their MDP is used as an inspiration for the MDP that we develop. This thesis differs in three ways from the paper of Westerweel et al. (2018a): 1) we consider ADI, 2) we assume a positive lead time for regular and printed parts instead of a zero lead time and 3) they consider three different supply sources. We also use Topan et al. (2018) as a starting point for this thesis. Furthermore, several key assumptions for the model have to be made (e.g. single-location, single-item and backordering). Another important part of modelling is to decide on how to evaluate the model with respect to cost or other measurements.

2. **What are the model input values for the AM and TM supply methods?**
The model developed at RQ1 needs several input parameters (e.g. supply lead time or production costs). It is important to use realistic values in order to make reasonable conclusions. The values can be collected via prior literature and studies or interviews with experts in the field of inventory control and AM. In this thesis, the goal is to collect input parameters both based on literature and previous studies (e.g. Coumans (2017), Jansman (2017)). The obtained values are evaluated in interviews with multiple experts in the field of inventory control and AM.

3. **What is the value of (im)perfect ADI within the AM and TM context? And what are the characteristics of the optimal policy?**
This research question provides insights on the value of incorporating ADI in a spare parts inventory control policy. Using the answers of RQ1-RQ2, we should be able to compute costs for different configurations. A numerical experiment can provide the exact insights on the value of ADI and AM for the different configurations compared to an inventory control system using TM. Furthermore, as parameters influence the outcome of the model, it is interesting to perform a sensitivity analysis by changing the values of the input parameters (e.g. precision, costs and lead times). Also, we provide insights on the characteristics of the optimal policy.
For example, as downtime cost are often very high, it might be required to have 3 regular parts on stock when only traditional manufacturing is available. When ADI is implemented, we can anticipate on some future demand. This could result in the fact that inventory can be reduced to 2 regular parts. When switching to AM, it is possible to print parts with a shorter lead time. Consequently, it could be the case that inventory is even further reduced to only 1 regular part as we have implemented ADI and AM.

4. **How does the inventory control system using AM perform compared to the system using TM?**
To answer this research question, we make a comparison between the inventory system using AM and the system using TM. Again, using the answers of RQ1-RQ2, we should be able to make a comparison between both systems. The comparison is made based on the total cost in both settings. Furthermore, the comparisons should provide insights on investment decisions for a firm that could either go for ADI precision/sensitivity (through sensors) or for AM.

3.3 Scope

In Section 1, we explained that ADI can be imperfect in three ways. In this thesis, we assume that the demand lead time is deterministic and identical for all parts. That means that the ADI can only be imperfect in two ways: 1) only a certain amount of demand can be predited (q) and 2) only a specific amount of demand signals will materialise (p).

Furthermore, in the thesis, we consider two different supply methods, which are Traditional Manufacturing (TM) and Additive Manufacturing (AM). We want to study the effect of ADI and its quality on the control policy considering different supply methods. We assume that traditional manufacturing has a significantly longer supply lead time than AM. More specifically, we assume that the traditional manufacturing lead time is larger than/equal to the demand lead time, but that the additive manufacturing lead time is shorter than/equal to the demand lead time. The downside of using AM is that it has significantly higher production cost than traditional manufacturing, which decreases the attractiveness of always using AM. Furthermore, we assume that the quality of printed parts is inferior to regular parts (non-strictly), which increases the probability that printed parts fail more often.

4 Model

In this chapter, we first describe the model and introduce notation in Section 4.1. In Section 4.2, we provide an example of how (un)predicted demand and ADI signals are generated. The formulation as MDP is provided in Section 4.3. In Section 4.4, we discuss the verification and validation of the model. This chapter provides the answer to RQ1:

How to model a spare parts inventory control system with ADI?

4.1 Model Description

We consider a single-item, single-location inventory system with periodic review and an infinite horizon. Let $N \in \mathbb{N}$ be a finite number of systems in service. Each system has one critical part. When this critical part fails, the machine is down and the part needs to be replaced by a spare part. Each part can only fail once during a period. The failure probability of a part is denoted by f.

Condition monitoring is used to collect data in order to produce a demand signal (ADI), or in other words, to predict a failure. We assume that each machine can only give one demand signal per period. W_t is a stochastic variable and denotes the collected number of demand signals that is available at the beginning of period t. w_t denotes the realisation of W_t. This can be interpreted as the system being updated overnight and receiving the new signals before the start of the new period. W_t is binomial distributed with parameters equal to $N - B_t - \sum_{u=t-\tau}^{t-1} w_u$ and P_{ADI}, where B_t denotes the total number of backorders in the system at the beginning of period t, which is elaborated on later in this section, and P_{ADI} denotes the corrected probability of giving a demand signal. Section 4.2 provides an example of the model and explains why a corrected probability is required. In Section 5.2 it is further elaborated on how the correction is derived. $\mathbf{w}$ is a vector containing the demand signals that are in the system. Each collected demand signal either turns out to be a true positive with probability p or a false positive with probability $1-p$; p is also known as the precision. In the former case, the signal belongs to an actual demand in period $t+\tau$. In the latter case, the signal leaves the system at the beginning of period $t+\tau+1$. τ is the time between a demand signal becomes available to the system and when it becomes an actual demand or leaves the system, also known as the demand lead time. The demand lead time is deterministic and identical for all parts.

The variable D_t^{p} denotes the number of signals that turn into an actual demand in period $t+\tau$. This variable is binomial distributed with parameters $w_{t-\tau}$ and p. So, the total *predicted* realised demand in period t is given by D_t^{p}. As we also consider *unpredicted* demand, the variable D_t^{u} is introduced. This variable is defined as the unpredicted demand in period t and follows a binomial distribution with parameters $N - B_t - w_{t-\tau}$ and P_{R}. The first parameter indicates the number of parts that can still fail in period t, i.e. parts that are not part of the *predicted* demand in period t, and the second indicates the random failure probability, which is further elaborated on in Sections 4.2 and 5.2. This random failure probability is partly based on the sensitivity q, i.e., the fraction of demand that can be predicted. So, the total demand in period t consists of D_t^{p} and D_t^{u} and is denoted by D_t.

Demand for parts is immediately satisfied from stock, if sufficient parts are on stock. The on-hand stock is denoted by I. The stock is re-supplied by an ample supplier with a deterministic lead lime L (> 0) at a cost of c (> 0) per part. In each period t, the size of the replenishment order placed in period $t - L + l$ and due in period $t + l$ is denoted by z_l for $l = 0, ..., L$. $\mathbf{z}$ is a vector containing the stock in the pipeline. When a part is required but there is no available stock on hand, the demand is backlogged. In this situation, a penalty cost b (> 0) per unit of unmet demand per period is incurred. A holding cost h (> 0) needs to be paid for each unit of stock carried over from one period to the next. An overview of all mathematical notation is provided in Appendix B.

The sequence of events in period t is as follows:

1. The collected signals w_t are observed.
2. The replenishment order z_0 that has been placed in period $t - L$ and due in period t arrives.

3. The current system state (B_t, I_t, $\mathbf{z}$, $\mathbf{w}$) is now completely known.
4. The order size z_L is determined. It will arrive in period $t + L$.
5. Both the predicted (D_t^{p}) and unpredicted demands (D_t^{u}) are realised and fulfilled from stock, if spare parts are available. The unmet demand is backlogged. There is no distinction between predicted and unpredicted demand. Also, for both demands, the same backorder costs are incurred, so costs are linear in the number of backorders. If required, a First Come First Served (FCFS) policy is applied.
6. Finally, at the end of period t, the ordering, holding and penalty costs are incurred.

4.2 Demand & ADI Generation

In this section, we provide an example on how the demand and ADI signals are generated. Also, we explain why it is required to do corrections for the probability of ADI signals and random demand. The derivation of the correction terms are further elaborated on in Section 5.2.

The demand that is coming from the ADI signals is generated in two steps. First, the machines should give ADI signals based on a binomial distribution and, second, the demand signals become true or false, which is again based on a binomial distribution. For the first step, the number of ADI signals follows a binomial distribution and one would expect with parameters $N - B_t - \sum_{u=t-\tau}^{t-1} w_u$ and $\frac{q \cdot f}{p}$. The first parameter indicates how many parts are left over that could give an ADI signal and the second parameter indicates the probability that a signal is given. The probability is based on the fact that the fraction of failures we can predict is q. So, the expected number of failures that can be predicted is $q \cdot f$. Then, we need to take into account the precision of the system. In other words, if $p = 1$, all of the predicted demand is true, so we get $q \cdot f$. However if $p = 0.5$, the number of signals that we receive increases, because now only in 50% of the cases the demand signal is true. This leads to the usage of $\frac{q \cdot f}{p}$.

The second step for the ADI demand consists of calculating whether the ADI signal(s) become true or false. This is done by using a binomial distribution with parameters $w_{t-\tau}$ and p, which are the number of demand signals that have been in the system for exactly τ periods, and the precision.

We now introduce two examples to show how the ADI signals and predicted demand are generated. These examples demonstrate that the effective failure rate, i.e. the actual observed failures, deviate from the input failure rate. Consequently, it is not possible to make fair comparisons between different settings.

Example 1. Consider $N = 2$, $\tau = 2$, $f = 0.025$ and $p = q = 1$. Notice that precision and sensitivity are both 1, so that all demands are predicted and all predictions become demands. These input values result in the following probability of ADI: $\frac{q \cdot f}{p} = 0.025$. Table 1 shows how the generation of ADI and the demand following from the ADI, evolves over time using expected values.

The first column of Table 1 shows that at $t = 0$, there are 2 systems available for providing an ADI signal. Then, the expected number of ADI signals is $2 \cdot 0.025 = 0.050$. There is no predicted demand, in this first period. Next, at $t = 1$, there are in expectation $N - 0.050 = 1.950$ systems available that can give a signal. So, the expected number of ADI signals is $1.950 \cdot 0.025 = 0.049$. Again, there is no predicted demand. At $t = 2$, the expected number of machines that can give a signal is $N - 0.50 - 0.49 = 1.901$ and the expected number of signals $1.951 \cdot 0.025 = 0.049$. We now also have some predicted demand as a result from the ADI signals that were given in period $t - \tau$. Because $p = 1$, all of the given demand signals turn out to be true. So, the expected predicted demand at $t = 2$ is 0.050. The effective failure rate, i.e. the actual observed number of failures, is $0.050/N = 0.025$. Repeating all of these steps for $t = 3$, we find that the effective failure rate has dropped to 0.024 and stays at this level as t goes to infinity. In other words, the long run effective failure rate is not equal to the input failure rate.

Table 1: Example of generation of (ADI) demand and ADI signals with $p = q = 1$

t	**0**	**1**	**2**	**3**	**4**	∞
Available for ADI	2.000	1.950	1.901	1.904	1.905	1.905
ADI signals ($\mathbf{w_t}$)	0.050	0.049	0.048	0.048	0.048	0.048
$\mathbf{D_t^P}$	0.000	0.000	0.050	0.049	0.048	0.048
Effective failure rate	0.000	0.000	0.025	0.024	0.024	0.024

Example 2. Consider $N = 2$, $\tau = 2$, $f = 0.025$, $q = 1$ and $p = 0.5$; half of the predicted demands turn out to become an actual demand. These input values result in the following probability of ADI signals: $\frac{q \cdot f}{p} = 0.05$. The probability of random demand is zero, as $q = 1$. Table 2 shows how the generation of ADI and the demand following from the ADI, evolves over time.

Table 2: Example of generation of (ADI) demand and ADI signals with $p = 0.5$ and $q = 1$

t	**0**	**1**	**2**	**3**	**4**	∞
Available for ADI	2.000	1.900	1.805	1.815	1.819	1.818
ADI signals ($\mathbf{w_t}$)	0.100	0.095	0.090	0.091	0.091	0.091
$\mathbf{D_t^P}$	0.000	0.000	0.050	0.048	0.045	0.045
Effective failure rate	0.000	0.000	0.025	0.024	0.023	0.023

The difference between Tables 1 and 2 is that in the latter, only half of the predicted demands turn out to be an actual demand. For example, at $t = 0$ the expected number of ADI signals is 0.100. Then, τ periods later at $t = 2$, it turns out that the expected realised demand is 0.025. As t goes to infinity, we see that the expected realised demand is 0.023, which is not equal to the input failure rate.

As Tables 1 and 2 show, when t goes to infinity, the long run effective failure rate is not equal to the input failure rate. This already happens in the most straightforward case of $p = q = 1$. Also, the effective failure rate increases as the precision increases, which is caused by the finite installed base size. The intuition behind this is that machines provide demand signals, resulting in the situation where machines have provided ADI and are therefore 'free of failing'. Meaning, for a specific time period nothing can happen with these machines. As the precision decreases, the ADI does not result in an actual failure, which decreases the effective failure rate. As the precision increases, more of the ADI becomes an actual failure, which increases the effective failure rate. This, of course, needs to be corrected, because a better precision should not result in extra failures. The mathematical derivations of the correction term can be found in Section 5.2.

The other part of the total demand is the random demand. The random demand is generated by using a binomial distribution with parameters $N - B_t - w_{t-\tau}$ and $\frac{(1-q) \cdot f}{1 - \frac{q \cdot f}{p}}$. The probability is based on that the expected number of unpredicted failures is $(1 - q) \cdot f$ and we need to compensate for the fraction of demand signals that has been given for a specific period, as this is the *predicted* demand. So, to compensate for the fact that not all machines can still randomly fail, we subtract the probability that a demand signal has been given earlier. This leads to the usage of $1 - \frac{q \cdot f}{p}$.

Example 3. Consider $N = 2$, $\tau = 2$, $f = 0.025$ and $p = q = 0.5$. These input values result in the following probability of ADI signals: $\frac{q \cdot f}{p} = 0.025$ and of random demand: $\frac{(1-q) \cdot f}{1 - \frac{q \cdot f}{p}} = 0.013$. Table 3 shows how the generation of ADI, the demand following from the ADI and the generation random demand, evolves over time.

Table 3: Example of generation of (ADI) demand and ADI signals with $p = q = 0.5$

t	**0**	**1**	**2**	**3**	**4**	∞
Available for ADI	2.000	1.950	1.901	1.904	1.905	1.905
ADI signals ($\mathbf{w_t}$)	0.050	0.049	0.048	0.047	0.048	0.047
$\mathbf{D_t^p}$	0.000	0.000	0.025	0.024	0.024	0.023
Available for random	2.000	2.000	1.975	1.976	1.976	1.997
$\mathbf{D_t^u}$	0.026	0.026	0.025	0.025	0.025	0.026
$\mathbf{D_t^p + D_t^u}$	0.026	0.026	0.050	0.049	0.049	0.049
Effective failure rate	0.013	0.013	0.024	0.024	0.024	0.024

As Table 3 shows, when t goes to infinity, the effective failure rate is lower than the input failure rate. Furthermore, if p increases to 1, we find that the effective failure increases (effective $f = 0.025$). Therefore, for both the probability of ADI signals and random demand, it is required to do a correction to keep the effective failure rate the same as the input rate. The mathematical derivations of the correction terms can be found in Section 5.2.

4.3 Markov Decision Process

We use a discrete-time Markov Decision model to formulate the optimisation problem. A state of the system is defined as $\mathcal{S} = (B, I, \mathbf{z}, \mathbf{w})$, where:

- B denotes the number of backorders in the system.
- I denotes the on-hand inventory level.
- $\mathbf{z}$ is a vector containing the stock in the pipeline, $\mathbf{z} = (z_1, ..., z_{L-1})$, with z_j, $j = 1, ..., L-1$, denoting the number of parts to arrive in j periods.
- $\mathbf{w} = (w_{t-\tau}, ..., w_t)$ is a vector containing the number of demand signals that are available in the system at the beginning of period t.

The objective is to determine z_L, the order size that will arrive at time $t + L$, such that total costs are minimised. Therefore, the action space is defined as $\mathcal{A}_t = \{(z_L) \mid z_L \geq 0\}$.

The direct costs that consist of ordering, inventory holding, and backorder costs, is defined as:

$$C(B, I, z_0, z_L, d) = cz_L + h(I_{t-1} + z_0 - B_{t-1} - d)^+ + b(B_{t-1} + d - I_{t-1} - z_0)^+ \tag{1}$$

As we consider an infinite horizon MDP, the problem can be solved using backward induction. We define $V_t(B, I, \mathbf{z}, \mathbf{w})$ as the value function in period t. The objective is formulated as:

$$\text{Minimise} \lim_{t\to\infty} V_t \tag{2}$$

Then, for all t the following Bellman equation is formulated:

$$V_t(B, I, \mathbf{z}, \mathbf{w}) = \min_{(z_L)\in\mathcal{A}_t} C(B, I, z_0, z_L, d) + \gamma \sum_{d=0}^{N} P(D = d) V_{t+1}(B + d - I - z_0, I + z_0 - B - d, \bar{\mathbf{z}}, \bar{\mathbf{w}}, W_{t+1}), \tag{3}$$

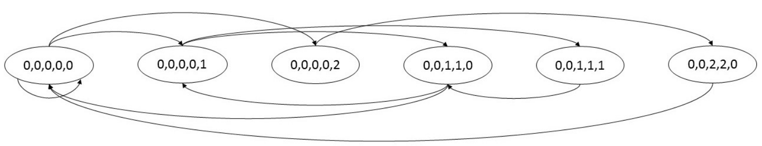
where $\bar{\mathbf{z}} = (z_L)$ and $\bar{\mathbf{w}} = (w_{t-\tau+1}, ..., w_{t+1})$. Also, d denotes the realisation of the variable D_t. d is calculated using the convolution of D_t^p and D_t^u. Equation (3) represents the value function and consists of the direct cost for the corresponding state plus the discounted value of successor states. These successor states are dependent on the demand and the replenishment sizes. An example of the model's output is given in Section 4.4.

4.4 Verification and Validation of Model

Verification and validation are important steps in modelling, as these steps are used for confirming that the model is correctly implemented based on the conceptual model and that the output is correct. In this thesis, verification and validation have been done by manually checking the value function for multiple states. For small problems, it is possible to manually track the steps that can be taken in the MDP and also to calculate the corresponding value functions. When the manually calculated values are the same as the values calculated by the model, we can assume that the model is implemented correctly. Furthermore, when the model works for small problems, it can be expected that it also works for larger problems.

For the extreme situation where we have a precision = recall = 1.0, it is possible to formulate a Markov-chain problem instead of a MDP, due to the low number of possible states. Furthermore, because in this situation only predicted demand from the ADI can occur and all of the signals are true, we can formulate the optimal policy by hand. As the lead time is only one period, it is optimal to order when the ADI demand is also one period from occurring. The optimal solution of the Markov-chain should correspond to the optimal solution of the formulated MDP.

Example 4. The input parameters that are used to present the solution of the Markov-chain and the corresponding MPD, are as follows: $N = 2$, $\tau = 1$, $L = 1$, $f = 0.01$, $c = 10$, $h = 1$, $b = 25$, $\gamma = 0.99$, $p = q = 1.0$. The situation in which $p = q = 1.0$ results in the following Markov-chain and probability matrix:



$$\begin{bmatrix} 0.9797 & 0.0202 & 0.0001 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.9898 & 0.0102 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0.9797 & 0.0202 & 0.0001 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.9898 & 0.0102 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Figure 2: *Markov-chain example*

This Markov-chain can be solved using the following matrix notation:

$$v_\pi = (I - \gamma P^\pi)^{-1} R^\pi, \tag{4}$$

where

v_π	Value function corresponding to policy π
P^π	Probability matrix corresponding to policy π
R^π	Reward values corresponding to policy π
I	Identity matrix
γ	discount factor

When solving this Markov-chain, we find that the value for the (0,0,0,0,0) state is 20.00. Solving the MDP using Python gives the exact same number. So, we find that both methods result in the same value. This also holds for the system states (B,I,$\mathbf{z}$,$\mathbf{w}$) and transition probabilities of both methods. So, based on these verification steps, we can conclude that the model solves the problem in the correct way.

Another extreme situation that could be used to validate the MDP, is when precision = recall = 0. In this situation, only random demand can occur. However, because of only random demand, it is hard to manually derive what the optimal policy should look like. Therefore, this situation cannot be used as an extra situation to validate the model's output.

We now check the solutions of the model for lower values of p and q. Because we cannot manually determine what the optimal policy must be for lower values, we check whether the solutions evolve as expected. For example, as the precision of the system improves, it can be expected that the total cost decreases. To show the behaviour of the model for lower values for the precision, we introduce an example that is discussed next.

Example 5. In order to show the behaviour of the model, another small example is presented. The following parameters are considered in this example: $N = 2$, $\tau = 1$, $L = 1$, $f = 0.2$, $c = 10$, $h = 1$, $b = 25$, $\gamma = 0.9$, $p = \{0.5, 0.7, 0.9\}$, $q = 0.5$. The values do not represent parameters in reality, but do show the behaviour of the model as long as the cost parameters make sense relative to each other. Furthermore, because the same model is used for the TM and the AM context, the behaviour of the model will be the same, only the input values that are used will be different. The results of the example are shown in Table 4. The values represent the state in which all values are zero, so $(B, I, \mathbf{z}, \mathbf{w}) = (0, 0, 0, 0)$.

Table 4: Small example of MDP

Precision	**V (€)**
0.5	65.35
0.7	65.33
0.9	64.56

As Table 4 shows, the costs are decreasing when the precision of the ADI increases. This makes sense, because when you can predict more precisely what your total demand from ADI will be, you can better anticipate on this demand. The better anticipation means that you can order the required parts just-in-time, reducing the amount of inventory needed. Furthermore, you are able to reduce the backorder cost, because you know there will be a part needed with high certainty (because the precision is high) and you can order this part just-in-time making sure you have the part available when required.

5 Test Bed Design

A numerical study is performed to evaluate the performance of the MDP. In Section 5.1, we describe the different test bed that is used for the numerical study. Next, we provide a mathematical correction term for the generation of ADI and random demand in Section 5.2. We thus answer RQ2 in this chapter.

What are the model input values for the AM and TM supply methods?

5.1 Test Bed

We design a test bed that is used for the regular supply source, as well as for the AM supply source. The test bed can be placed in a context where the printed parts are produced by a Fused Deposition Modelling (FDM) process. In other words, the printed parts consist of polymers. This test bed is presented in Table 5, which has a total of 36 instances for traditional manufacturing and 324 instances for AM.

Table 5: Setup test bed

Parameters	Options	Value	Reference
N	1	3	
τ (days)	2	1,2	Topan et al. (2018)
b (€/day)	2	50, 250	Topan et al. (2018), Experts
p	3	0.5, 0.75, 1.0	Topan et al. (2018)
q	3	0.5, 0.75, 1.0	Topan et al. (2018)
γ	1	0.995	
ϵ	1	10^{-6}	
L^{r} (days)	1	2	Experts
f^{r}	1	0.001	Westerweel et al. (2018a)
c^{r} (€)	1	100	Experts
h^{r} (€/€/day)	1	$\frac{20\% c^{\mathrm{r}}}{365}$	Van Houtum and Kranenburg (2015)
L^{p} (days)	1	1	Experts
f^{p}	3	0.001, 0.005, 0.025	Westerweel et al. (2018a)
c^{p} (€)	3	100, 200, 400	Experts
h^{p} (€/€/day)	3	$\frac{20\% c^{\mathrm{p}}}{365}$	Van Houtum and Kranenburg (2015)
			Heinen and Hoberg (2019)

The difference between the traditional and additive manufactured parts is in the lead time, the production costs and the failure probability (reliability). The lead times of the printed parts are shorter compared to the traditionally produced parts. This assumption is made in many other papers (e.g. Knofius et al. (2020); Pijnappels (2019); Westerweel et al. (2018a)). A reason why it is possible to assume such a short lead time, is because often a printer is located on-site, which eliminates a large amount of transportation time.

Considering the production costs, Heinen and Hoberg (2019) suggest that parts produced by AM have a cost premium between zero and three compared to regular manufacturing. Knofius et al. (2020) mention that also the costs of raw materials used for AM, are high. Furthermore, based on the interviews with multiple experts, it became clear that the cost premium can even be up to a factor 10, especially for metal parts. For this type of parts, the development costs are much higher than for plastic parts. Therefore, the cost factor is higher for metal parts compared to plastic parts. Based on the two papers and conversations with experts, we consider a cost premium between 2 and 4 (including investment/development costs), as this thesis is placed in the context of inexpensive polymer parts.

The failure rate represents the reliability of parts. To differentiate between the reliability of traditional and additive manufactured parts, we use several rates for printed parts. Three different rates for AM are used to emphasise the difference in quality, two of three rates are higher than the rate used for the conventional produced parts. The third rate is equal in both contexts to analyse if both part types have the same reliability. Examples of papers that also use this assumption are: Westerweel et al. (2018a), Westerweel et al. (2018b), Knofius et al. (2020) and Holmström et al. (2010).

Two different values are used for parameter τ; 1 and 2. These values are used to analyse situations where the demand lead time is equal to the supply lead time ($L = \tau$), where the supply lead time is longer than the demand lead time ($L > \tau$) and where the demand lead time is longer than the supply lead time ($L < \tau$). Furthermore, we can provide insights on a setting where we change from $L > \tau$ to $L = \tau$ (see TM context).

For the precision and recall, three different values are considered, because we want to study the effect of (im)perfect ADI. Using different values makes it possible to provide insights in which characteristics ADI must have to be valuable. The chosen values are based on the study of Tan et al. (2009).

The holding costs are based on 20% of the production costs of the corresponding supply source. For example, Van Houtum and Kranenburg (2015) suggest that inventory holding costs per part are often 20% of its value, also Heinen and Hoberg (2019) consider a value of 20% and Lamghari-Idrissi et al. (2020) consider 17%. Therefore, it is reasonable to use 20% of the production costs.

The data is validated by multiple practitioners/experts in the field of inventory control and AM. The experts have been consulted individually to ensure the validity of the collected values, i.e., to prevent that the experts will influence each other on what they consider to be realistic values. Also, the final test bed has been evaluated with two experts.

For computational purposes, the order size (action space) is restricted by a specific value, which is set to $2 * N$. This value is chosen, because it means that in every state it is possible to order two times the size of the installed base. So, in case that the entire installed base size is a backorder, it is possible to satisfy all of the backorders plus putting the complete installed base size on stock as well. For the optimal policy, it is verified that the order limit is never reached, but is always below this limit. In other words, setting the order limit does not influence the optimal values and policy. Another restriction is placed on the number of parts that can be in the system (state space). So, the maximum number of parts that can be on stock and on order during $L + 1$ states, can never exceed $2 * N * (L + 1)$. Meaning, it is possible in each stage during the lead time to have the maximum order size in the system. It has been checked whether it was possible to reach that maximum state, which was found to be possible. However, the results showed that is never optimal to be in that state.

5.2 Correction on Failure Probabilities

In Section 4.2, it is explained that when applying the model, the effective failure rate is not equal to the input failure rate. In this section, a corrected failure rate ($\hat{f}_{(q)}$) is introduced to correct for this issue. Now f can be interpreted as the target or effective failure rate and $\hat{f}_{(q)}$ as a derived failure rate to guarantee that the effective failure rate is not influenced by other variables. $\hat{f}_{(q)}$ is a function of f, q, N, p and τ.

To define $\hat{f}_{(q)}$, we explain how the probabilities of giving an ADI signal and of random demand are corrected. First, we elaborate on the correction for the probability of generating an ADI signal. Next, we provide the correction term for random demand. We show the same example as in Section 4.2, but now with these correction terms. With this example, the intuition behind this correction is provided.

ADI Demand

In a period t, the number of machines that could give a demand signal is denoted by x_t and the number of machines with a demand signal is denoted by ADI_t. So, x_t can be calculated by $x_t = x_{t-1} + ADI_{t-(\tau+1)}$. From Section 4.1, we know that $x_t = N - B_t - \sum_{u=t-\tau}^{t-1} w_u$. Furthermore, we know that $\sum_{t-\tau}^{t-1} ADI_t + x_t = N$. For an infinite horizon, we define X and ADI as follows:

$$X_\infty = \lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} \mathrm{x}_t \tag{5}$$

$$ADI_\infty = \lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} \mathrm{ADI}_t \tag{6}$$

Where X_∞ is the expected number of machines that could give a demand signal and ADI_∞ the expected number of machines that actually provided a demand signal. The expected (effective) number of failures that are a result from the ADI should be $q \cdot f \cdot N$ (see Section 4.2). In the long run, the following equation should hold.

$$ADI_t \cdot p = q \cdot f \cdot N \tag{7}$$

We now introduce $\hat{f}_{(q)}$ to denote the corrected failure probability for ADI. The uncorrected failure probability of getting ADI was $\frac{q \cdot f}{p}$, while the adjusted probability of getting ADI is defined as $\frac{q\cdot\hat{f}_{(q)}}{p}$. The expected number of parts that give a demand signal is then:

$$ADI_t = \frac{q \cdot \hat{f}_{(q)}}{p} \cdot X_{t-1} \tag{8}$$

When filling in Equation (8) into Equation (7), we get:

$$\begin{aligned} \frac{q \cdot \hat{f}_{(q)}}{p} \cdot X_{t-1} \cdot p &= q \cdot f \cdot N \\ q \cdot \hat{f}_{(q)} \cdot X_{t-1} &= q \cdot f \cdot N \\ \hat{f}_{(q)} \cdot X_{t-1} &= f \cdot N \\ X_{t-1} &= \frac{f \cdot N}{\hat{f}_{(q)}} \end{aligned} \tag{9}$$

it further holds that:

$$\sum_{t-\tau}^{t-1} ADI_t + X_t = N \tag{10}$$

In the steady state:

$$... = ADI_{t-2} = ADI_{t-1} = ADI_t = ADI_{t+1} = ADI_{t+2} = ... = ADI_\infty \tag{11}$$
$$... = X_{t-2} = X_{t-1} = X_t = X_{t+1} = X_{t+2} = ... = X_\infty \tag{12}$$

from (10), (11) and (12) follows:

$$\tau \cdot ADI_\infty + X_\infty = N \tag{13}$$

Filling in Equation (8) into Equation (13) (using (11) and (12)) results in:

$$\begin{aligned} \tau \cdot \frac{q \cdot \hat{f}_{(q)}}{p} \cdot X_\infty + X_\infty &= N \\ X_\infty \left(\frac{\tau \cdot q \cdot \hat{f}_{(q)}}{p} + 1\right) &= N \\ X_\infty &= \frac{N}{\left(\frac{\tau\cdot q\cdot\hat{f}_{(q)}}{p} + 1\right)} \end{aligned} \tag{14}$$

Combining Equations (9) and (14), gives the following equality:

$$
\begin{aligned}
\frac{f \cdot N}{\hat{f}_{(q)}} &= \frac{N}{\left(\frac{\tau \cdot q \cdot \hat{f}_{(q)}}{p} + 1\right)} \\
\frac{f}{\hat{f}_{(q)}} &= \frac{p}{\tau \cdot q \cdot \hat{f}_{(q)} + p} \\
p \cdot \hat{f}_{(q)} &= f \cdot \tau \cdot q \cdot \hat{f}_{(q)} + f \cdot p \\
\hat{f}_{(q)}(p - f \cdot \tau \cdot q) &= f \cdot p \\
\hat{f}_{(q)} &= \frac{f \cdot p}{p - f \cdot \tau \cdot q}
\end{aligned} \tag{15}
$$

The adjusted probability on ADI was defined as $\frac{q \cdot \hat{f}_{(q)}}{p}$. So, filling in Equation (15) gives the actual probability of ADI:

$$
\begin{aligned}
P_{\text{ADI}} &= \frac{q \cdot \hat{f}_{(q)}}{p} \\
&= \frac{q \cdot f}{p - \tau \cdot q \cdot f}
\end{aligned} \tag{16}
$$

However, it should be noted that this results in a corrected probability. Consequently, there are certain limits belonging to the adjustment. For example, if $p - q\tau f = 0$, there will be a division by zero. Also, if $p < q\tau f$, there will be a negative probability, which by definition is not possible. Finally, if $qf > p - q\tau f$, there will be a probability larger than one, which is also by definition not possible. In other words, there are certain mathematical limits for which this correction term will work, but outside these limits it will not function.

We now introduce two examples, which are the same as Example 1 and 2 in Section 4.2, but are now based on the correction terms. Both examples show that as t goes to infinity, the effective failure rate is the same as the input failure rate, as is required to make fair comparisons.

Example 6. Consider $N = 2$, $\tau = 2$, $f = 0.025$ and $p = q = 1$. These input values result in the following probability of ADI signals: $P_{\text{ADI}} = 0.026$. The probability of random demand is zero, as $q = 1$. Table 6 shows how the generation of ADI and the demand following from the ADI, evolves over time using expected values.

Table 6: Example of corrected generation of (ADI) demand and ADI signals with $p = q = 1$

t	**0**	**1**	**2**	**3**	**4**	∞
Available for ADI	2.000	1.947	1.896	1.899	1.900	1.900
ADI signals ($\mathbf{w_t}$)	0.053	0.051	0.050	0.050	0.050	0.050
$\mathbf{D_t^P}$	0.000	0.000	0.053	0.051	0.050	0.050
Effective failure rate	0.000	0.000	0.026	0.026	0.025	0.025

Example 7. Consider $N = 2$, $\tau = 2$, $f = 0.025$, $q = 1$ and $p = 0.5$. These input values result in the following probability of ADI signals: $P_{\text{ADI}} = 0.053$. The probability of random demand is zero, as $q = 1$. Table 7 shows how the generation of ADI and the demand following from the ADI, evolves over time.

Table 7: Example of corrected generation of (ADI) demand and ADI signals with $p = 0.5$ and $q = 1$

t	**0**	**1**	**2**	**3**	**4**	∞
Available for ADI	2.000	1.889	1.784	1.796	1.801	1.800
ADI signals ($\mathbf{w_t}$)	0.111	0.105	0.099	0.100	0.100	0.100
$\mathbf{D_t^P}$	0.000	0.000	0.056	0.052	0.050	0.050
Effective failure rate	0.000	0.000	0.028	0.026	0.025	0.025

Random Demand
The other part of the total demand is the random demand. The random demand is generated using a Binomial distribution with parameters $N - B_t - w_{t-\tau}$ and P_R. $N - B_t - w_{t-\tau}$ denotes the number of parts that could fail during a period (installed base size - backorders - the realised predicted ADI demand for that specific period). Now, the derivation of the random failure probability is explained.

In each period in steady state, the expected effective failure rate should be the same as in the input failure rate. In steady state, the expected number of unpredicted failures per period can be given by:

$$E[D^\mathrm{u}] = (1-q)\cdot f \cdot N \tag{17}$$

The actual number of machines that could fail randomly at time t is denoted by $y_t = N - ADI_\tau \cdot p$. In a random period t, the random failures are calculated by $y_t \cdot \hat{f}_{(r)}$, where $\hat{f}_{(r)}$ denotes the adjusted random failure probability. On average for an infinite horizon, the following is formulated:

$$Y_\infty = \lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} \mathrm{y}_t \tag{18}$$

$$Y_\infty = N - \mathrm{ADI}_\infty \cdot p \tag{19}$$

$$E[D^\mathrm{u}] = Y_\infty \cdot \hat{f}_{(r)} \tag{20}$$

Furthermore, the expected number of parts that have provided ADI per period in steady state is $\frac{q\cdot f\cdot N}{p}$, (see Equation (7)). So, when combining Equations (17) and (20), the following random failure probability can be formulated:

$$\begin{aligned}
(1-q)\cdot f\cdot N &= Y_\infty \cdot \hat{f}_{(r)} \\
(1-q)\cdot f\cdot N &= (N - ADI_\infty \cdot p)\cdot \hat{f}_{(r)} \\
(1-q)\cdot f\cdot N &= \left(N - \frac{q\cdot f\cdot N}{p}\cdot p\right)\cdot \hat{f}_{(r)} \\
(1-q)\cdot f\cdot N &= (N - q\cdot f\cdot N)\cdot \hat{f}_{(r)} \\
\hat{f}_{(r)} &= \frac{(1-q)\cdot f\cdot N}{N - q\cdot f\cdot N} \\
\hat{f}_{(r)} &= \frac{(1-q)\cdot f}{1-q\cdot f}
\end{aligned} \tag{21}$$

Example 8. Consider $N = 2$, $\tau = 2$, $f = 0.025$ and $p = q = 0.5$. These input values result in the following probability of ADI signals: $P_\mathrm{ADI} = 0.026$ and of random demand: $\hat{f}_{(r)} = 0.013$. Table 8 shows how the generation of ADI, the demand following from the ADI and the generation random demand, evolves over time.

Table 8: Example of corrected generation of (ADI) demand and ADI signals with $p = q = 0.5$

t	0	1	2	3	4	∞
Available for ADI	2.000	1.947	1.896	1.899	1.900	1.900
ADI signals ($\mathbf{w_t}$)	0.053	0.051	0.050	0.050	0.050	0.050
$\mathbf{D_t^p}$	0.000	0.000	0.026	0.026	0.025	0.025
Available for random	2.000	2.000	1.974	1.975	1.975	1.975
$\mathbf{D_t^u}$	0.025	0.025	0.025	0.025	0.025	0.025
$\mathbf{D_t^p + D_t^u}$	0.025	0.025	0.051	0.050	0.050	0.050
Effective failure rate	0.013	0.013	0.026	0.025	0.025	0.025

6 Results

In this chapter, the results of the numerical experiment are discussed. First, in Section 6.1, we further elaborate on how the performance (total cost) of the MDP is evaluated. Then, in Section 6.2, we present the results of the additive manufacturing context. Third, the results of the traditional manufacturing context are presented in Section 6.3. Last, in Section 6.4, we discuss the differences between the traditional and additive manufacturing context. We thus answer RQs 3 and 4 in this chapter.

What is the value of (im)perfect ADI within the AM and TM context? And what are the characteristics of the optimal policy?

How does the inventory control system using AM perform compared to the system using TM?

6.1 Performance Evaluation

The optimal solutions for the different parameter settings are compared to each other and the gaps between the solutions are evaluated. Furthermore, we want to find the optimal starting inventory on-hand for each setting of p and q ($OH^*_{q,p}$) by taking the value function and adding the corresponding production costs. We consider starting OH's from zero to six and we add $OH^*_{q,p} \cdot c$ to the value function of that state. If we omit to do this, states with OH > 0 are receiving parts for free. In 'normal' inventory systems, it is not needed to add the production costs in this way, because these costs are seen as unavoidable costs. In other words, these costs have to be made to deal with demand and are therefore, most of the time, not considered. However, in this thesis, the production costs are used as a fundamental characteristics of both the traditional and the additive manufacturing source.

The states that will be compared are the states that resulted in the optimal starting inventory on-hand, so $(B, I, \mathbf{z}, \mathbf{w}) = (0, \text{OH}^*_{q,p}, 0, 0)$. This state is chosen, because it is important to use the optimal state for every setting in order to make fair comparisons. Furthermore, to not give any state any kind of benefits of already having parts on stock, in transit or any ADI signals, all other parameters are set to zero. This makes it possible to make justified comparisons.

The total expected cost of the MDP with perfect ADI ($p = q = 1$) are denoted as $V_{1,1}$ and with other values for p and q as $V_{q,p}$. The gap %GAP, which is also referred to as the value of (im)perfect ADI, is the percentage cost difference between the different levels of ADI quality, which can be determined as follows:

$$\%\text{GAP} = \frac{V_{q,p}(0, \text{OH}^*_{q,p}, 0, 0) - V_{1,1}(0, \text{OH}^*_{1,1}, 0, 0)}{V_{1,1}(0, \text{OH}^*_{1,1}, 0, 0)} \cdot 100\% \tag{22}$$

Then, to calculate the relative cost difference between the TM and AM context, we define:

$$\%\text{AM Value} = \frac{V^{\text{AM}}_{q,p}(0, \text{OH}^*_{q,p}, 0, 0) - V^{\text{TM}}_{q,p}(0, \text{OH}^*_{q,p}, 0, 0)}{V^{\text{TM}}_{q,p}(0, \text{OH}^*_{q,p}, 0, 0)} \cdot 100\% \tag{23}$$

6.2 Additive Manufacturing

In this section, we present the results of the numerical experiment for the additive manufacturing context. We start with discussing the value of (im)perfect ADI for the different failure rates. Comparisons between the different failure rates are made throughout the section. Furthermore, we discuss the characteristics of the optimal policy for the different failure rates and the effect of imperfect ADI on the optimal policy.

As mentioned in Section 5.1, two different values are used for τ; 1 and 2. In this section, we only discuss the results for $\tau = 1$, as there are only minimal differences in total cost between using either $\tau = 1$ or $\tau = 2$. The relative cost difference compared to perfect ADI with $\tau = 2$ is shown in Appendix C.2. Appendix C.3 shows the relative cost difference between $\tau = 1$ and $\tau = 2$ for each individual failure rate.

In general, we find that for higher failure rates it is more desirable to have fewer false negatives (high q) than having fewer false positives (high p). As the failure rates decreases, it becomes more important to predict demand more precisely. Also, the value that can be gained by using ADI, increases for lower failure rates. For the characteristics of the optimal policy, we find that as the ADI improves, it is possible to keep a minimum amount of stock. Stock level can even be zero for low demand rates. Depending on the precision of the system, the order size is the same as the number of demand signals or some signals are ignored. Also, the values of b and c^{p} have a large effect on determining the optimal order size. Furthermore, we find that, in this context, increasing the demand lead time does not result in large cost savings. The reason is that we have a supply lead time that is equal to the demand lead time ($L^{\mathrm{p}} = \tau$). In other words, the predicted demand can already be satisfied JIT. Increasing the demand lead time does therefore not result in much value that can be gained, because it is possible to react to ADI anyway.

6.2.1 The Value of (im)perfect ADI

In this section, we discuss the value of (im)perfect ADI for the different failure rates. The relative cost differences are calculated following Equation (22). We present the results for $c^{\mathrm{p}} = 100$ and $c^{\mathrm{p}} = 400$, see Appendix C.1 for the results with $c^{\mathrm{p}} = 200$.

6.2.1.1 Failure Rate 0.025

Table 9: Relative cost difference compared to perfect ADI with $f^{\mathrm{p}} = 0.025$ and $\tau = 1$

		$b = 50$				$b = 250$			
q	p	$c^{\mathrm{p}} = 100$		$c^{\mathrm{p}} = 400$		$c^{\mathrm{p}} = 100$		$c^{\mathrm{p}} = 400$	
		%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*
0.5	0.5	19.50	1	11.66	0	19.61	2	19.60	1
	0.75	19.41	1	10.83	0	19.60	2	19.60	1
	1.0	19.00	1	9.85	0	19.60	2	19.38	1
0.75	0.5	18.81	1	9.73	0	18.90	1	18.70	1
	0.75	18.09	1	7.38	0	18.89	1	18.30	1
	1.0	17.94	1	4.98	0	18.89	1	18.05	1
1.0	0.5	10.17	0	8.69	0	10.22	0	10.19	0
	0.75	4.42	0	4.41	0	4.42	0	4.42	0
	1.0	-	0	-	0	-	0	-	0

Table 9 shows the relative cost difference between the different values for q and p compared to the ideal setting where $p = q = 1$ (see Appendix G.1 for the actual values). As can be seen in Table 9, increasing q results in a relatively larger cost decrease than increasing the precision. The situation where $p = q = 0.5$ is when costs have increased the most compared to the situation with perfect ADI. This makes sense, as this situation in which both parameters are equal to 0.5, is the worst scenario that has been considered. Some small performance gains are achieved when increasing p, except for cases where $q = 1$, as in this setting only the precision can further decrease total cost. These small gains are a result of the fact that when p increases, the probability of predicting the demand correctly increases as well. Consequently, the predicted demand can be ordered Just-in-Time (JIT) and will be used immediately when arrived. In contrast to the situation with lower values for p, where the ordered parts might not be required and are put on stock. As a result, the costs are relatively higher in situations where p is lower.

Hence, in this setting, it is more beneficial to predict more failures than having more precise predictions (unless $q = 1$). This is in line with Topan et al. (2018), as they conclude that having fewer false negatives (high q) is more desirable than having fewer false positives (high p). However, Topan et al. (2018) find that the (average) value of ADI is slightly higher. A reason for the difference in value of ADI is that Topan et al. (2018) use higher values for the emergency costs. As costs become higher to not be able to satisfy demand, it becomes more beneficial to invest in better ADI.

The relatively low holding costs and the high backorder costs (setting where $b = 250$) are causing the effect that parts are put on stock, as it is relatively cheap to have stock to prevent backorders from happening. A higher level of q can result in a lower level of inventory, as more demand is predicted, which decreases the probability of random demand. In other words, the (safety) stock that is required to fulfil or to anticipate on random demand can be reduced. Hence, as q increases, less inventory is needed, because the predicted demand can be satisfied JIT. These findings are in line with Benjaafar et al. (2011), as they concluded that when the backorder/holding cost ratio is large, the base-stock levels are high for systems both with and without ADI, and the probability of backorders is relatively low. Hence, the demand information becomes relatively less useful and makes little difference for decisions taken.

6.2.1.2 Failure Rate 0.005

Table 10: Relative cost difference compared to perfect ADI with $f^{\mathrm{p}} = 0.005$ and $\tau = 1$

		$b = 50$				$b = 250$			
q	p	$c^{\mathrm{p}} = 100$		$c^{\mathrm{p}} = 400$		$c^{\mathrm{p}} = 100$		$c^{\mathrm{p}} = 400$	
		%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*
0.5	0.5	37.50	1	18.76	0	41.15	1	37.71	1
	0.75	37.46	1	14.80	0	41.05	1	37.69	1
	1.0	37.42	1	11.97	0	38.67	1	37.50	1
0.75	0.5	29.43	0	17.19	0	39.07	1	33.38	0
	0.75	26.75	0	11.01	0	39.00	1	32.00	0
	1.0	24.75	0	6.00	0	37.53	1	31.00	0
1.0	0.5	16.66	0	16.01	0	16.73	0	16.73	0
	0.75	7.61	0	7.60	0	7.61	0	7.61	0
	1.0	-	0	-	0	-	0	-	0

Similar to $f_p = 0.025$, it is observed that increasing q has a larger effect on cost reduction than increasing the precision (see Appendix G.2 for the actual values). However, considering the case with $b = 50$, we observe that the effect of an increasing precision becomes larger for higher values of q. In contrast to the case with $b = 250$, in which an increasing recall clearly has the largest effect on cost reduction (especially when q becomes one). The difference in the effect of precision is caused by the relatively large effect of the size of b. In case b is high, it has a relative large impact on the total cost compared to the holding costs, which are relatively small. As a result, it becomes more important to predict more demand than having the predicted demand right. However, in case b gets lower, the relative effect it has on the total cost decreases as well. This results in a situation where it is also important to correctly predict demand, as the relative impact of b and the holding costs become more equal. Furthermore, as q increases, the probability of random demand decreases and therefore, the probability of a backorder decreases as well (predicted demand can be delivered JIT as $L = \tau$). This results in a decrease in the relative effect that the backorder costs have on the total cost compared to the holding costs. So, now the holding costs become relatively more important and these can be further reduced by increasing the precision. Hence, precision plays a more important role to further decrease the total cost. This also explains the fact why in the case of $b = 250$ and $q = 1$, a relatively larger effect of a higher precision is visible.

Consider $b = 50$ and $c^{\mathrm{p}} = 400$, an interesting observation is that the setting with $q = 0.75$ and $p = 1.0$ is closer to the ideal setting than $q = 1.0$ combined with $p = 0.75$. The same is observed for $q = 0.5$ and $p = 0.75$ compared to $q = 0.75$ and $p = 0.5$ (for some settings in case of $c^{\mathrm{p}} = 200$ the same is observed). These observations show that in some specific situations a higher precision can result in a lower cost increase compared to situations with a higher recall but lower precision. In other words, a higher precision results in a higher probability on true demand signals, which results in less unnecessary ordered parts that are placed on stock. Consequently, holding costs will be lower in these situations with higher precision.

Looking at the optimal starting OH*, we observe some interesting changes in OH*, especially in the case of $b = 250$. Considering the highest value for b, we observe that for some specific value of q, OH* decreases from one part to zero inventory. Depending on the value of c^{p}, the change in OH* happens when

q increases from 0.75 to 1.0 or from 0.5 to 0.75. Consider $c^{\mathrm{p}} = 100$, the reason why for this value the change in OH* occurs later, is that the ratio between backorder and production costs is relatively smaller than in the case where $c^{\mathrm{p}} = 400$. As a result, the backorder cost has a relatively larger effect on the order decision, as it is more expensive to have a backorder than to order a part. Therefore, it is relatively less expensive to keep a part on stock compared to the situation where $c^{\mathrm{p}} > b$. This implies that it becomes relatively less expensive to have a penalty than to order a part. Hence, the inventory on-hand is reduced sooner.

Table 10 shows that the relative cost increase is almost the same in all cases where $q = 1$. This is caused by the fact that the same decision is made regardless of the different backorder costs, as these have a relative to no effect on the total cost. Because $q = 1$ and the supply lead time is equal to the demand lead time, parts can be delivered JIT. The only situation where backorder costs can have an influence, is when for a lower value of precision it is decided not to order a part, while a demand signal is received (see Section 6.2.2 for characteristics of the optimal policy with imperfectness in p). Consequently, with a certain probability the demand signal can turn into an actual failure, but no part is available. Therefore, in situations with $q = 1$ and $p < 1$, there is a certain probability that backorder costs need to be incurred.

6.2.1.3 Failure Rate 0.001

Table 11: Relative cost difference compared to perfect ADI with $f^{\mathrm{p}} = 0.001$ and $\tau = 1$

		$b = 50$				$b = 250$			
q	p	$c^{\mathrm{p}} = 100$		$c^{\mathrm{p}} = 400$		$c^{\mathrm{p}} = 100$		$c^{\mathrm{p}} = 400$	
		%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*
0.5	0.5	71.42	0	24.15	0	186.20	1	81.98	0
	0.75	57.97	0	22.59	0	186.18	1	69.76	0
	1.0	49.98	0	12.42	0	186.12	1	62.50	0
0.75	0.5	60.30	0	23.84	0	138.67	0	65.23	0
	0.75	38.80	0	21.56	0	130.43	0	44.52	0
	1.0	25.00	0	6.21	0	125.20	0	31.26	0
1.0	0.5	50.69	0	23.56	0	50.96	0	50.74	0
	0.75	20.66	0	20.59	0	20.68	0	20.67	0
	1.0	-	0	-	0	-	0	-	0

As Table 11 shows, the effect of the different values for p and q can again be observed clearly (see Appendix G.3 for the actual values). Especially in the case when $b = 250$, large cost reductions can be achieved by improving the ADI quality. The explanation for why there is a relatively large ADI value in the case of this lower failure rate, is that the holding costs have become more relevant now. A lower failure rate implies that the reliability of a part is high and that the probability of a failure is low. For example, the failure rate of 0.001 implies that a part on average will fail once every 1000 periods, while a rate of 0.025 implies a failure on average once every 40 periods. In other words, in the case of a lower failure rate, a wrong predicted failure will result in a part that on average will be longer on stock compared to a higher rate. Consequently, the holding costs will increase.

Therefore, the relative effect of a better precision is now higher compared to the (higher) failure rates discussed before. Hence, more value can be gained from the ADI in case of a relatively lower failure rate, which is supported by Topan et al. (2018).

Similar to $f_p = 0.005$, we observe some parameter settings in which a combination with a lower q but higher precision results in lower total cost than a setting with a higher q and lower precision (e.g. $q = 0.75$ with $p = 1.0$ versus $q = 1$ with $p = 0.75$ for $c^{\mathrm{p}} = 400$ and $b = 50$). This observation is in line with the previous section, as a wrong predicted failure results in an ordered part that on average will be on stock for a longer period.

Looking at the values of OH*, we observe that for all parameter settings it is optimal to keep zero inventory. It makes sense to keep zero stock, because the probability of expected and random failures is relatively low. Even in the case of $p = q = 0.5$, the probability of a random failure is low. Consequently, it would be relatively expensive to order and to keep a part on stock, while having a failure probability of 0.001. These findings are again in line with Topan et al. (2018). They concluded that a 'spare parts manufacturer subject to low demand can keep minimum - most of the time zero - stock' (Topan et al., 2018). This conclusion appears also to be valid for the other failure rates, as a higher failure (demand) rate requires that some amount of inventory needs to be kept.

6.2.2 Characteristics of the optimal Policy

In this section, we discuss the characteristics of the optimal policy for the different failure rates and the effect of (im)perfect ADI on the policy. The optimal values of the decision variable z_1^* (the order size) are displayed for different values of ($\mathbf{w}$, I), where $\mathbf{w}$ denotes the number of demand signals that are present in the system $(w_{t-\tau}, w_t)$ and I denotes the on-hand inventory after receiving the replenishment order z_0. So, in each cell, the value represents the optimal order size for that specific state of the system. Notice that in this section we only discuss the setting where $\tau = 1$. Appendix D shows an example of how the optimal policy looks like when $\tau = 2$.

6.2.2.1 Failure Rate 0.025

First, we show the optimal policy in a situation with perfect ADI ($p = q = 1$). For these values of p and q, the optimal policy remains the same for the different values of c^{p} and b. Table 12 demonstrates the optimal values of the decision variable, the order size, for different values of ($\mathbf{w}$, I).

Table 12: Values of z_1^* for different ($\mathbf{w}$, I) with $p = q = 1$ and $f^{\mathrm{p}} = 0.025$

a) $\mathbf{w}$ = (0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	0	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

c) $\mathbf{w}$ = (0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

d) $\mathbf{w}$ = (0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	3	2	1	0	0

The first setting in Table 12 (a) is when there are no demand signals in the system, $\mathbf{w} = (0, 0)$. Independent of the value of I, the optimal order decision z_1^* is zero. As seen in Table 12 (b), when there is 1 signal that has arrived at the beginning of the period ($\mathbf{w} = (0, 1)$) and available inventory is zero ($I = 0$), then the optimal action is to order 1 unit ($z_1^* = 1$). If $I > 0$, then the optimal action is to order nothing. Also, as seen in Table 12 (d), when there are 3 signals that have arrived at the beginning of the period ($\mathbf{w} = (0, 3)$) and available inventory is zero ($I = 0$), then the optimal action is to order 3 unit ($z_1^* = 1$). If $I > 0$, then the optimal action decreases linearly with I.

As can be seen in Table 12, the order size increases with the number of demand signals that are present in the system. So, this can be seen as a situation where a part is only shipped to a warehouse/customer, if a demand signal is issued in the system. Furthermore, this also explains why the OH* in Table 9 on page 20 is equal to zero. Orders are only placed in the case demand signals are present within the system. Furthermore, the order size is equal to the number of signals minus the available inventory, so that all ordered parts are needed and no inventory is held.

In order to show the effect of $q < 1$ and how OH* can be recognised in the optimal policy, we introduce Table 13, which shows $p = 1$ with $q = 0.75$.

Table 13: Values of z_1^* for different ($\mathbf{w}$, I) with $p = 1$, $q = 0.75$ and $f^{\mathrm{p}} = 0.025$

a) $\mathbf{w}$ = (0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

c) $\mathbf{w}$ = (0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	3	2	1	0	0

d) $\mathbf{w}$ = (0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	4	3	2	1	0

As Table 13 shows, the characteristics have now changed compared to the policy where $p = q = 1$. As can be seen in Table 13 (a), when there are no signals in the system at the beginning of the period ($\mathbf{w} = (0, 0)$) and $I = 0$, the optimal action is to order one part ($z_1^* = 1$). Then, as move through Table 13 (b)-(d), we observe that the optimal action is always to order one part more than the number of demand signals. The reason is that there is a certain probability of random demand as $q = 0.75$, while with $q = 1$ this probability of random demand is non existing. To deal with this uncertainty of random demand, some extra inventory is required.

The extra inventory that is required to deal with the uncertainty of random demand, was shown in Table 9 on page 20. The OH* is either 1 or 2, depending on the exact values of the parameters. The value of the optimal OH can be seen in the optimal order policy, because orders are being placed as long as OH* has not been reached. After reaching the optimal level, the orders are stopped. So, OH* can be found by looking for the state in which the ordering process is stopped. Furthermore, the order quantity is mostly one unit more than the number of demand signals that are present in the system (except for the setting with $p = q = 1$). This implies that it is optimal to have one extra part on stock, which also has been shown in Table 9 on page 20.

6.2.2.2 Failure Rate 0.005

We start with showing the optimal policy in the situation where perfect ADI is available. The other parameters are $c^{\text{P}} = 100$ and $b = 50$. Note that the optimal policy is the same for other values of c^{P} and b. Characteristics of the optimal policy are shown in Table 14.

Table 14: Values of z_1^* for different ($\mathbf{w}$, I) with $p = q = 1$ and $f^{\text{P}} = 0.005$

a) $\mathbf{w}$ = (0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	0	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

c) $\mathbf{w}$ = (0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

d) $\mathbf{w}$ = (0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	3	2	1	0	0

As seen in Table 14, the order size increases with the number of demand signals that are present in the system. The actual order size also takes into account the number of parts that is already in the pipeline. So, this can be seen as a situation where a part is only shipped to a warehouse/customer, if a demand signal is issued in the system. Furthermore, this also explains why the OH* in Table 10 on page 21 is equal to zero. Orders are only placed in the case demand signals are present within the system. Furthermore, the order size is equal to the number of signals, so that all ordered parts are needed and no inventory is held. Table 15 shows characteristics of the optimal policy in the case that the precision has decreased to 0.5.

Table 15: Values of z_1^* for different ($\mathbf{w}$, I) with $p = 0.5$, $q = 1$ and $f^{\text{P}} = 0.005$

a) $\mathbf{w}$ = (0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	0	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

c) $\mathbf{w}$ = (0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

d) $\mathbf{w}$ = (0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

As Table 15 shows, the difference is that in some situations it is optimal to ignore a demand signal. This makes sense, as there is some degree of imperfectness in p. Referring back to Section 6.2.1, where we stated that when $p \neq 1$, a relatively small probability is present that a backorder could occur can now be visualised. For example, Table 15 (d) shows that the optimal decision is to order two parts, while three signals have arrived at the beginning of the period. So, we are ignoring one demand signal. In the end, there is a probability > 0 that all of the three signals turn out to be true. Consequently, we are short on one part and we have to pay a penalty.

Another interesting comparison can be made between the situations where $c^{\text{P}} = 100$ or $c^{\text{P}} = 400$, combined with $b = 250$, $p = 1$ and $q = 0.75$. Both situations are presented in Table 16 and Table 17.

Table 16: Values of z_1^* for different ($\mathbf{w}$, I) with $p = 1.0$, $q = 0.75$, $c^{\mathrm{p}} = 100$ and $f^{\mathrm{p}} = 0.005$

a) $\mathbf{w}$ = (0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

c) $\mathbf{w}$ = (0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	3	2	1	0	0

d) $\mathbf{w}$ = (0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	3	2	1	0	0

Table 17: Values of z_1^* for different ($\mathbf{w}$, I) with $p = 1.0$, $q = 0.75$, $c^{\mathrm{p}} = 400$ and $f^{\mathrm{p}} = 0.005$

a) $\mathbf{w}$ = (0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	0	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

c) $\mathbf{w}$ = (0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

d) $\mathbf{w}$ = (0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	3	2	1	0	0

As Table 16 and Table 17 show, there are some differences in the optimal order policy. These differences also explain why the OH* for both situations, displayed in Table 10 on page 21, are different. In the case of $c^{\mathrm{p}} = 100$, the OH* is found to be one, while for $c^{\mathrm{p}} = 400$, the OH* equals zero. For both situations we know that all of the demand signals are true, as $p = 1$. In other words, the order size should at least be equal to the number of signals to satisfy all predicted demand. This is something that can be observed in the setting with $c^{\mathrm{p}} = 400$, while for $c^{\mathrm{p}} = 100$, we observe that in some states the order size is larger than the number of demand signals. At first sight, you might expect that this is caused by having $q \neq 1$. However, in both settings the probability of having random demand is equal. The actual reason why the optimal policy changes is a result of lower order/production costs, because a lower c^{p} also results in a lower holding costs, as these are calculated by $\frac{20\% * c^p}{365}$. Due to the lower holding costs, it becomes relatively cheaper to keep a part on stock compared to the higher c^{p}. Also, considering the high penalty cost of 250, it is therefore attractive to change the optimal policy.

Next, we compare the previous described setting with $b = 250$, $c^{\mathrm{p}} = 400$, $p = 1$ and q is either 0.75 or 0.5. In other words, if q decreases from 0.75 to 0.5, a smaller part of the total demand can be predicted and the probability of random demand increases. The setting with $q = 0.75$ is shown in Table 17 and with $q = 0.5$ in Table 18.

Table 18: Values of z_1^* for different ($\mathbf{w}$, I) with $p = 1.0$, $q = 0.5$, $c^{\mathrm{p}} = 400$ and $f^{\mathrm{p}} = 0.005$

a) $\mathbf{w}$ = (0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

c) $\mathbf{w}$ = (0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	3	2	1	0	0

d) $\mathbf{w}$ = (0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	3	2	1	0	0

Looking at Table 17 and Table 18, it is observed that also now for this cost parameter the optimal policy changes. This is caused by a further decrease of the recall from 0.75 to 0.5, which implies a smaller part of predicted demand and a higher probability of random demand. In order to deal with the uncertainty of a higher probability of random demand, it is required to increase the inventory level to prevent a backorder from happening. As c^{p} has an effect on the holding costs, the decision to increase the inventory level for c^{p} = 400 happens at a later stage compared to c^{p} = 100. The holding costs are higher in the first situation and have a relatively larger effect on what the optimal order decision should be.

6.2.2.3 Failure Rate 0.001

The analysis in Section 6.2.1 has shown that the optimal value function is obtained when $\mathrm{OH}^* = 0$ for all different parameter settings. Table 19 shows the characteristics of the optimal policy in the case when $p = q = 1$ with $c^{\mathrm{p}} = 100$ and $b = 250$.

Table 19: Values of z_1^* for different ($\mathbf{w}$, I) with $p = q = 1$ and $f^{\mathrm{p}} = 0.001$

a) $\mathbf{w}$ = (0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	0	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

c) $\mathbf{w}$ = (0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

d) $\mathbf{w}$ = (0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	3	2	1	0	0

As seen in Table 19, the moments that an order is placed is only when a demand signal is received (or when a backorder is present in the system. However, this situation is not possible when $p = q = 1$ and $L = \tau$). Furthermore, the order size grows with the number of ADI signals that is present in the system taking into account the number of parts that is on stock. In order to show the difference between a system perfect ADI and a system with imperfectness in p, we also analyse the situation in which $p = 0.5$ and $q = 1.0$. The results are displayed in Table 20.

Table 20: Values of z_1^* for different ($\mathbf{w}$, I) with $p = 0.5$, $q = 1.0$, $b = 250$ and $f^{\mathrm{p}} = 0.001$

a) $\mathbf{w}$ = (0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	0	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

c) $\mathbf{w}$ = (0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

d) $\mathbf{w}$ = (0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

As Table 20 shows, due to imperfectness in p, we observe that the optimal action may involve ignoring a demand signal. Also, as seen in Table 20, the number of parts that is on stock and/or in transit is taken into account while making the optimal decision. An interesting observation is made when b is decreased from 250 to 50. These results are displayed in Table 21.

Table 21: Values of z_1^* for different ($\mathbf{w}$, I) with $p = 0.5$, $q = 1.0$, $b = 50$ and $f^{\mathrm{p}} = 0.001$

a) $\mathbf{w}$ = (0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	0	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	0	0	0	0	0

c) $\mathbf{w}$ = (0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

d) $\mathbf{w}$ = (0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

As Table 21 shows, we observe that for this lower value of b, the number of demand signals that is being ignored has increased. It makes sense that the magnitude of b has a certain effect on the order size, as missing demand results in a backorder. A higher penalty affects the decision in such way that backorder are relatively less desirable compared to a situation with a lower penalty. Hence, the optimal order size decreases slightly for situations with a lower backorder costs.

6.3 Traditional Manufacturing

In this subsection, we present the results of the numerical experiment for the traditional manufacturing context. First, we present the value of (im)perfect ADI with the setting where $\tau = 1$. Then, we show the amount of cost savings that can be achieved by increasing the demand lead time from 1 to 2. The value of (im)perfect ADI with the setting where $\tau = 2$ is shown in Appendix E.1. Next, we discuss the characteristics of the optimal policy and the effect of imperfect ADI on the optimal policy.

In general, we find that large value can be gained by using ADI, especially in the case of a low value for b. For a high value of b, the demand information is relatively less useful, as we find that keeping inventory diminishes the effect of an increasing precision. The optimal policy shows the same characteristics as were observed for the AM context. Furthermore, we find that increasing the demand lead time results in large possible cost savings. The savings are a result from changing from a setting where $L > \tau$ to a setting where $L = \tau$, which makes it possible to deliver predicted demand JIT instead of receiving late demand signals. Also, using the extended demand lead time, larger cost savings can be achieved by using (im)perfect ADI compared to the shorter demand lead time. Now, we find that the largest value can be gained in the case of a high value for b.

6.3.1 The Value of (im)perfect ADI

In this subsection, we discuss the value of (im)perfect ADI for the failure rate of 0.001. Note that we now consider a situation where the supply lead time is larger than the demand lead time ($L^r > \tau$). The relative cost difference, %GAP, is calculated following Equation (22) in Section 6.1. The results for this case are presented in Table 22.

Table 22: Relative cost difference compared to perfect ADI with $f^r = 0.001$ and $\tau = 1$

		$b = 50$		$b = 250$	
q	p	$c^r = 100$		$c^r = 100$	
		%GAP	OH*	%GAP	OH*
0.5	0.5	42.47	0	25.05	1
	0.75	36.75	0	25.03	1
	1.0	33.34	0	24.94	1
0.75	0.5	33.03	0	24.69	1
	0.75	23.06	0	24.62	1
	1.0	16.68	0	24.60	1
1.0	0.5	24.85	0	6.78	0
	0.75	10.02	0	2.73	0
	1.0	-	0	-	0

As can be seen in Table 22, relatively large value can be achieved by incorporating (im)perfect ADI (see Appendix H for the actual values). In the case of $b = 50$, cost reductions of more than 40% can be achieved when using perfect ADI, while in the case of $b = 250$, it can go up to around 25%.

The differences in value between $q = 1$ and $q \neq 1$ are caused by the fact that in the former case no random demand can happen. Consequently, there is a lower probability of having backorders, while in the case of $q \neq 1$, there is a relatively larger probability of having backorders, as $L^r > \tau$. Furthermore, this shows that the demand lead time has an important role as well. Also, increasing the OH* helps to prevent backorders from happening. This, of course, comes at a certain cost, but this cost is lower than having backorders and also stops a further large increase of the total cost. This can be seen by the fact that the relative cost..

Considering $b = 50$, an interesting observation is that a higher precision results in much lower total cost than a higher q. This observation was also made in Section 6.2.1.3. In that section, it was stated that due to a lower failure rate, the relative effect of a better precision is higher compared to cases with a higher failure rate. Hence, more value can be gained from the ADI in case of a relatively lower failure rate. Furthermore, we can again agree with the results in the paper of Benjaafar et al. (2011), as they argued that a high backorder/holding cost ratio results in relatively less useful demand information. So, in the case of $b = 250$, the demand information is relatively less useful, as we observe a relatively small effect of p and q. While in the case of $b = 50$, the ratio is smaller and the demand information becomes relatively more useful.

In the TM context, increasing the demand lead time (τ) from 1 to 2 results in changing from a setting where $L^r < \tau$ to a setting where $L^r = \tau$. In other words, it is now possible to satisfied all predicted demand JIT. In order to determine what the exact value is that can be gained from increasing the demand lead time, Equation (22) is used to calculate the relative cost difference between the different settings of τ. The results are shown in Table 23. Appendix E shows the value of (im)perfect ADI in the TM context with $\tau = 2$.

Table 23: Relative cost difference in the TM context between $\tau = 2$ and $\tau = 1$

q	p	$b = 50$	$b = 250$
		%GAP	%GAP
0.5	0.5	-9.73	-34.08
	0.75	-11.37	-34.08
	1.0	-12.40	-34.18
0.75	0.5	-14.49	-34.15
	0.75	-18.43	-34.15
	1.0	-21.29	-34.16
1.0	0.5	-19.18	-59.34
	0.75	-26.71	-66.26
	1.0	-33.16	-71.30

As can be seen in Table 23, large cost savings can be achieved by increasing the demand lead time from 1 to 2 periods. As mentioned before, this makes it possible to satisfy the predicted demand JIT. This is the main reason why such extensive cost savings can be achieved. In the case where $\tau = 1$, demand could only be satisfied JIT by keeping some level of inventory or otherwise backorder costs have to be incurred. The amount of cost savings that can be achieved as the ADI improves becomes larger, because more demand is predicted and can be deliver JIT compared to the previous setting where $\tau = 1$, in which predicted demand was satisfied too late. This is especially observable in the setting where $b = 250$, as the largest cost savings can be achieved in this setting. In this setting, large backorder costs are now prevented due to the extended demand lead time. Furthermore, we do not observe any changes in the optimal OH* when changing the demand lead time from 1 to 2. The reason is that because of longer supply lead time, there is still some uncertainty if $q \neq 1$. To deal with this uncertainty, it is optimal to keep some level of inventory. As observed before, the effect of increasing the precision is minimal when it is optimal to keep inventory.

6.3.2 Characteristics of the optimal Policy

In this subsection, we discuss the characteristics of the optimal policy and the effect of (im)perfect ADI on the policy where $\tau = 1$. Appendix D shows an example of how the optimal policy looks like when $\tau = 2$. The optimal values of the decision variable z_2^* are displayed for different values of ($\mathbf{w}$, I, $\mathbf{z}$), where $\mathbf{w}$ denotes the number of demand signals that are present in the system $(w_{t-\tau}, w_t)$, I denotes the on-hand inventory and $\mathbf{z}$ denotes the pipeline stock z_1. Table 24 shows the optimal policy in the case of $p = q = 1$.

Table 24: Values of z_2^* for different ($\mathbf{w}$, I, $\mathbf{z}$) with $p = q = 1$ and $f^r = 0.001$

a) $\mathbf{w}$ = (0,0)

$\mathrm{I} + \mathbf{z_1}$	**0**	**1**	**2**	**3**	**4**
z_2^*	0	0	0	0	0

b) $\mathbf{w}$ = (0,1)

$\mathrm{I} + \mathbf{z_1}$	**0**	**1**	**2**	**3**	**4**
z_2^*	1	0	0	0	0

c) $\mathbf{w}$ = (0,2)

$\mathrm{I} + \mathbf{z_1}$	**0**	**1**	**2**	**3**	**4**
z_2^*	2	1	0	0	0

d) $\mathbf{w}$ = (0,3)

$\mathrm{I} + \mathbf{z_1}$	**0**	**1**	**2**	**3**	**4**
z_2^*	3	2	1	0	0

As Table 24 shows, orders are being placed from the moment demand signals are present in the system. As the number of signal increases, the order size increases with the same amount. Furthermore, in the case of backorders being present in the system, the order size increases with the number of backorders. Note that the presence of backorders decreases the number of possible demand signals in the system. As shown in previous sections, imperfectness in p results in ignoring demand signals. In other words, the order size is less than the number of signals. In order to show also imperfectness in q, we introduce Table 25. This table also shows why the OH*, in the setting with $q = 0.5$, is one.

Table 25: Values of z_2^* for different $(\mathbf{w}, \mathrm{I}, \mathbf{z})$ with $p = 1$, $q = 0.5$ and $f^{\mathrm{r}} = 0.001$

a) $\mathbf{w}$ = (0,0)

I + $\mathbf{z_1}$	**0**	**1**	**2**	**3**	**4**
z_2^*	1	0	0	0	0

b) $\mathbf{w}$ = (0,1)

I + $\mathbf{z_1}$	**0**	**1**	**2**	**3**	**4**
z_2^*	2	1	0	0	0

c) $\mathbf{w}$ = (0,2)

I + $\mathbf{z_1}$	**0**	**1**	**2**	**3**	**4**
z_2^*	3	2	1	0	0

d) $\mathbf{w}$ = (0,3)

I + $\mathbf{z_1}$	**0**	**1**	**2**	**3**	**4**
z_2^*	4	3	2	1	0

As can be seen in Table 25, the optimal order size is always one unit more than the number of demand signals. This supports the claim of Table 22 on page 27 that the optimal inventory on-hand should be one part. The extra inventory is required to deal with the uncertainty that is associated with $q = 0.5$, but also because of the uncertainty of the longer supply lead time. As the supply lead time is now two periods compared to the single period in the AM context, some extra safety stock is needed to deal with the uncertainty of that extra period. Hence, the OH* in the case of $q = 0.5$ becomes one.

6.4 Traditional vs. Additive Manufacturing

In this section, we discuss the differences between the results of the traditional and additive manufacturing context and show the %AM Value. In Section 6.4.1 the results in the case where $c^{\mathrm{p}} > c^{\mathrm{r}}$ are presented. For this configuration, we mainly discuss the results where $\tau = 1$. Then, in Section 6.4.2, the results in the situation where $c^{\mathrm{p}} \leq c^{\mathrm{r}}$ are discussed. For this setting, we both discuss the results where $\tau = 1$ and 2.

In general, we find that the system based on traditional manufacturing outperforms the system based on additive manufacturing. The system using AM results in lower total cost only in specific settings, such when failure rates and production costs are equal or when productions costs are lower, the reliability is slightly worse and backorder costs are high. So, in these specific settings it is beneficial to change from TM to AM. In other settings, its more beneficial to invest in improving the ADI. Different values for the demand lead time resulted in even better outcomes for the TM context, except for the setting where the failure rates and productions costs are equal. The results show that the characteristics of ADI are not relevant for whether AM can outperform TM, but that the characteristics of AM (production costs and quality) itself are most relevant.

6.4.1 Case $c^{\mathrm{p}} > c^{\mathrm{r}}$

Notice that from the AM context only $f^{\mathrm{p}} = 0.001$ is discussed in this section, because with higher failure rates the total costs are much higher compared to the TM context, in which $f^{\mathrm{r}} = 0.001$ and $c^{\mathrm{r}} = 100$. The exact values for all failure rates can be found in Appendix F.1. Table 26 shows the %AM Value following Equation (23).

Table 26: %AM Value for setting where $\tau = 1$, $f^{\mathrm{p}} = 0.001$, $f^{\mathrm{r}} = 0.001$ and $c^{\mathrm{p}} > c^{\mathrm{r}}$

		$b = 50$		$b = 250$	
q	p	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$
0.5	0.5	39.79	132.98	7.77	67.08
	0.75	31.39	139.69	4.99	55.88
	1.0	25.26	125.43	3.42	49.31
0.75	0.5	49.30	148.92	-12.62	52.16
	0.75	38.33	164.12	-20.24	33.14
	1.0	28.87	143.39	-25.10	20.94
1.0	0.5	58.64	164.62	-20.35	32.86
	0.75	46.48	192.79	-32.57	34.78
	1.0	33.69	167.38	-42.60	14.81

As Table 26 shows, in general the total cost in the AM context are higher than in the TM context. Consider the situation with $b = 50$, we observe that the relative cost difference increases as the ADI improves. This is caused by the fact that as the perfectness of the ADI increases, the correctness of the prediction is better and as a result the order size increases. In other words, as you become more certain about the future demand, you want to ensure that you can satisfy this predicted demand. Because the production costs of printed parts are significantly higher than of regular parts, the total cost become higher as more parts are ordered due to more perfect ADI.

The significantly higher production costs outweigh the fact that in the TM context $L^{\mathrm{r}} > \tau$, which means that the predicted demand cannot be delivered JIT. Consequently, backorder costs of 50 are incurred as demand is not satisfied on time. However, because printed parts are significantly more expensive than regular parts, it is possible to 'use' this difference in cost price to cover up the backorder costs that are incurred. This also explains why the relative cost difference between the AM and TM context further increases as c^{p} becomes 400.

As Table 26 shows, there is a setting where the AM context results in lower total cost than the TM context. Referring back to the discussion earlier in this section, where it was mentioned that the backorder costs of 50 could be covered by the difference between c^{p} and c^{r}, now due to the higher value b, this is not possible anymore. Because in the TM context the predicted demand cannot be delivered JIT ($L^{\mathrm{r}} > \tau$), each time a backorder penalty is incurred. As a result of the higher value of b, the late delivery of demand has now become a real disadvantage, as it results in higher backorder costs. The reason why the TM context in the case of imperfect ADI has the better performance, is because of the part that has been placed on stock. As can be seen in Table 22, the OH* is raised to one when q equals 0.5. The inventory ensures that demand can be satisfied immediately, which prevents a backorder from happening. Because in the AM context no inventory is used, still a backorder can happen and corresponding costs need to be incurred. The holding costs of one part is significantly less than the backorder costs. As a result, the total cost in the TM context are stabilising, while in the AM context, the total cost further increases as the ADI becomes worse. Consequently, the TM context results in lower total cost.

As mentioned in Section 6.2, extending the demand lead time does not results in significant cost savings in the AM context. The reason is that the demand lead time was equal to the supply lead time, so that JIT delivery is possible. A demand lead time longer than the supply lead time does therefore not result in large cost savings. However, in the TM context, extending the demand lead time does result in large cost savings (see Table 23). So, in the AM context the total cost are almost equal, while in the TM context the total cost have decreased. Consequently, the value of AM decreases. As can be seen in Appendix F.2, in all settings the TM context results in the lowest total cost.

As can be seen in Table 26, the relative cost difference between both contexts decreases as the imperfectness in ADI increases. We observe that the percentage difference between the situation with perfect ADI ($p = q = 1$) and the most imperfect ADI ($p = q = 0.5$), increases relatively faster in the TM context than in the AM context. Still, because c^{p} is significantly higher than c^{r}, and therefore the holding costs as well, we obtain a situation in which the total cost of printed parts are still significantly higher than in the case of traditional manufactured parts.

Consider $b = 250$, we observe a different trend compared to the situation with $b = 50$. Now, the cost difference between the two contexts becomes larger as the imperfectness increases. As mentioned before, in the case of $b = 50$, the total cost in the TM context increases relatively faster than in the AM context. Now, we observe that in the case of a higher backorder cost, the AM total cost increases relatively faster than in the TM context. The first reason is that in the TM context a part is put on stock, which is shown in Table 22. As a result, the inventory can be used to immediately satisfy a part of the demand and to avoid backorders, while in the AM context no inventory is used. In other words, random demand results in a backorder. Because the penalty that is incurred for a backorder is now higher, it increases the total cost.

Another reason is that a higher value of b results in placing more and/or larger orders, which can be seen in Table 20 and Table 21 on page 26. A higher value of b (e.g. 250) ensures that backorders are relatively less desirable compared to a lower value of b (e.g. 50). So, based on the fact that backorders are less desirable and that more and/or larger orders are placed, results in higher production costs. Furthermore, because c^{p} is significantly higher than c^{r}, the total production costs of printed parts are a relatively larger fraction of the total cost compared to the case of regular parts. Also, as c^{p} effects the holding costs, these costs will increase as well due to imperfectness of the ADI.

Based on the results, we can conclude that the requirements of ADI do not have an effect on the question whether additive manufacturing can result in lower total cost than traditional manufacturing. It is shown that the characteristics of AM itself (production costs and reliability) are the most important factors. This is in line with Westerweel et al. (2018b) (note that they did not consider ADI), as they concluded part reliability and production costs are crucial to the success of AM components. It is expected that in the nearby future, the production costs of AM will decrease substantially. Westerweel et al. (2018b) conclude that 'typically allowed deficits compared to regular parts in terms of reliability and production costs are approximately 5% and 10%, respectively'. Furthermore, Knofius et al. (2020) mention that reduction in lead time alone does not compensate for high AM production costs, while the short supply lead time is often mentioned as the key advantage of AM. This supports the findings based on Table 26, as we observed that in almost all cases TM outperforms AM. Hence, in almost all settings it is not beneficial to switch from traditional to additive manufacturing, but it is more beneficial to invest in ADI (precision, sensitivity and/or demand lead time).

6.4.2 Case $c^{\mathrm{p}} \leq c^{\mathrm{r}}$

Notice that in this section, we discuss $f^{\mathrm{p}} = 0.001$ combined with $c^{\mathrm{p}} = 100$. Furthermore, we introduce an extra value for c^{p}, which is 50. This value is only used for $f^{\mathrm{p}} = 0.005$ and $f^{\mathrm{p}} = 0.025$ to provide insights in settings where $f^{\mathrm{p}} > f^{\mathrm{r}}$, but $c^{\mathrm{p}} < c^{\mathrm{r}}$. The values of the TM context are still $f^{\mathrm{r}} = 0.001$ and $c^{\mathrm{r}} = 100$. The exact values for all settings can be found in Appendix F.3 and are not displayed in this section, because the total costs for certain settings are much higher compared to the TM context. Table 27 shows the relative cost difference (%AM Value) between the TM and AM context following Equation (23).

Table 27: %AM Value for setting where $\tau = 1$, $f^{\mathrm{p}} = 0.001$, $f^{\mathrm{p}} = 0.005$, $f^{\mathrm{r}} = 0.001$ and $c^{\mathrm{p}} \leq c^{\mathrm{r}}$

		$f^{\mathrm{p}} = 0.001$		$f^{\mathrm{p}} = 0.005$
		$b = 50$	$b = 250$	$b = 250$
q	p	$c^{\mathrm{p}} = 100$	$c^{\mathrm{p}} = 100$	$c^{\mathrm{p}} = 50$
0.5	0.5	-27.44	-34.31	-16.44
	0.75	-25.91	-34.30	-17.35
	1.0	-24.82	-34.27	-19.47
0.75	0.5	-30.65	-45.05	-18.42
	0.75	-29.44	-46.93	-18.44
	1.0	-28.39	-48.13	-20.57
1.0	0.5	-33.53	-59.42	-21.55
	0.75	-33.37	-66.28	-24.83
	1.0	-33.16	-71.30	-28.24

As can be seen in Table 27, in cases where $c^{\mathrm{p}} \leq c^{\mathrm{r}}$ it becomes more attractive to use AM, especially when the failure rate (reliability) of AM parts is the same as TM parts. In Section 6.4.1, we mentioned that the difference between c^{p} and c^{r} can be used to cover up the backorder costs that need to be paid in the TM context. Now, as $c^{\mathrm{p}} = c^{\mathrm{r}}$, this is not possible anymore and the total AM cost have decreased significantly due to lower production costs (compared to previous values of c^{p}).

We now also observe that is very beneficial to have the supply lead time equal to the demand lead time. In the AM context, all predicted demand can be deliver JIT, while in the TM context JIT is not possible. Consequently, in the TM context, backorder costs need to be paid or parts are put on stock. As Tables 11 and 22 on page 22 and 27 show, in both contexts the optimal OH* is zero. So, if demand cannot be satisfied immediately, a penalty must be incurred. In other words, the relative cost difference in the setting where $b = 50$ is purely caused by backorder costs, while in the setting where $b = 250$, the difference is caused by both holding and backorder costs (for both the AM and TM context the optimal $\text{OH}^* = 1$). When c^p would further decrease, it can be expected that it becomes even more beneficial to use AM compared to TM.

In settings where $f^\text{p} > f^\text{r}$, we find that the AM context in only one specific setting results in lower total cost. This setting is described by $f^\text{p} = 0.005$, $c^\text{p} = 50$ and $b = 250$. As can be seen in Table 10 on page 21, for the AM context $\text{OH}^* = 1$ as long as $q \neq 1$. So, this means that there is a very small probability that a backorder cost must be incurred, as there is some stock available and predicted demand can be deliver JIT. As mentioned before, in the TM context this is not possible and therefore, a large backorder costs must be incurred for demand that cannot be satisfied immediately. Despite that the AM productions costs and failure rate are higher, it does not outweigh the higher backorder costs. Therefore, also in this setting, the AM context outperforms the TM context.

Also for the case where $c^\text{p} \leq c^\text{r}$ we tested for the setting where $\tau = 2$. The results are shown in Table 28.

Table 28: %AM Value for setting where $\tau = 2$, $f^\text{p} = 0.001$, $f^\text{r} = 0.001$ and $c^\text{p} \leq c^\text{r}$

		$b = 50$	$b = 250$
q	p	$c^\text{p} = 100$	$c^\text{p} = 100$
0.5	0.5	-11.08	-0.44
	0.75	-13.03	-0.43
	1.0	-14.31	-0.23
0.75	0.5	-6.10	-16.71
	0.75	-7.87	-19.54
	1.0	-9.29	-21.35
1.0	0.5	-0.64	-0.66
	0.75	-0.54	-0.54
	1.0	0.00	0.00

Table 28 shows that in the case where $b = 50$ some relatively small cost savings can be achieved by using AM compared to TM. However, as these savings are small, it is questionable whether this in practice will result in actual cost savings. For example, we do not consider costs for training people how to work with additive technologies, but this knowledge is required. When taking into account such costs, it eventually might turn out that switching to AM does not result in actual cost savings. The same is valid for the setting where $b = 250$ combined with q is either 0.5 or 1.0

A setting that stands out is where $b = 25$ and $q = 0.75$. In this setting, large cost savings can be achieved compared to other values of q. The reason is that in the AM context it is optimal to keep zero inventory, while in the TM context some level of inventory is optimal. This increases the total cost difference between both contexts, especially as the failure rate is lower, which implies that failures are relatively rare (and are even more rare as $q = 0.75$). In other words, the parts are on average placed on stock for a relatively long period, which results in large holding costs.

For $q = 0.5$, in both contexts it is optimal to keep inventory to prevent backorders from happening. Still, in case a backorder occurs, the AM context has the benefit of the short supply lead time compared the TM context. Therefore, the total cost is slightly lower. The same is valid for the setting where $q = 1$. In both contexts, it is possible to use JIT to satisfy all predicted demand. As we have seen before, when $p \neq 1$, it is optimal to ignore some demand signals. Still, it is possible that all of the demand signals turn out to be true, resulting in a backorder. In that situation, the AM context has an advantage, which results in slighlty lower total cost.

The results shown in Tables 27 and 28 support the conclusion made at the end of Section 6.4.1. We conclude that the characteristics of AM itself (production costs and reliability) are the most important factors. As can be seen in Table 27, as these characteristics are further optimised (lower production costs and higher reliability), more settings where AM is predominate are observed. Hence, in more settings it becomes attractive to change from traditional manufacturing to additive manufacturing, as large cost savings can be achieved. In other settings, it is more beneficial to invest in improving ADI.

7 Conclusions

In this final chapter, conclusions for the research are drawn. First, answers to the research questions formulated in Section 3.2 are provided in Section 7.1. Section 7.2 discusses the managerial insights. In Section 7.3, we discuss the limitations of this research and provide suggestions for future additional research.

7.1 Conclusions

The main research question of this research has been:

What are the characteristics that (im)perfect ADI and Additive Manufacturing must have to be valuable in a spare parts inventory control system compared to an inventory system using TM?

To answer the main research question, several research questions were formulated. Below, the conclusions per research question are given.

1. **How to model a spare parts inventory control system with ADI?**
   We have formulated a discrete-time Markov Decision Process (MDP). An MDP is helpful in decision making in situations where outcomes are partly random and partly under the control of a decision maker. The MDP is inspired by the work of Topan et al. (2018) and Westerweel et al. (2018a). However, several key changes had to be made to fulfil the specific requirements of our research (e.g. positive supply lead times and backordering). Furthermore, considerable effort has been made to verify and validate the outcomes of the model (e.g. a solid mathematical foundation and Markov-chains to verify outputs).
2. **What are the model input values for the AM and TM supply methods?**
   The input parameter values are collected via prior literature and studies that are related to our problem definition. To validate whether realistic values have been collected, multiple experts in the field of inventory control and AM have been consulted. The experts have been consulted individually to ensure the validity of the collected values, i.e., to prevent that the experts will influence each other on what they consider to be realistic values.
3. **What is the value of (im)perfect ADI within the AM and TM context? And what are the characteristics of the optimal policy?**
   Firstly, experimental results demonstrated that the total cost performance can be significantly improved by incorporating (im)perfect ADI. We reveal that more perfect ADI results in a large cost decrease, especially in the case of relatively low failure rates. Furthermore, for relatively low failure rates, it is better to have a high precision instead of a high value of q. Meaning, it is more important to correctly predict demand than to predict more demand. This unlike for higher failure rates, for which we concluded that an increasing q results in a larger cost decrease. In other words, it is more beneficial to predict more failures than having more precise predictions.

   Secondly, we showed that knowing the exact timing of a demand occurrence has a large impact on the benefit of the information. Having a demand lead time that is longer than the supply lead time does not result in large value to be gained, because it is possible to react to ADI anyway. In a setting where the supply lead time is longer than the demand lead time, increasing the demand lead time can results in large cost savings.

   Thirdly, the characteristics of the optimal policy showed that the optimal policy depends on both the inventory on-hand and the pipeline stock. Concluding, the optimal policy is dependent on the state of the system. Further, more perfect ADI results in lower inventory levels, which can be most of the time either one or zero. So, the optimal policy shows that it is possible to keep a minimum level of inventory.
4. **How does the inventory control system using AM perform compared to the system using TM?**
   The comparison between the AM and TM context showed that in general the system based on traditional manufacturing outperforms the system based on additive manufacturing. The system using

AM results in lower total cost only in specific settings, such when failure rates and production costs are equal or when productions costs are lower, the reliability is slightly worse and backorder costs are high. Different values for the demand lead time resulted in even better outcomes for the TM context, except for the setting where the failure rates and productions costs are equal, as in this setting AM still outperforms TM. Based on the results, we can conclude that the requirements of ADI do not have an effect on the question whether additive manufacturing can result in lower total cost than traditional manufacturing. It is shown that the characteristics of AM itself (production costs and reliability) are the most important factors.

To conclude, this study has shown that a significant amount of cost savings can be achieved by incorporating (im)perfect ADI. This is valid for both a system that is based on traditional manufacturing as well as on additive manufacturing. Increasing the demand lead time resulted only in the TM context in large cost savings, as JIT delivery became possible. Having a demand lead time that is longer than the supply lead time does not result in large value to be gained, because it is possible to react to ADI anyway. Furthermore, this study has quantified the difference between a system using either traditional or additive manufacturing. Only in settings where both failure rates and productions costs are equal or when production costs are lower, the failure rate slightly higher and backorder costs are high, the additive manufacturing based system can outperform the traditional manufacturing system. The production costs and reliability of AM parts are key factors that influence the future potential of AM.

7.2 Managerial Insights

- An important factor that determines the extend in cost savings, is the failure rate. So, it should be questioned whether the value gained from better ADI outweighs the required investment to collect better demand information (e.g. sensors in machines for condition monitoring). In other words, the return on investment (or payback period) is something that must be taken into account when making decisions about investing in ADI. For example, in Section 6.2.1.1, it was shown that improving the ADI only resulted in small cost savings. Such small savings do probably not outweigh the investment costs that are required to make to collect better ADI. In contrast to Section 6.2.1.3, where it was shown that small increases in p or q, result in large cost savings. These large cost savings make it beneficial to invest in better ADI, as the investment can easily be earned back.
- Another consideration that depends on the failure rate, is whether to invest in more demand information (high q) or in more precise demand information (high p). For the relatively high failure rates, the numerical experiments showed that increasing q results in more value from the ADI. On the other hand, for low failure rates, it was more important to have precise predictions (high p), especially in situations with low backorder costs. For settings with the specific combination of a low failure rate and high backorder costs, it is beneficial to invest in predicting more demand as well as in predicting more precisely.
- Increasing the demand lead time only results in substantial cost savings in settings where the demand lead time is not already equal to or longer than the supply lead time. In such a situation, it is possible to react to ADI anyway. Only if the demand lead time is shorter than the supply lead time, it is beneficial to invest in increasing the demand lead time. Otherwise, it is more beneficial to invest in improving the ADI precision and/or sensitivity.
- Considering the characteristics of the optimal policies, in the cases of relatively low demand, parts are only requested when a demand signal (or backorder) is present in the system. In practice, such characteristics corresponds to situations where local manufacturers do not have to keep any inventory. This not only results in cost savings, but also in savings in terms of space. Furthermore, this makes it possible to store inventory at a central warehouse, resulting in a more centralised inventory system.
- The comparison between the additive and traditional manufacturing based system showed that in general, it is not beneficial to switch from TM to AM. Only in settings where both failure rates and production costs are equal or when production costs are lower, the reliability slightly worse and backorder costs are high (assuming that the same (im)perfectness of ADI can be used in both systems), using additive technologies results in lower total cost. So, the significantly higher failure rates (lower reliability) and production costs of printed parts do not outweigh the benefit of having a shorter supply lead time. To make the additive technologies more attractive, it is required to further increase the reliability or to decrease the production costs of printed parts, as shown in Section 6.4.2. As

discussed in Section 6.4, this is in line with previous literature (e.g. Knofius et al. (2020); Pijnappels (2019); Westerweel et al. (2018b)).

- The magnitude of the backorder penalty (b) has a relatively large effect on whether or not to keep inventory, but also on the value that can be gained from ADI. In practical settings where penalties are considerably high, it can be attractive to implement a type of (im)perfect ADI.

7.3 Limitations and Future Research

- The first limitation is that we have considered a deterministic demand lead time that is equal for all demand signals. However, in practice it could be the case that a time window is provided for the demand occurrences instead of an exact timing. The model may be extended by adding a time window for the demand lead time. A probability function can be used to model the probability that a signal turns out to be true during the time window. Also, it is required to keep track of all the demand signals that are given within the window to determine the predicted demand. Topan et al. (2018) can be used as a reference.
- Second, we did not extend our model to a multi-item, multi-location inventory model. It may be interesting to investigate how the model using traditional manufacturing could be extended to a multi-echelon model and what the effect of (im)perfect ADI is across multiple echelons. A suggestion is to solve the multi-echelon model as a single-location problem. Meaning, for the highest echelon (N) it is possible to formulate a single-echelon problem. The formulated cost function can be used to derive a penalty function for echelon $n-1$. Because the penalty costs for echelon N can be seen as that echelon $n-1$ cannot deliver to echelon n. So, it is possible to derive some penalty function for echelon $n-1$, this procedure can be repeated for each echelon. For example, Gallego and Özer (2003) can be used as a starting point. It is expected that total cost and inventory levels will decrease as the demand information is more perfect across the supply chain. Like in this research, it can be expected that when the demand lead time is at least the same as the sum of the supply lead times of all echelons, it is possible to deliver demand JIT.
- Third, value-iteration optimally solves the model, but has the disadvantage of computational inefficiency. As we did not propose a heuristic to solve the model, this would be a direction for future research. Traditional base-stock policies based on predicted demand cannot be used for the model, due to imperfect demand signals. Therefore, a heuristic should be developed that takes into account the characteristics of (im)perfect ADI. A suggestion is to use the expected demand from the demand signals plus the expected random demand during the supply lead time, resulting in the total expected demand. Then, this total expected demand can be used to determine the inventory position of the system.
- Last, it may be interesting to extend this model to a dual sourcing inventory model, in which both traditional and additive manufacturing can be used within an inventory system. For example, in the case of imperfect ADI, there are random failures that occur. To deal with these random failures, it is possible to keep some level of inventory. Another option is to use additive manufacturing with a short lead time. If there is no available inventory, a printed part can be produced and used as a temporary replacement, while a regular part is being manufactured. This can be interesting, because using a temporary replacement decreases the downtime of a system. However, as both a temporary AM part and a regular part need to be manufactured, the consequence is an increase in production costs. The question is whether the savings in downtime costs outweigh the increase of in production costs, both cost values are dependent on the context of the industry. For example, Knofius et al. (2020) can be used as a starting point, because they consider a dual-sourcing inventory problem combining AM and TM technologies.

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Appendix A List of Abbreviations

ADI	Advance Demand Information
AM	Additive Manufacturing
CM	Condition Monitoring
FCFS	First Come First Served
FDM	Fused Deposition Modelling
FN	False Negatives
FP	False Positives
JIT	Just-in-Time
MDP	Markov Decision Process
OEM	Original Equipment Manufacturer
TM	Traditional Manufacturing
TP	True Positives

Appendix B Mathematical Notation

Variable	**Description**
Input Variables	
N	Installed base size
f^{r}	Failure probability of regular parts
L^{r}	Lead time of a regular part
c^{r}	Production cost of a regular part
h^{r}	Holding cost per regular part
f^{p}	Failure probability of printed parts
L^{p}	Lead time of a printed part
c^{p}	Production cost of a printed part
h^{p}	Holding cost per printed part
b	Backordering cost per part
τ	Demand lead time
p	Precision
q	Sensitivity
γ	Discount factor
Decision Variables	
z_L	Order size
State Variables	
I	On-hand inventory level
$\mathbf{z}$	Vector containing the stock in the pipeline
B_t	Number of backorders in period t
t	Current time period
W_t	Binomial distributed variable denoting the collected number of demand signals available at beginning of period t
w_t	Realisation of W_t
$\mathbf{w}$	Vector containing the number of demand signals that are available in the system at the beginning of period t
D_t^{p}	Binomial distributed *predicted* demand in period t
D_t^{u}	Binomial distributed *unpredicted* demand in period t
D_t	Total demand in period t
Output Variables	
$C(B, I, z_0, z_L, d)$	Direct expected cost
$V_{\mathrm{t}}(B, I, \mathbf{z}, \mathbf{w})$	Total expected cost for period t

Appendix C Results AM Value of (im)perfect ADI

C.1 Relative Cost Difference with $c^{\mathrm{p}} = 200$ and $\tau = 1$

		$b = 50$						$b = 250$					
q	p	$f^{\mathrm{p}} = 0.025$		$f^{\mathrm{p}} = 0.005$		$f^{\mathrm{p}} = 0.001$		$f^{\mathrm{p}} = 0.025$		$f^{\mathrm{p}} = 0.005$		$f^{\mathrm{p}} = 0.001$	
		%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*
0.5	0.5	18.23	1	27.90	0	48.98	0	19.60	2	38.94	1	134.75	0
	0.75	18.16	1	25.87	0	34.40	0	19.60	2	38.85	1	128.68	0
	1.0	17.62	1	24.44	0	24.94	0	19.60	2	37.89	1	125.09	0
0.75	0.5	13.94	0	21.25	0	48.57	0	18.90	1	37.75	1	89.78	0
	0.75	12.41	0	16.26	0	27.33	0	18.90	1	37.66	1	73.16	0
	1.0	11.20	0	12.25	0	12.48	0	18.53	1	37.34	1	62.58	0
1.0	0.5	9.76	0	16.30	0	48.16	0	10.22	0	16.73	0	50.93	0
	0.75	4.42	0	7.61	0	20.66	0	4.42	0	7.61	0	20.68	0
	1.0	-	0	-	0	-	0	-	0	-	0	-	0

C.2 Relative Cost Difference with $\tau = 2$

C.2.1 Failure Rate 0.025

		$b = 50$						$b = 250$					
q	p	$c^{\mathrm{p}} = 100$		$c^{\mathrm{p}} = 200$		$c^{\mathrm{p}} = 400$		$c^{\mathrm{p}} = 100$		$c^{\mathrm{p}} = 200$		$c^{\mathrm{p}} = 400$	
		%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*
0.5	0.5	19.87	1	18.61	1	11.96	0	19.97	2	19.98	1	19.98	1
	0.75	19.79	1	18.54	1	11.13	0	19.96	2	19.98	1	19.98	1
	1.0	19.38	1	18.00	1	10.16	0	19.95	2	19.98	1	19.76	1
0.75	0.5	18.36	1	14.14	0	9.89	0	19.16	1	19.17	1	18.97	1
	0.75	18.21	1	12.60	0	7.54	0	19.16	1	19.16	1	18.58	1
	1.0	18.09	1	11.38	0	5.14	0	19.16	1	18.80	1	18.31	1
1.0	0.5	10.19	0	9.78	0	8.71	0	10.25	0	10.25	0	10.22	0
	0.75	4.43	0	4.43	0	4.42	0	4.43	0	4.43	0	4.43	0
	1.0	-	0	-	0	-	0	-	0	-	0	-	0

C.2.2 Failure Rate 0.005

		$b = 50$						$b = 250$					
q	p	$c^{\mathrm{p}} = 100$		$c^{\mathrm{p}} = 200$		$c^{\mathrm{p}} = 400$		$c^{\mathrm{p}} = 100$		$c^{\mathrm{p}} = 200$		$c^{\mathrm{p}} = 400$	
		%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*
0.5	0.5	37.90	1	28.28	0	19.08	0	41.68	1	39.28	1	38.17	1
	0.75	37.86	1	26.25	0	15.12	0	41.58	1	39.21	1	38.13	1
	1.0	37.84	1	24.81	0	12.28	0	39.11	1	38.33	1	37.94	1
0.75	0.5	29.69	0	21.56	0	17.36	0	39.38	1	38.06	1	33.67	0
	0.75	27.00	0	16.45	0	11.17	0	39.31	1	37.97	1	32.28	0
	1.0	25.00	0	12.44	0	6.16	0	37.84	1	37.65	1	31.28	0
1.0	0.5	16.69	0	16.32	0	16.03	0	16.77	0	16.77	0	16.76	0
	0.75	7.62	0	7.62	0	7.61	0	7.62	0	7.62	0	7.62	0
	1.0	-	0	-	0	-	0	-	0	-	0	-	0

C.2.3 Failure Rate 0.001

		$b = 50$						$b = 250$					
q	p	$c^{\mathrm{P}} = 100$		$c^{\mathrm{P}} = 200$		$c^{\mathrm{P}} = 400$		$c^{\mathrm{P}} = 100$		$c^{\mathrm{P}} = 200$		$c^{\mathrm{P}} = 400$	
		%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*	%GAP	OH*
0.5	0.5	71.93	0	49.31	0	24.45	0	187.38	1	135.64	0	82.56	0
	0.75	58.48	0	34.78	0	22.91	0	187.37	1	129.56	0	70.32	0
	1.0	50.48	0	25.31	0	12.73	0	187.30	1	125.97	0	63.06	0
0.75	0.5	60.58	0	48.65	0	23.99	0	139.43	0	90.24	0	65.54	0
	0.75	39.06	0	27.53	0	21.73	0	131.19	0	73.60	0	44.81	0
	1.0	25.25	0	12.66	0	6.37	0	125.96	0	63.02	0	31.55	0
1.0	0.5	50.74	0	47.98	0	23.55	0	51.01	0	50.98	0	50.79	0
	0.75	20.69	0	20.67	0	20.61	0	20.69	0	20.69	0	20.69	0
	1.0	-	0	-	0	-	0	-	0	-	0	-	0

C.3 Relative Cost Difference between $\tau = 1$ and $\tau = 2$

C.3.1 Failure Rate 0.025

		$b = 50$			$b = 250$		
q	p	$c^{\mathrm{P}} = 100$	$c^{\mathrm{P}} = 200$	$c^{\mathrm{P}} = 400$	$c^{\mathrm{P}} = 100$	$c^{\mathrm{P}} = 200$	$c^{\mathrm{P}} = 400$
		%GAP	%GAP	%GAP	%GAP	%GAP	%GAP
0.5	0.5	-0.18	-0.18	-0.22	-0.19	-0.18	-0.18
	0.75	-0.18	-0.18	-0.22	-0.20	-0.18	-0.18
	1.0	-0.18	-0.18	-0.22	-0.20	-0.18	-0.18
0.75	0.5	-0.26	-0.33	-0.34	-0.27	-0.27	-0.27
	0.75	-0.27	-0.33	-0.35	-0.28	-0.27	-0.27
	1.0	-0.27	-0.33	-0.35	-0.27	-0.27	-0.27
1.0	0.5	-0.47	-0.47	-0.47	-0.47	-0.47	-0.47
	0.75	-0.48	-0.48	-0.48	-0.48	-0.48	-0.48
	1.0	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50

C.3.2 Failure Rate 0.005

		$b = 50$			$b = 250$		
q	p	$c^{\mathrm{P}} = 100$	$c^{\mathrm{P}} = 200$	$c^{\mathrm{P}} = 400$	$c^{\mathrm{P}} = 100$	$c^{\mathrm{P}} = 200$	$c^{\mathrm{P}} = 400$
		%GAP	%GAP	%GAP	%GAP	%GAP	%GAP
0.5	0.5	-0.18	-0.20	-0.22	-0.19	-0.18	-0.18
	0.75	-0.18	-0.20	-0.22	-0.19	-0.18	-0.18
	1.0	-0.18	-0.20	-0.22	-0.18	-0.18	-0.18
0.75	0.5	-0.29	-0.33	-0.34	-0.28	-0.27	-0.28
	0.75	-0.30	-0.33	-0.35	-0.27	-0.27	-0.28
	1.0	-0.30	-0.33	-0.35	-0.27	-0.27	-0.28
1.0	0.5	-0.47	-0.47	-0.47	-0.47	-0.47	-0.47
	0.75	-0.48	-0.48	-0.48	-0.48	-0.48	-0.48
	1.0	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50

C.3.3 Failure Rate 0.001

		$b = 50$			$b = 250$		
q	p	$c^{\mathrm{P}} = 100$	$c^{\mathrm{P}} = 200$	$c^{\mathrm{P}} = 400$	$c^{\mathrm{P}} = 100$	$c^{\mathrm{P}} = 200$	$c^{\mathrm{P}} = 400$
		%GAP	%GAP	%GAP	%GAP	%GAP	%GAP
0.5	0.5	-0.20	-0.28	-0.25	-0.09	-0.12	-0.18
	0.75	-0.18	-0.22	-0.24	-0.09	-0.12	-0.17
	1.0	-0.17	-0.20	-0.22	-0.09	-0.11	-0.15
0.75	0.5	-0.32	-0.44	-0.38	-0.18	-0.26	-0.31
	0.75	-0.31	-0.34	-0.36	-0.17	-0.24	-0.30
	1.0	-0.30	-0.33	-0.35	-0.17	-0.23	-0.29
1.0	0.5	-0.47	-0.62	-0.51	-0.47	-0.47	-0.47
	0.75	-0.49	-0.49	-0.49	-0.49	-0.49	-0.49
	1.0	-0.50	-0.50	-0.50	-0.50	-0.50	-0.50

Appendix D Example of optimal Policy with $\tau = 2$

In this appendix, we show the optimal policy in a situation where $f^{\mathrm{p}} = 0.005$, $p = 1$ and $q = 1$. Table 1 demonstrates the optimal values of the decision variable, the order size, for different values of ($\mathbf{w}$, I).

Table 1: Values of z_1^* for different ($\mathbf{w}$, I) with $f^{\mathrm{p}} = 0.001$, $p = 1.0$, $q = 0.75$, $b = 250$ and $c^{\mathrm{p}} = 100$

a) $\mathbf{w}$ = (0,0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

b) $\mathbf{w}$ = (0,0,1)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

c) $\mathbf{w}$ = (0,0,2)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

d) $\mathbf{w}$ = (0,0,3)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

As Table 1 shows, the optimal policy is in every setting of $\mathbf{w}$ the same. The reason is that the predicted demand occurs at time $t+2$, while an order arrives at time $t+1$. So, as it is possible to satisfy the predicted demand JIT, the order will be placed one period before the demand is due (see Table 2. Still, the optimal action is to order 1 part, because the optimal OH* was found the be 1. This part is used for dealing with the (im)perfect ADI, as still some random failures can occur.

Table 2: Values of z_1^* for different ($\mathbf{w}$, I) with $f^{\mathrm{p}} = 0.001$, $p = 1.0$, $q = 0.75$, $b = 250$ and $c^{\mathrm{p}} = 100$

a) $\mathbf{w}$ = (0,0,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	1	0	0	0	0

b) $\mathbf{w}$ = (0,1,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	2	1	0	0	0

c) $\mathbf{w}$ = (0,2,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	3	2	1	0	0

d) $\mathbf{w}$ = (0,3,0)

I	**0**	**1**	**2**	**3**	**4**
z_1^*	4	3	2	1	0

As can be seen in Table 2, now the optimal action takes into account the number of demand signals that are available at the beginning of the period. The optimal action is to order 1 part more than the number of demand signals, because the optimal OH* was found to be 1.

Appendix E Results TM Value of (im)perfect ADI

E.1 Relative Cost Difference with $\tau = 2$

Table 3: Relative cost difference compared to perfect ADI with $f^{\mathrm{r}} = 0.001$ and $\tau = 2$

		$b = 50$		$b = 250$	
q	p	$c^{\mathrm{r}} = 100$		$c^{\mathrm{r}} = 100$	
		%GAP	OH*	%GAP	OH*
0.5	0.5	92.40	0	187.22	1
	0.75	81.31	0	187.18	1
	1.0	74.74	0	186.53	1
0.75	0.5	70.17	0	186.04	1
	0.75	50.18	0	185.89	1
	1.0	37.40	0	185.88	1
1.0	0.5	50.95	0	51.26	0
	0.75	20.74	0	20.74	0
	1.0	-	0	-	0

Appendix F Results AM vs. TM

F.1 Case $c^{\mathrm{p}} > c^{\mathrm{r}}$ with $\tau = 1$

Table 4: %AM Value for setting where $f^{\mathrm{p}} = 0.025$ and $f^{\mathrm{r}} = 0.001$

		$b = 50$		$b = 250$	
q	p	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$
0.5	0.5	2389.50	4626.54	1272.65	2645.20
	0.75	2671.06	5098.27	1272.82	2645.54
	1.0	2863.49	5407.06	1273.70	2642.41
0.75	0.5	2364.87	4647.34	1268.66	2623.69
	0.75	2757.28	5358.98	1269.17	2633.86
	1.0	3085.26	5914.53	1265.14	2619.15
1.0	0.5	2320.58	4694.06	1381.43	2861.92
	0.75	2782.56	5664.54	1358.73	2817.46
	1.0	3242.24	6584.49	1335.11	2770.22

Table 5: %AM Value for setting where $f^{\mathrm{p}} = 0.005$ and $f^{\mathrm{r}} = 0.001$

		$b = 50$		$b = 250$	
q	p	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$
0.5	0.5	500.07	1014.38	218.53	531.82
	0.75	515.30	1022.37	218.74	532.19
	1.0	523.86	1022.69	216.77	531.75
0.75	0.5	509.80	217.15	282.52	514.75
	0.75	531.48	1105.94	217.07	508.05
	1.0	543.10	1114.58	216.36	503.54
1.0	0.5	522.66	212.62	292.93	523.70
	0.75	553.18	1206.22	200.67	501.28
	1.0	568.46	1236.91	187.03	474.06

F.2 Case $c^{\mathrm{p}} > c^{\mathrm{r}}$ with $\tau = 2$

Table 6: %AM Value for setting where $f^{\mathrm{p}} = 0.025$ and $f^{\mathrm{r}} = 0.001$

		$b = 50$		$b = 250$	
q	p	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$
0.5	0.5	2951.42	5690.53	1978.36	4056.67
	0.75	3152.77	5999.08	1978.66	4057.27
	1.0	3277.05	6172.83	1983.31	4059.02
0.75	0.5	3237.01	6325.96	1972.76	4024.98
	0.75	3630.22	7025.42	1973.79	4040.88
	1.0	3933.25	7514.23	1967.52	4018.23
1.0	0.5	3518.30	7066.13	3526.56	7150.82
	0.75	4203.06	8505.14	4203.06	8506.12
	1.0	4875.34	9850.68	4875.34	9850.68

Table 7: %AM Value for setting where $f^{\mathrm{p}} = 0.005$ and $f^{\mathrm{r}} = 0.001$

		$b = 50$		$b = 250$	
q	p	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$
0.5	0.5	563.44	1131.77	382.29	856.67
	0.75	592.87	1163.57	382.62	857.26
	1.0	610.77	1178.82	380.40	858.09
0.75	0.5	610.82	1272.58	380.30	830.02
	0.75	671.60	1373.23	380.24	820.86
	1.0	714.32	1437.65	379.13	813.95
1.0	0.5	666.81	1429.82	668.17	1436.28
	0.75	786.95	1673.68	786.95	1673.91
	1.0	895.09	1890.19	895.09	1890.19

Table 8: %AM Value for setting where $f^{\mathrm{p}} = 0.001$ and $f^{\mathrm{r}} = 0.001$

		$b = 50$		$b = 250$	
q	p	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$	$c^{\mathrm{p}} = 200$	$c^{\mathrm{p}} = 400$
0.5	0.5	54.44	157.45	63.27	152.98
	0.75	47.93	169.80	59.08	136.06
	1.0	42.72	156.77	56.95	126.50
0.75	0.5	73.84	190.00	32.35	130.33
	0.75	69.00	222.62	20.84	101.61
	1.0	63.18	208.13	13.48	83.15
1.0	0.5	95.09	225.76	98.64	296.77
	0.75	98.89	297.57	98.92	297.84
	1.0	99.01	298.01	99.01	298.01

F.3 Case $c^{\mathrm{p}} \leq c^{\mathrm{r}}$ with $\tau = 1$

Table 9: %AM Value for setting where $f^{\mathrm{p}} = 0.025$ and $f^{\mathrm{r}} = 0.001$

		$b = 50$		$b = 250$	
q	p	$c^{\mathrm{p}} = 50$	$c^{\mathrm{p}} = 100$	$c^{\mathrm{p}} = 50$	$c^{\mathrm{p}} = 100$
0.5	0.5	532.85	1164.55	243.16	586.33
	0.75	601.23	1300.22	243.21	586.41
	1.0	649.43	1391.38	243.42	586.85
0.75	0.5	543.00	1174.28	242.18	584.34
	0.75	655.42	1400.80	242.31	584.60
	1.0	747.43	1589.22	242.34	584.66
1.0	0.5	507.71	1114.83	270.36	640.71
	0.75	620.64	1341.28	264.68	629.36
	1.0	735.56	1571.12	258.78	617.56

Table 10: %AM Value for setting where $f^{\text{p}} = 0.005$ and $f^{\text{r}} = 0.001$

		$b = 50$		$b = 250$
q	p	$c^{\text{p}} = 50$	$c^{\text{p}} = 100$	$c^{\text{p}} = 100$
0.5	0.5	190.81	46.37	61.89
	0.75	222.38	62.27	62.02
	1.0	244.47	72.62	59.28
0.75	0.5	179.99	48.71	60.09
	0.75	222.19	74.63	60.08
	1.0	257.36	96.65	58.40
1.0	0.5	157.30	28.72	56.90
	0.75	197.08	48.54	50.34
	1.0	234.23	67.12	43.51

F.4 Case $c^{\text{p}} \leq c^{\text{r}}$ with $\tau = 2$

Table 11: %AM Value for setting where $f^{\text{p}} = 0.025$ and $f^{\text{r}} = 0.001$

		$b = 50$		$b = 250$	
q	p	$c^{\text{p}} = 50$	$c^{\text{p}} = 100$	$c^{\text{p}} = 50$	$c^{\text{p}} = 100$
0.5	0.5	675.65	1449.92	419.61	939.10
	0.75	723.08	1543.57	419.81	939.16
	1.0	754.00	1599.46	420.98	941.44
0.75	0.5	771.02	1626.26	418.12	936.35
	0.75	886.80	1860.55	418.35	936.86
	1.0	973.68	2040.28	418.49	936.94
1.0	0.5	808.48	1715.94	806.64	1713.28
	0.75	975.77	2051.53	975.76	2051.53
	1.0	1150.00	2400.00	1150.00	2400.00

Table 12: %AM Value for setting where $f^{\text{p}} = 0.005$ and $f^{\text{r}} = 0.001$

		$b = 50$		$b = 250$	
q	p	$c^{\text{p}} = 50$	$c^{\text{p}} = 100$	$c^{\text{p}} = 50$	$c^{\text{p}} = 100$
0.5	0.5	79.40	256.44	26.50	145.09
	0.75	90.47	278.41	25.15	145.29
	1.0	96.71	292.53	22.14	141.56
0.75	0.5	101.45	279.19	23.49	142.43
	0.75	128.11	320.77	23.53	142.44
	1.0	149.15	352.65	20.29	139.91
1.0	0.5	92.43	284.61	92.05	284.09
	0.75	121.74	343.48	121.74	343.48
	1.0	150.00	400.00	150.00	400.00

Appendix G Results Additive Manufacturing

G.1 Failure Rate 0.025

G.1.1 $\tau = 1$

b	c^{P}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
50	50	0.5	0.5	0	1	0	0	892.54
50	50	0.75	0.5	0	1	0	0	892.54
50	50	1	0.5	0	1	0	0	892.49
50	50	0.5	0.75	0	1	0	0	887.26
50	50	0.75	0.75	0	1	0	0	887.12
50	50	1	0.75	0	1	0	0	883.09
50	50	0.5	1	0	0	0	0	822.51
50	50	0.75	1	0	0	0	0	779.20
50	50	1	1	0	0	0	0	746.25
50	100	0.5	0.5	0	1	0	0	1783.46
50	100	0.75	0.5	0	1	0	0	1782.24
50	100	1	0.5	0	1	0	0	1776.07
50	100	0.5	0.75	0	1	0	0	1762.45
50	100	0.75	0.75	0	1	0	0	1760.29
50	100	1	0.75	0	1	0	0	1758.36
50	100	0.5	1	0	0	0	0	1644.24
50	100	0.75	1	0	0	0	0	1558.40
50	100	1	1	0	0	0	0	1492.50
50	200	0.5	0.5	0	1	0	0	3529.18
50	200	0.75	0.5	0	1	0	0	3527.09
50	200	1	0.5	0	1	0	0	3511.06
50	200	0.5	0.75	0	0	0	0	3401.24
50	200	0.75	0.75	0	0	0	0	3355.40
50	200	1	0.75	0	0	0	0	3319.28
50	200	0.5	1	0	0	0	0	3276.19
50	200	0.75	1	0	0	0	0	3116.81
50	200	1	1	0	0	0	0	2985.00
50	400	0.5	0.5	0	0	0	0	6666.06
50	400	0.75	0.5	0	0	0	0	6616.52
50	400	1	0.5	0	0	0	0	6558.28
50	400	0.5	0.75	0	0	0	0	6550.78
50	400	0.75	0.75	0	0	0	0	6410.69
50	400	1	0.75	0	0	0	0	6267.58
50	400	0.5	1	0	0	0	0	6488.62
50	400	0.75	1	0	0	0	0	6233.00
50	400	1	1	0	0	0	0	5970.00
250	50	0.5	0.5	0	2	0	0	892.56
250	50	0.75	0.5	0	2	0	0	892.55
250	50	1	0.5	0	2	0	0	892.50
250	50	0.5	0.75	0	2	0	0	887.31
250	50	0.75	0.75	0	2	0	0	887.31
250	50	1	0.75	0	2	0	0	887.27
250	50	0.5	1	0	0	0	0	822.53
250	50	0.75	1	0	0	0	0	779.20
250	50	1	1	0	0	0	0	746.25
250	100	0.5	0.5	0	2	0	0	1785.11
250	100	0.75	0.5	0	2	0	0	1785.10
250	100	1	0.5	0	2	0	0	1785.00
250	100	0.5	0.75	0	1	0	0	1774.56
250	100	0.75	0.75	0	1	0	0	1774.56
250	100	1	0.75	0	1	0	0	1774.48

b	c^{P}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
250	100	0.5	1	0	0	0	0	1645.06
250	100	0.75	1	0	0	0	0	1558.40
250	100	1	1	0	0	0	0	1492.50
250	200	0.5	0.5	0	2	0	0	3570.22
250	200	0.75	0.5	0	2	0	0	3570.20
250	200	1	0.5	0	2	0	0	3570.00
250	200	0.5	0.75	0	1	0	0	3549.05
250	200	0.75	0.75	0	1	0	0	3549.05
250	200	1	0.75	0	1	0	0	3538.11
250	200	0.5	1	0	0	0	0	3290.12
250	200	0.75	1	0	0	0	0	3116.81
250	200	1	1	0	0	0	0	2985.00
250	400	0.5	0.5	0	1	0	0	7140.18
250	400	0.75	0.5	0	1	0	0	7140.13
250	400	1	0.5	0	1	0	0	7127.03
250	400	0.5	0.75	0	1	0	0	7086.49
250	400	0.75	0.75	0	1	0	0	7062.77
250	400	1	0.75	0	1	0	0	7047.37
250	400	0.5	1	0	0	0	0	6578.15
250	400	0.75	1	0	0	0	0	6233.62
250	400	1	1	0	0	0	0	5970.00

G.1.2 $\tau = 2$

b	c^{P}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
50	50	0.5	0.5	0	1	0	0	892.54
50	50	0.75	0.5	0	1	0	0	892.54
50	50	1	0.5	0	1	0	0	892.49
50	50	0.5	0.75	0	1	0	0	887.26
50	50	0.75	0.75	0	1	0	0	887.12
50	50	1	0.75	0	1	0	0	883.09
50	50	0.5	1	0	0	0	0	822.51
50	50	0.75	1	0	0	0	0	779.20
50	50	1	1	0	0	0	0	746.25
50	100	0.5	0.5	0	1	0	0	1783.46
50	100	0.75	0.5	0	1	0	0	1782.24
50	100	1	0.5	0	1	0	0	1776.07
50	100	0.5	0.75	0	1	0	0	1762.45
50	100	0.75	0.75	0	1	0	0	1760.29
50	100	1	0.75	0	1	0	0	1758.36
50	100	0.5	1	0	0	0	0	1644.24
50	100	0.75	1	0	0	0	0	1558.40
50	100	1	1	0	0	0	0	1492.50
50	200	0.5	0.5	0	1	0	0	3529.18
50	200	0.75	0.5	0	1	0	0	3527.09
50	200	1	0.5	0	1	0	0	3511.06
50	200	0.5	0.75	0	0	0	0	3401.24
50	200	0.75	0.75	0	0	0	0	3355.40
50	200	1	0.75	0	0	0	0	3319.28
50	200	0.5	1	0	0	0	0	3276.19
50	200	0.75	1	0	0	0	0	3116.81
50	200	1	1	0	0	0	0	2985.00
50	400	0.5	0.5	0	0	0	0	6666.06
50	400	0.75	0.5	0	0	0	0	6616.52
50	400	1	0.5	0	0	0	0	6558.28
50	400	0.5	0.75	0	0	0	0	6550.78

b	c^{p}	p	q	B	I	**z**	**w**	Value
50	400	0.75	0.75	0	0	0	0	6410.69
50	400	1	0.75	0	0	0	0	6267.58
50	400	0.5	1	0	0	0	0	6488.62
50	400	0.75	1	0	0	0	0	6233.00
50	400	1	1	0	0	0	0	5970.00
250	50	0.5	0.5	0	2	0	0	892.56
250	50	0.75	0.5	0	2	0	0	892.55
250	50	1	0.5	0	2	0	0	892.50
250	50	0.5	0.75	0	2	0	0	887.31
250	50	0.75	0.75	0	2	0	0	887.31
250	50	1	0.75	0	2	0	0	887.27
250	50	0.5	1	0	0	0	0	822.53
250	50	0.75	1	0	0	0	0	779.20
250	50	1	1	0	0	0	0	746.25
250	100	0.5	0.5	0	2	0	0	1785.11
250	100	0.75	0.5	0	2	0	0	1785.10
250	100	1	0.5	0	2	0	0	1785.00
250	100	0.5	0.75	0	1	0	0	1774.56
250	100	0.75	0.75	0	1	0	0	1774.56
250	100	1	0.75	0	1	0	0	1774.48
250	100	0.5	1	0	0	0	0	1645.06
250	100	0.75	1	0	0	0	0	1558.40
250	100	1	1	0	0	0	0	1492.50
250	200	0.5	0.5	0	2	0	0	3570.22
250	200	0.75	0.5	0	2	0	0	3570.20
250	200	1	0.5	0	2	0	0	3570.00
250	200	0.5	0.75	0	1	0	0	3549.05
250	200	0.75	0.75	0	1	0	0	3549.05
250	200	1	0.75	0	1	0	0	3538.11
250	200	0.5	1	0	0	0	0	3290.12
250	200	0.75	1	0	0	0	0	3116.81
250	200	1	1	0	0	0	0	2985.00
250	400	0.5	0.5	0	1	0	0	7140.18
250	400	0.75	0.5	0	1	0	0	7140.13
250	400	1	0.5	0	1	0	0	7127.03
250	400	0.5	0.75	0	1	0	0	7086.49
250	400	0.75	0.75	0	1	0	0	7062.77
250	400	1	0.75	0	1	0	0	7047.37
250	400	0.5	1	0	0	0	0	6578.15
250	400	0.75	1	0	0	0	0	6233.62
250	400	1	1	0	0	0	0	5970.00

G.2 Failure Rate 0.005

G.2.1 $\tau = 1$

b	c^{p}	p	q	B	I	**z**	**w**	Value
50	50	0.5	0.5	0	1	0	0	206.54
50	50	0.75	0.5	0	1	0	0	206.44
50	50	1	0.5	0	1	0	0	205.57
50	50	0.5	0.75	0	1	0	0	205.20
50	50	0.75	0.75	0	1	0	0	205.07
50	50	1	0.75	0	1	0	0	204.92
50	50	0.5	1	0	0	0	0	174.22
50	50	0.75	1	0	0	0	0	160.61
50	50	1	1	0	0	0	0	149.25

b	c^{p}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
50	100	0.5	0.5	0	1	0	0	410.34
50	100	0.75	0.5	0	1	0	0	410.22
50	100	1	0.5	0	1	0	0	410.15
50	100	0.5	0.75	0	0	0	0	386.36
50	100	0.75	0.75	0	0	0	0	378.36
50	100	1	0.75	0	0	0	0	372.40
50	100	0.5	1	0	0	0	0	348.24
50	100	0.75	1	0	0	0	0	321.22
50	100	1	1	0	0	0	0	298.51
50	200	0.5	0.5	0	0	0	0	763.57
50	200	0.75	0.5	0	0	0	0	751.48
50	200	1	0.5	0	0	0	0	742.95
50	200	0.5	0.75	0	0	0	0	724.50
50	200	0.75	0.75	0	0	0	0	694.07
50	200	1	0.75	0	0	0	0	670.17
50	200	0.5	1	0	0	0	0	694.31
50	200	0.75	1	0	0	0	0	642.44
50	200	1	1	0	0	0	0	597.01
50	400	0.5	0.5	0	0	0	0	1418.02
50	400	0.75	0.5	0	0	0	0	1370.77
50	400	1	0.5	0	0	0	0	1337.01
50	400	0.5	0.75	0	0	0	0	1399.24
50	400	0.75	0.75	0	0	0	0	1325.46
50	400	1	0.75	0	0	0	0	1265.70
50	400	0.5	1	0	0	0	0	1385.19
50	400	0.75	1	0	0	0	0	1284.73
50	400	1	1	0	0	0	0	1194.03
250	50	0.5	0.5	0	1	0	0	217.34
250	50	0.75	0.5	0	1	0	0	214.95
250	50	1	0.5	0	1	0	0	209.29
250	50	0.5	0.75	0	1	0	0	211.49
250	50	0.75	0.75	0	1	0	0	211.47
250	50	1	0.75	0	1	0	0	205.85
250	50	0.5	1	0	0	0	0	174.23
250	50	0.75	1	0	0	0	0	160.61
250	50	1	1	0	0	0	0	149.25
250	100	0.5	0.5	0	1	0	0	421.06
250	100	0.75	0.5	0	1	0	0	421.35
250	100	1	0.5	0	1	0	0	413.94
250	100	0.5	0.75	0	1	0	0	415.12
250	100	0.75	0.75	0	1	0	0	414.94
250	100	1	0.75	0	1	0	0	410.55
250	100	0.5	1	0	0	0	0	348.46
250	100	0.75	1	0	0	0	0	321.22
250	100	1	1	0	0	0	0	298.51
250	200	0.5	0.5	0	1	0	0	828.93
250	200	0.75	0.5	0	1	0	0	828.48
250	200	1	0.5	0	1	0	0	823.23
250	200	0.5	0.75	0	1	0	0	822.39
250	200	0.75	0.75	0	1	0	0	821.88
250	200	1	0.75	0	1	0	0	819.93
250	200	0.5	1	0	0	0	0	696.90
250	200	0.75	1	0	0	0	0	642.44
250	200	1	1	0	0	0	0	597.01
250	400	0.5	0.5	0	1	0	0	1644.10
250	400	0.75	0.5	0	1	0	0	1643.33
250	400	1	0.5	0	1	0	0	1641.81
250	400	0.5	0.75	0	0	0	0	1592.61

b	c^{P}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
250	400	0.75	0.75	0	0	0	0	1576.13
250	400	1	0.75	0	0	0	0	1564.22
250	400	0.5	1	0	0	0	0	1393.76
250	400	0.75	1	0	0	0	0	1284.88
250	400	1	1	0	0	0	0	1194.03

G.2.2 $\tau = 2$

b	c^{P}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
50	50	0.5	0.5	0	1	0	0	206.17
50	50	0.75	0.5	0	1	0	0	206.07
50	50	1	0.5	0	1	0	0	205.20
50	50	0.5	0.75	0	1	0	0	204.65
50	50	0.75	0.75	0	1	0	0	204.52
50	50	1	0.75	0	1	0	0	204.37
50	50	0.5	1	0	0	0	0	173.41
50	50	0.75	1	0	0	0	0	159.83
50	50	1	1	0	0	0	0	148.51
50	100	0.5	0.5	0	1	0	0	409.60
50	100	0.75	0.5	0	1	0	0	409.48
50	100	1	0.5	0	1	0	0	409.41
50	100	0.5	0.75	0	0	0	0	385.23
50	100	0.75	0.75	0	0	0	0	377.24
50	100	1	0.75	0	0	0	0	371.29
50	100	0.5	1	0	0	0	0	346.59
50	100	0.75	1	0	0	0	0	319.67
50	100	1	1	0	0	0	0	297.03
50	200	0.5	0.5	0	0	0	0	762.04
50	200	0.75	0.5	0	0	0	0	749.97
50	200	1	0.5	0	0	0	0	741.47
50	200	0.5	0.75	0	0	0	0	722.13
50	200	0.75	0.75	0	0	0	0	691.78
50	200	1	0.75	0	0	0	0	667.95
50	200	0.5	1	0	0	0	0	691.02
50	200	0.75	1	0	0	0	0	639.33
50	200	1	1	0	0	0	0	594.06
50	400	0.5	0.5	0	0	0	0	1414.84
50	400	0.75	0.5	0	0	0	0	1367.71
50	400	1	0.5	0	0	0	0	1334.05
50	400	0.5	0.75	0	0	0	0	1394.42
50	400	0.75	0.75	0	0	0	0	1320.83
50	400	1	0.75	0	0	0	0	1261.26
50	400	0.5	1	0	0	0	0	1378.61
50	400	0.75	1	0	0	0	0	1278.50
50	400	1	1	0	0	0	0	1188.12
250	50	0.5	0.5	0	1	0	0	216.90
250	50	0.75	0.5	0	1	0	0	214.57
250	50	1	0.5	0	1	0	0	208.92
250	50	0.5	0.75	0	1	0	0	210.88
250	50	0.75	0.75	0	1	0	0	210.84
250	50	1	0.75	0	1	0	0	205.30
250	50	0.5	1	0	0	0	0	173.42
250	50	0.75	1	0	0	0	0	159.83
250	50	1	1	0	0	0	0	148.51
250	100	0.5	0.5	0	1	0	0	420.53
250	100	0.75	0.5	0	1	0	0	420.26

b	c^{p}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
250	100	1	0.5	0	1	0	0	413.99
250	100	0.5	0.75	0	1	0	0	413.79
250	100	0.75	0.75	0	1	0	0	413.20
250	100	1	0.75	0	1	0	0	409.44
250	100	0.5	1	0	0	0	0	346.84
250	100	0.75	1	0	0	0	0	319.67
250	100	1	1	0	0	0	0	297.03
250	200	0.5	0.5	0	1	0	0	827.41
250	200	0.75	0.5	0	1	0	0	826.97
250	200	1	0.5	0	1	0	0	821.75
250	200	0.5	0.75	0	1	0	0	820.18
250	200	0.75	0.75	0	1	0	0	819.65
250	200	1	0.75	0	1	0	0	817.71
250	200	0.5	1	0	0	0	0	693.66
250	200	0.75	1	0	0	0	0	639.34
250	200	1	1	0	0	0	0	594.06
250	400	0.5	0.5	0	1	0	0	1641.13
250	400	0.75	0.5	0	1	0	0	1640.38
250	400	1	0.5	0	1	0	0	1638.85
250	400	0.5	0.75	0	0	0	0	1588.15
250	400	0.75	0.75	0	0	0	0	1571.68
250	400	1	0.75	0	0	0	0	1559.79
250	400	0.5	1	0	0	0	0	1387.27
250	400	0.75	1	0	0	0	0	1278.67
250	400	1	1	0	0	0	0	1188.12

G.3 Failure Rate 0.001

G.3.1 $\tau = 1$

b	c^{p}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
50	100	0.5	1	0	0	0	0	102.34
50	100	0.75	0.5	0	0	0	0	94.31
50	100	1	0.5	0	0	0	0	89.54
50	100	0.5	0.75	0	0	0	0	95.70
50	100	0.75	0.75	0	0	0	0	82.86
50	100	1	0.75	0	0	0	0	74.63
50	100	0.5	1	0	0	0	0	89.96
50	100	0.75	1	0	0	0	0	72.04
50	100	1	1	0	0	0	0	59.70
50	200	0.5	0.5	0	0	0	0	177.88
50	200	0.75	0.5	0	0	0	0	160.47
50	200	1	0.5	0	0	0	0	149.18
50	200	0.5	0.75	0	0	0	0	177.39
50	200	0.75	0.75	0	0	0	0	152.04
50	200	1	1	0	0	0	0	134.30
50	200	0.5	1	0	0	0	0	176.90
50	200	0.75	1	0	0	0	0	144.07
50	200	1	1	0	0	0	0	119.40
50	400	0.5	0.5	0	0	0	0	296.46
50	400	0.75	0.5	0	0	0	0	292.74
50	400	1	0.5	0	0	0	0	268.46
50	400	0.5	0.75	0	0	0	0	295.74
50	400	0.75	0.75	0	0	0	0	290.30
50	400	1	1	0	0	0	0	253.64
50	400	0.5	1	0	0	0	0	295.07

b	c^{P}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
50	400	0.75	1	0	0	0	0	287.98
50	400	1	1	0	0	0	0	238.80
250	100	0.5	0.5	0	1	0	0	170.86
250	100	0.75	0.5	0	1	0	0	170.85
250	100	1	0.5	0	1	0	0	170.81
250	100	0.5	0.75	0	0	0	0	142.49
250	100	0.75	0.75	0	0	0	0	137.57
250	100	1	0.75	0	0	0	0	134.45
250	100	0.5	1	0	0	0	0	90.13
250	100	0.75	1	0	0	0	0	72.04
250	100	1	1	0	0	0	0	59.70
250	200	0.5	0.5	0	0	0	0	280.30
250	200	0.75	0.5	0	0	0	0	273.05
250	200	1	0.5	0	0	0	0	268.76
250	200	0.5	0.75	0	0	0	0	226.60
250	200	0.75	0.75	0	0	0	0	206.75
250	200	1	1	0	0	0	0	194.12
250	200	0.5	1	0	0	0	0	180.21
250	200	0.75	1	0	0	0	0	144.09
250	200	1	1	0	0	0	0	119.40
250	400	0.5	0.5	0	0	0	0	434.58
250	400	0.75	0.5	0	0	0	0	405.38
250	400	1	0.5	0	0	0	0	388.04
250	400	0.5	0.75	0	0	0	0	394.56
250	400	0.75	1	0	0	0	0	345.12
250	400	1	1	0	0	0	0	313.46
250	400	0.5	1	0	0	0	0	359.97
250	400	0.75	1	0	0	0	0	288.18
250	400	1	1	0	0	0	0	238.80

G.3.2 $\tau = 2$

b	c^{P}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
50	100	0.5	0.5	0	0	0	0	102.13
50	100	0.75	0.5	0	0	0	0	94.14
50	100	1	0.5	0	0	0	0	89.39
50	100	0.5	0.75	0	0	0	0	95.39
50	100	0.75	0.75	0	0	0	0	82.60
50	100	1	0.75	0	0	0	0	74.40
50	100	0.5	1	0	0	0	0	89.54
50	100	0.75	1	0	0	0	0	71.69
50	100	1	1	0	0	0	0	59.40
50	200	0.5	0.5	0	0	0	0	177.39
50	200	0.75	0.5	0	0	0	0	160.12
50	200	1	0.5	0	0	0	0	148.88
50	200	0.5	0.75	0	0	0	0	176.61
50	200	0.75	0.75	0	0	0	0	151.52
50	200	1	0.75	0	0	0	0	133.85
50	200	0.5	1	0	0	0	0	175.80
50	200	0.75	1	0	0	0	0	143.37
50	200	1	1	0	0	0	0	118.80
50	400	0.5	0.5	0	0	0	0	295.71
50	400	0.75	0.5	0	0	0	0	292.04
50	400	1	0.5	0	0	0	0	267.86
50	400	0.5	0.75	0	0	0	0	294.61
50	400	0.75	0.75	0	0	0	0	289.24

b	c^{p}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
50	400	1	0.75	0	0	0	0	252.74
50	400	0.5	1	0	0	0	0	293.56
50	400	0.75	1	0	0	0	0	286.57
50	400	1	1	0	0	0	0	237.61
250	100	0.5	0.5	0	1	0	0	170.71
250	100	0.75	0.5	0	1	0	0	170.70
250	100	1	0.5	0	1	0	0	170.66
250	100	0.5	0.75	0	0	0	0	142.23
250	100	0.75	0.75	0	0	0	0	137.33
250	100	1	0.75	0	0	0	0	134.22
250	100	0.5	1	0	0	0	0	89.70
250	100	0.75	1	0	0	0	0	71.69
250	100	1	1	0	0	0	0	59.40
250	200	0.5	0.5	0	0	0	0	279.95
250	200	0.75	0.5	0	0	0	0	272.73
250	200	1	0.5	0	0	0	0	268.46
250	200	0.5	0.75	0	0	0	0	226.02
250	200	0.75	0.75	0	0	0	0	206.25
250	200	1	0.75	0	0	0	0	193.67
250	200	0.5	1	0	0	0	0	179.37
250	200	0.75	1	0	0	0	0	143.39
250	200	1	1	0	0	0	0	118.80
250	400	0.5	0.5	0	0	0	0	433.78
250	400	0.75	0.5	0	0	0	0	404.70
250	400	1	0.5	0	0	0	0	387.45
250	400	0.5	0.75	0	0	0	0	393.33
250	400	0.75	0.75	0	0	0	0	344.09
250	400	1	0.75	0	0	0	0	312.56
250	400	0.5	1	0	0	0	0	358.29
250	400	0.75	1	0	0	0	0	286.77
250	400	1	1	0	0	0	0	237.61
250	200	0.5	0.5	0	1	0	0	827.41
250	200	0.75	0.5	0	1	0	0	826.97
250	200	1	0.5	0	1	0	0	821.75
250	200	0.5	0.75	0	1	0	0	820.18
250	200	0.75	0.75	0	1	0	0	819.65
250	200	1	0.75	0	1	0	0	817.71
250	200	0.5	1	0	0	0	0	693.66
250	200	0.75	1	0	0	0	0	639.34
250	200	1	1	0	0	0	0	594.06
250	400	0.5	0.5	0	1	0	0	1641.13
250	400	0.75	0.5	0	1	0	0	1640.38
250	400	1	0.5	0	1	0	0	1638.85
250	400	0.5	0.75	0	0	0	0	1588.15
250	400	0.75	0.75	0	0	0	0	1571.68
250	400	1	0.75	0	0	0	0	1559.79
250	400	0.5	1	0	0	0	0	1387.27
250	400	0.75	1	0	0	0	0	1278.67
250	400	1	1	0	0	0	0	1188.12

Appendix H Results Traditional Manufacturing

H.1 $\tau = 1$

b	c^{p}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
50	100	0.5	0.5	0	0	0	0	141.03
50	100	0.75	0.5	0	0	0	0	127.28
50	100	1	0.5	0	0	0	0	119.09
50	100	0.5	0.75	0	0	0	0	137.99
50	100	0.75	0.75	0	0	0	0	117.43
50	100	1	0.75	0	0	0	0	104.21
50	100	0.5	1	0	0	0	0	135.35
50	100	0.75	1	0	0	0	0	108.13
50	100	1	1	0	0	0	0	89.31
250	100	0.5	0.5	0	1	0	0	260.09
250	100	0.75	0.5	0	1	0	0	260.06
250	100	1	0.5	0	1	0	0	259.88
250	100	0.5	0.75	0	0	0	0	259.31
250	100	0.75	0.75	0	0	0	0	259.21
250	100	1	0.75	0	0	0	0	259.18
250	100	0.5	1	0	0	0	0	222.09
250	100	0.75	1	0	0	0	0	213.67
250	100	1	1	0	0	0	0	208.00

H.2 $\tau = 2$

b	c^{p}	p	q	B	I	$\mathbf{z}$	$\mathbf{w}$	Value
50	100	0.5	0.5	0	0	0	0	114.86
50	100	0.75	0.5	0	0	0	0	108.24
50	100	1	0.5	0	0	0	0	104.32
50	100	0.5	0.75	0	0	0	0	101.59
50	100	0.75	0.75	0	0	0	0	89.66
50	100	1	0.75	0	0	0	0	82.03
50	100	0.5	1	0	0	0	0	90.12
50	100	0.75	1	0	0	0	0	72.08
50	100	1	1	0	0	0	0	59.70
250	100	0.5	0.5	0	1	0	0	171.47
250	100	0.75	0.5	0	1	0	0	171.44
250	100	1	0.5	0	1	0	0	171.05
250	100	0.5	0.75	0	1	0	0	170.76
250	100	0.75	0.75	0	1	0	0	170.68
250	100	1	0.75	0	1	0	0	170.66
250	100	0.5	1	0	0	0	0	90.30
250	100	0.75	1	0	0	0	0	72.08
250	100	1	1	0	0	0	0	59.70