# Optimising the ordering and inventory process for an efficient workflow in machine manufacturing

MASTER THESIS – PRODUCTION AND LOGISTICS MANAGEMENT

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# Research information

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Optimising the ordering and inventory process for an efficient workflow in machine manufacturing

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# Preface

Dear reader,

The paper you have in front of you is my master's thesis, and the final examination of my study Industrial Engineering and Management. After about 6 years, this marks the end of my life as a student, and my life in Enschede. I am grateful for the years of studying and living I had in Enschede and have never considered any other way.

I would like to thank my first supervisor Dennis Prak. Dennis was also my first supervisor for my bachelor's thesis, and I enjoyed that so much that I wanted to do it again. Dennis was always open for brainstorming when I got stuck, and never failed at getting me to be a bit more optimistic. Of course, I would also like to thank my second supervisor Matthieu van der Heijden, for the detailed feedback and the additional perspective.

Next to that, I would also like to thank Laurens Maatje and Ton Eijsermans, the purchasing department at IMS. They provided me with the necessary practical information and were always happy to help. This made it easier to work but also enjoy my time at IMS.

Last, but definitely not least I would like to thank my friends and family for supporting me during this research. By listening to me when things got hard or distracting me when necessary. I would especially like to my roommates, who had to suffer me through the toughest period of my graduation, and who lent their laptops to me when I needed it the most.

This thesis would not have been possible without any of you!

Marrit Flach

Enschede, October 2024

# Management summary

This research was performed at IMS in Almelo. IMS is a manufacturer of high-quality machines, typically for product line development or high-precision assembly processes. Historically, IMS has built machines on a project basis, referred to as Customized Solutions. However, they now want to become an OEM for a specific type of machine, namely their HP-Molder, a glass moulding machine. By becoming an OEM, they hope to generate a steadier level of work in the workplace, as well as a steadier turnover. To do this, they would like to know how to structure their ordering and inventory process, as they do not typically keep inventory and just order components when the engineering department releases them. The main research question is therefore determined to be:

***"How can IMS best structure their ordering and inventory processes to realize their OEM goal and minimise holding, ordering and penalty costs?"***

Currently, IMS orders long lead items early on, sometimes even during the design phase, but there is no clear idea of when to order which component. All other components are generally ordered whenever they are released by the engineering department, but not in a structured way. This way of ordering results in inefficiencies, a lack of overview, and additional urgency-driven communication between the engineering and purchasing department. Furthermore, they usually deal with highly variable lead times.

The literature review explores the academic landscape on assembly processes and multi-item inventory systems. This shows that it is generally quite hard to obtain an optimal solution due to the large solution space and interdependencies. Simpler solutions such as heuristics and simulation can provide satisfactory results with lower computational time. Also, the value of safety lead time to combat lead time variability is highlighted. To explore how IMS can best structure their ordering and inventory processes while minimising costs, it is decided to use a simulation optimisation model, with an optimisation heuristic. The idea of this optimisation is to decide when to order which component. From an initial solution, algorithm will compare the effects on order, holding, and penalty costs, by changing order dates by a week (5 working days). In this way, a good solution can be found in a relatively quick and understandable way.

To decrease the size of the solution space, components are clustered. It makes the most sense to cluster components of the same supplier together, as these are assumed to have the same lead time distribution anyway, and this should decrease the number of orders. A heuristic, inspired by literature on multi-item lot sizing was therefore created to form clusters of suppliers. The idea of these clusters is to group components from the same supplier that should arrive at the same time. The number of orders, i.e. clusters, was limited to five per supplier. This led to 119 clusters in total.

Three Base Solutions were devised to serve as a starting point for analysis.

- Base Solution 1: Deterministic lead time assumption
- Base Solution 2: 'Smart' starting solution
- Base Solution 3: Start assembly

Base Solution 1 orders each cluster only the mean lead time before they are supposed to arrive. Base Solution 2 attempts to be a bit safer and orders each cluster the mean lead time plus twice the standard deviation before they are supposed to arrive. Base Solution 3 is even more cautious and wants all clusters to arrive before the start of the assembly process, and also orders all components the mean lead time plus twice the standard deviation before the required date. This therefore leads to only 65 clusters, namely one for each supplier. Using the simulation, these Base Solutions were evaluated. These results are not that good yet, even in the best performing Base Solution (3), final assembly is on average 58% too late. Therefore, Base Solution 2 and 3 were also simulated using higher values for the standard deviation for the safety lead time. This showed that Base Solution 2, with a safety lead time of four standard deviations performs significantly better than with two standard deviations. The average total costs reduce from 1582 thousand to 1476 thousand. This shows that there are some clusters for which the simple rule of thumb is less appropriate. However, the rule of thumb does perform quite well already.

Sensitivity analysis was done to investigate the effects of changing variables. As the lead time variability plays a significant role, the simulation was used to investigate different settings for the lead time variability. This showed that even a 20% reduction in lead time variability could reduce the average total costs from 1476 thousand to 1128 thousand. In this case, the safety lead time would be the mean lead time plus three times the standard deviation. Also, limiting the number of orders was investigated, as IMS would like more structure in the purchasing department. This showed that the order dates that resulted from the optimisation method could be brought back down to 36, by combining order dates that fall in the same week into one order date. This also led to just slightly higher costs, which is promising to keep the number of orders to a minimum.

The research results into the following conclusions for IMS:

1. Using a safety lead time of the average lead time plus four times the standard deviation of lead time provides the best result when using one common 'rule of thumb' for all clusters.
2. The effect of lead time variability complicates the search for an optimal solution. The number of replications needed to accurately search neighbour solutions is too high.
3. Some clusters benefit from a more 'targeted' approach than one rule of thumb for the safety lead time. These are clusters that are needed later in the assembly sequence, clusters that have a high lead time variability and clusters with a high component value. These clusters should have a lower safety lead time, using generally between 3-3.5 standard deviations.
4. Lower lead time variability reduces costs quite significantly.
5. Limiting the number of order dates to 10 is possible, if IMS is willing to sacrifice lower costs for more overview in the purchasing department.

Based on these conclusions, the following recommendations are presented to IMS:

1. Create planning based on safety lead times

To improve the efficiency and effectiveness of the purchasing department, the purchasing department should make a planning using the average lead time plus four times the standard deviation as safety lead time. For clusters late in the assembly process, as well as clusters with highly variable lead times and high components values, the safety lead time should be slightly lower, between 3 and 3.5. When deciding on order dates, attention should be paid to combining order dates if they are reasonably close. This makes the planning less chaotic and the purchasing department more specific.

2. Registering lead time data

As the quality and lack of data heavily influenced this research, it is important to have a better understanding of the lead times to incorporate safety lead times. If these registered dates were more accurate, the lead time distributions would be more accurate, and the value of the solution would better represent reality.

3. Reduce lead time variability

Reducing lead time variability is the simplest way to further bring down costs. This could also improve the value of the solution and give more certainty on costs.

4. Decreasing the supplier base

Ims could also investigate decreasing the supplier base, as this would make ordering more efficient. Furthermore, this could strengthen supplier relationships, as there are less suppliers to focus on, which in turn could positively impact lead time variability.

# Contents

# 1 Introduction

This report details the research undertaken at IMS, a machine manufacturer. The aim of this research is to provide recommendations on how to structure the ordering and inventory process to best support machine assembly at the workplace. With the use of a simulation, various scenarios and settings are evaluated. Optimisation algorithms are used to determine the best dates for ordering components.

This chapter provides an introduction to this research. Section 1.1 provides a more detailed introduction of the company. Section 1.2 provides the research context and motivation of this research. Section 1.3 outlines the problem identification. Section 1.4 provides the research design.

## 1.1 Company introduction

Integrated Mechanization Solutions (IMS) is a machine manufacturer located in Almelo. IMS started as the mechanisation department of Texas Instruments (probably best known for their calculators) but they separated from them in 1999 after a management buy-out. Since then, they have grown considerably. In 2001 they got their current facility in Almelo, which they expanded on in 2011. They have an experienced team of about 130 engineers and a loyal customer base all over the world, with for example customers in Mexico and China.

IMS builds high-precision machines and is always looking to help improve production processes for their customers. They specialise in product line development and precision processes for very small and complex products. They design and produce machines from semi-automated machines to fully automated machines to unmanned production lines. Their expertise is applicable to several industries; namely the medical, automotive and smart devices industry.

Historically they have mostly built so-called ‘Customized Solutions’, in a project-based way of working. These are machines that are requested by a customer for a particular manufacturing process, for which IMS will design a machine. This can be both for low and high-volume companies. IMS’ specialties include plasma cleaning, surface inspection, laser cutting, high-accuracy positioning, micro-optics and fibre alignment. For Customized Solutions, their installed base currently consists of more than 750 machines.

IMS is part of IMS Holding, which also consists of another company, PSE. PSE (Precision Systems Engineering) is another expert in high precision and complexity that became part of IMS Holding in 2021. PSE is located in Poland. As IMS’s specialty is the design of complex machines, they often collaborate with other companies to outsource the assembly process there.

## 1.2 Research context and motivation

With ‘Customized Solutions’, the process at IMS includes a design phase, as the customer is requesting a ‘new’ product, which IMS has to design. When a customer orders a ‘Customized Solution’, IMS will typically start with 1 or 2 prototypes, which will usually take about a year. The purchasing for these prototypes is done based on the design release. Most parts will therefore only be ordered once the design phase is completed.  As soon as the concept has been approved, risk items (which in this case usually means long lead items) can already be ordered in consultation with the customer. This means that in the case of ‘Customized Solutions’, it is not desirable to hold much inventory, as demands for specific components are only known after the design is approved. Also, machines can be quite different between different project, which results in a small number of common parts.

More recently, IMS has been focusing on the direction of becoming an OEM (Original Equipment Manufacturer) for some machines (advertised as Standardized Solutions). In 2024 they will start with 1 to 5 so-called “demonstrators”. Around 2025 they hope to advance to series production. Customers should then be able to order these products immediately. There is therefore no (or a limited) design phase. This should limit the customer order lead time as well, as the design phase normally is a significant part of this. IMS do not currently have a target customer order lead time, as too much is still unknown for Standardized Solutions.

A reason for IMS to start emphasising OEM, is to maintain a balance in the amount of work in the workplace (where the machines are built). As they are originally a project-based company, the workflow deals with ups and downs, based on the number of projects. They could use the generated work from the OEM requests to fill the downs and to make the best use of the (limited) employee availability. Also, an added reason for IMS to focus on becoming an OEM supplier is to generate a yearly higher turnover.

The production of an OEM product could therefore be more standardised. This shift corresponds to a shift in the customer order decoupling point (CODP). The current way of working of IMS corresponds to an Engineer-To-Order supply chain, where the customer is fully involved in the specification of the machine, and the whole process is dependent on this. With their step into the OEM direction, IMS wants to shift the CODP more downstream in the supply chain, towards Make-To-Order.

However, their way of working (at least as visualised for the sake of this thesis) differs a bit from traditional ATO or MTO, as they will work based on a planning, and not in response to a customer order. The actual way of working for OEM is uncertain, as it is not decided yet how IMS will structure this, and it is also dependant on other factors, such as the market and the future direction of the company. But for the sake of this thesis, the way of working is planning-based. This means that a date is determined that a machine has to be completely finished, then a planning is devised based on that, and materials are ordered based on this planning. As the time between production cycles is currently unknown, and IMS will also keep making Customized Solutions, ordering will just be done for one production cycle, i.e. one machine or multiples of this one machine in parallel.

A specific machine that IMS wants to become OEM of, is their high-precision glass moulding machine, the HP-Molder. This machine can shape glass according to complex and specific customer specifications. It can be used to mould glass lenses. IMS currently offers the highest quality of glass moulding available. That is why they want to become an OEM for this machine. Currently, they only sell this machine to one specific customer, but they have sold several hundreds of this machine to them and feel it is a valuable product. That is why they are also exploring other potential customers, and the market seems promising. As previously mentioned, becoming OEM requires shifting the CODP. As IMS feels they are unfamiliar with this way of working, they would like to gain more insight into the ordering and inventory process for parts for manufacturing for an Assemble-To-Order supply chain, and specifically how best to structure it so machine assembly can be done as efficiently as possible. Demand is assumed to be large enough that everything that is produced can be sold. This is however dependent on the sales department.

## 1.3 Problem identification

This section details the research plan of this report. Section 1.3.1 provides further insight into different aspects of the research problem. The core problem is explained in Section 1.3.2.

### *1.3.1 Research problem*

As IMS wants to move into new territory with becoming an OEM supplier, they are interested in how to structure their ordering and inventory process. The current way of purchasing leads to several issues, which are further explained in this section.

As IMS builds large and complex machines, they need many different types of components. Some components are more common, such as for example some standard screws, washers or cables and are featured in many products that IMS produces. All of these standard products are classified as floor stock (grijpvooraad) and are generally checked once a week by the logistics employee and then ordered if necessary. Most components, however, are not that common, as they are only used in a specific machine which is maybe produced two or three times. A lot of components are designed by IMS themselves, with high specifications, and then a supplier has to be found who can make it. Therefore, the number of components that is regularly ordered is not that high, but the number of different components that IMS uses is quite high. This also results in a large supplier base. In their ERP system, there are 2032 suppliers listed. This also contains suppliers that they do not order from anymore, and some suppliers are listed twice, this results in a very cluttered supplier base. In practice, this currently leads to a lot of suppliers that they have only ordered from once, and a small group of suppliers that they order from very often. For the group of suppliers that they order from often, this leads to a high number of orders. As every single order leads to order costs, there is room for reducing order costs through reducing the number of orders at a supplier. Also, placing an order costs IMS money in terms of for example employee costs. Furthermore, a machine easily consists of a thousand different components, which also results in a high number of orders.

IMS also copes with long and especially variable procurement lead times. The COVID-19 crisis highlighted this issue. Machine assembly was halted because components were not available. Changes in lead time were also not always communicated clearly by suppliers. To combat these long lead times, IMS decided to put some (presumed) long lead items in inventory, but this has vastly increased inventory value, and not had the desired effect as of yet.

Some of the components that IMS orders are very high in value, due to the fact that they are highly specialised. If these components are ordered without a clear idea of when they are required, this could potentially lead to high holding costs. It is also not that desirable for IMS to hold too much inventory, as space is limited.

Furthermore, quality imposes an issue. The machine is high quality, so high quality components are needed. However, suppliers cannot always completely comply with the quality requirements of IMS, which results in components that cannot be used.

### 1.3.2 Core problem

The core problem lies in the fact that IMS wants to become an OEM for the HP-Molder, and therefore wants to shift the CODP, but this requires a slightly different approach than the one they are currently using. The purchasing department wants to know how they should structure their ordering and inventory process to become an OEM for the HP-Molder, but they want to limit total costs. The structuring of the ordering and inventory process mainly comes down to making informed decisions about when to order components, in a way that the number of unnecessary orders is kept to a minimum. Also, IMS would like to know whether there are components for which it is a good idea to keep inventory.

Furthermore, there are some interesting trade-offs to be considered. In an ideal world, if IMS knows when they want to finish assembly of the complete Molder, they can determine when they want to start each subassembly step. From this, they can also determine when they need which component. If lead times were deterministic, they would know exactly when to order. However, lead time variability is one of the biggest issues that IMS is currently facing. There is however some idea of when to order, as it is likely not desirable to order every day, as this increases (order) costs significantly. Also, high holding costs are not desirable, but neither is delay in the assembly process due to components arriving late. Another trade-off is that combining orders at suppliers could also reduce costs. These trade-offs combined come down to when each component should be ordered.

## 1.4 Research design

This section details the research design. Section 1.4.1 provides the scope of this research. Section 1.4.2 introduces the main research question, and the sub-questions needed to answer the main research question.

### 1.4.1 Research scope

The scope of this research is the aforementioned High Precision Molder (HP Molder), as IMS feels this machine has a lot of potential on the market and they are an expert in this field. Optimisation of the assembly process itself is left out of the scope, as IMS often works together with other companies for the assembly of machines. The duration and structure of the assembly process is therefore assumed to be fixed. Furthermore, capacity is assumed to be available on the work floor.

Spare parts for maintenance are out of the scope, as this is still a relatively new field within IMS and is generally not their focus. Therefore, the amount of data available on spare parts is too limited. Quality issues are also determined to be out of the scope, as there is simply not enough available data.

The focus of this research is determining when to order which component. Therefore, optimisation of order quantities is left out of the scope. Also, each component will only be ordered once, even if they are needed in different stages of the assembly process. This decision follows from the preference to keep the number of orders limited, to provide more structure. If a high number of a component is needed, this generally concerns a component of smaller value, and these often have to be ordered in higher quantities at the supplier due to a minimum ordering quantity (MOQ). It is therefore decided that the easiest way to handle this, is to leave quantity decisions out of the scope and order each component once for the quantity that is needed (or the MOQ) if this is larger. Also, as mentioned before, the research focusses on optimising the order moments for one production cycle.

As IMS has a large supplier base, mainly because they need a lot of specialised products, supplier selection is also interesting. However, it is left out of the scope of this research, because for most components there is not enough information on where they could be ordered from. For some components however, it could be interesting to investigate the effects of buying directly from the manufacturer or from a wholesaler, as this introduces trade-offs in lead time and costs.

### 1.4.2 Research questions

As IMS currently lacks the knowledge of how best to structure the ordering and inventory process for becoming an OEM supplier, the main research question of this report is the following:

***"How can IMS best structure their ordering and inventory processes to realize their OEM goal and minimise holding, ordering and penalty costs?"***

To answer the main research question, the current situation at IMS should first be explored. Next to that, the current academic landscape also needs to be explored, as this provides existing policies and solutions that might help shape recommendations for IMS. This provides input on the method that will be used to find a solution. The effects of different settings are analysed to investigate the effects on the costs. To guide this process, several sub-questions have been created, which are explained in this section.

1. What is the current situation at IMS?
    a. What does the current ordering and inventory process look like?
    b. What does the BOM of the HP Molder look like?
        i. What type of components are there?
        ii. Who are the suppliers?
    c. What do the lead times look like (in length and variability)?
    d. What do the order/transport costs look like?

These questions are answered in Chapter 2. The data needed to answer these questions, is extracted from the ERP and PLM systems that IMS uses. They have been using the ERP system Trimergo since 2017, and the PLM systems Windchill since about 2 years. Information about quality compliance, however, is not registered in either of these, and insight into this issue is obtained by consulting with the purchasing department.

2. What models and ideas exist in literature to help structure the ordering and inventory process at IMS?
    a. What inventory models exist for an assembly manufacturing company?
    b. What joint ordering models apply?

    c. How can uncertainties like lead time best be taken into account?
    d. What simulation optimisation methods are most suitable?

These questions are answered in Chapter 3 by way of a literature review. The goal of this is to find relevant methods and ideas that are used in a similar situation, and which can help shape the research method.

3. How should the model be designed?
    a. How should components be clustered to decrease the solution space?
    b. How should the simulation model be designed?
    c. How should the optimisation models be designed?
        i. What is a good initial solution?
        ii. How are neighbour solutions generated for the optimisation models?

The design of the simulation model and the optimisation algorithms are explained in Chapter 4.

4. What is the impact of different scenarios on the machine assembly and costs?
    a. What insights are provided by the simulation?
    b. What is the effect of lead time variability?
    c. What is the effect of limiting the number of order dates?

The results of the simulation optimisation model are discussed in Chapter 5. Various model settings are explored, and a sensitivity analysis is also performed.

5. What are the conclusions and recommendations that can be made regarding this thesis?
    a. What are the main conclusions?
    b. What are the main recommendations for IMS?
    c. What are the limitations of this research?
    d. What are interesting directions for further research?

These questions are answered in Chapter 6.

# 2 Context analysis

This chapter details the context analysis of the problem at IMS. Section 2.1 describes the current ordering and inventory process. Section 2.2 gives a more in-depth introduction to the HP-Molder and the building process. Section 2.3 provides an overview of the components that are in the Molder. Section 2.4 provides insight into lead times. Section 2.5 shows the order costs. Section 2.6 concludes this chapter.

## 2.1 Ordering and Inventory process

This section explores the current ordering and inventory process at IMS. In theory, a project at IMS runs through predetermined phases as shown in Figure 1.

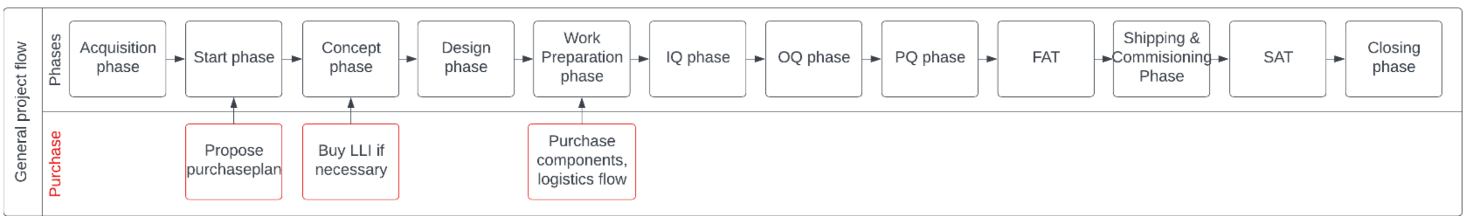



*Figure 1: General project flow*

*Table 1: Legend of Figure 2*

| Abbreviation | Meaning |
|---|---|
| LLI | Long lead items |
| IQ | Installation Qualification |
| OQ | Operational Qualification |
| PQ | Performance Qualification |
| FAT | Factory Acceptance Test |
| SAT | Site Acceptance Test |

At the start of the project, a purchase plan is proposed. In the next phase, possible LLI (long lead items), are already mapped and ordered if necessary. The number of LLI per machine is highly variable, and the components are not always registered as LLI in the ERP system. LLI are items that have historically had long lead times or are known to vary in lead times, such as lasers, robots, big purchase components, conductors, and certain motors. In general, 10 weeks is considered to be ‘long’. As the concept phase is before the design phase, this concerns items that are expected to be in the machine according to the engineers. This is often about 10 weeks before the technical drawings are released, but this is not a fixed number. There is a risk associated with this, as it is never completely sure what components are long lead items. Items that are expected to be long lead items may actually be delivered quickly, whereas other components turn out to be long lead items even though they were not expected to be. Also, it is possible that components from an early design turn out not to be required in the final design, or the number that is required is higher or lower, but they have already been ordered. This can lead to obsolescence or too much inventory.

Identified LLIs are then ordered on an LLI project, from which they will later be moved to the corresponding project. Due to recent problems with lead times, such as COVID-19, and a high workload, project managers fear that everything is a long lead item. They will then check when these items will be delivered. If problems arise, they will check if they can find an alternative, or if they need to move the planning.

Meanwhile, engineering is still working on the design and the technical drawings. When most drawings (until a certain level) are released, the 'planner' (werkvoorbereider in Dutch), will plan a meeting with the project team (consisting of the lead engineers, and sometimes the project manager) to discuss how to execute the purchasing. For this, there is a template, which consists of items to discuss.

These are the following:

1. Order as material or BOM? If it is ordered as BOM, then this will be assembled elsewhere. If it is ordered as material, IMS will assemble it themselves, i.e. it is either on order or to stock.
2. Amounts (keeping inventory, rejection, spares, etc. in mind)
3. Special components (wear-and-tear, adjustments, tooling, etc)
4. Long lead items
5. Desired delivery date
6. Extra treatment (brazing, cleaning, etc.)
7. Design changes
8. WBS structure

If all drawings are released, the planner will further design the WBS (work breakdown structure) in the ERP system. The purpose of the WBS is to create a structure for the logistics department and the builders. The design of the WBS ensures that components are put into the corresponding boxes and that these boxes do not overflow. A system integrator (builder) can then grab a box, and the box contains all the necessary components for the task at hand. After designing the WBS, the BOMs will be put under the right WBS code. The planner will also check if any of the components are currently in stock. All components that actually should be ordered, with the necessary amounts, are then released for purchasing. The planner will inform the purchasing department and project team, and the purchasing department will purchase the required components.

Ideally, the purchasing department would then order for the complete machine at once. There would then be only two order moments, as the long lead items are ordered in advance. In practice, however, this is usually not the case and is often done per subassembly. For a big machine, there may be a lot more order moments, an estimate (by the purchasing department) was that it can be close to 40. This is because project managers fear everything is a long lead item, and this results in a lot of email to the purchasing department about what needs to be purchased, often with a high urgency. This leads to inefficient purchasing and a lack of overview. Also, the conclusion can be drawn that the engineering department does not have an accurate impression of the way of working of the purchasing department, and this adds to the inefficiency.

As building the HP-Molder as an OEM is new terrain, and not currently being done, it is not possible to provide a performance measurement of the desired way of working.

## 2.2 HP-Molder

This section details the various aspects of the HP-Molder. Section 2.2.1 describes the design, Section 2.2.2 describes the assembly process.

### *2.2.1 Design*

As mentioned in Chapter 1, this research will focus on the HP-Molder. The HP-Molder is a long-standing development within IMS, together with their customer. The generation they are currently working on is already the third. This is because the technology is still developing, in part due to customer wishes, but also because it is an emerging field. Also, the basis of the Molder can be used for other purposes, and different customers. The design is modular and can thus be configured for different customer wishes. This is useful for IMS' wish to become an OEM.

The design of the Molder, however, does still vary because of the aforementioned topics. There are also still possible improvements to be made for the Molder. This research is based on the design of May 2024, so it is possible that in the final design there are some changes. A current overview of the structure of the different subassemblies of the Molder is shown in Appendix A.

### *2.2.2 Assembly process*

Due to the modularity in the design of the Molder, IMS can also build according to these different steps. The assembly process consists of 32 different subassembly steps. Ideally, the building of a specific subassembly will not start until all components that are needed are available. As assembling is paired with testing and certain subassemblies need to be built into other subassemblies, a sequence of assembling can be made. Due to the sequencing, IMS also prefers to finish building a subassembly before they move on to the next one, as building can be quite complex. Switching between building different subassemblies is therefore less efficient, as it requires switching between different tasks and therefore costs extra times. Also, it is preferred by the system integrators to finish a subassembly before moving on.

The planning for the building is made based on when it needs to be delivered to the customer. From there one can make assumptions about how long each subassembly will take, and so one can backwards engineer a planning. This also means that not all components have to be available at the start of the assembly process. For example, a component that is only required in the latest subassembly step can also arrive later than a component that is needed in the first subassembly step. And most likely, this is also preferred, as it is generally desirable to limit holding costs. Therefore, it is essential to know which components should be ordered when, to limit holding and delay costs. Also possibly order costs, if orders can be placed on the same day.

## 2.3 HP-Molder components

This section provides insight into the components of the most recent design of the HP-Molder.

### *2.3.1 Types of components*

The Molder consists of 1086 different components. These components all have an article type (even though one type is 'unspecified'. The most common ones are shown in Table 2.

*Table 2: Article types in Molder*

| Article type | Articles in Molder |
|---|---|
| Fasteners | 297 |
| Machining | 235 |
| Pneumatics | 140 |
| Sheet Metal | 118 |
| Vacuum | 71 |
| Connectors | 25 |
| Glanding | 17 |
| Positioning and Fixating | 15 |
| Sensors | 14 |
| Ducts | 14 |
| Cables | 13 |
| Safety Components | 13 |
| Electrical Cabinet Components | 12 |
| Bearing and Guiding | 11 |
| Sealing | 10 |
| Unspecified | 10 |
| Optics | 10 |

Of these, 155 components are classified as 'floor stock' (grijpvoorraad in Dutch). The inventory of these components is separately moderated by the logistics employee through a 2-bin system and can be assumed to always be in stock. Most of these components are fasteners, some are pneumatics parts and some are electrical cabinet components. These will not be considered in the analysis. This leaves 931 components. Some of these are removed, because they are of low importance to the analysis, such as warning stickers and labels, or there is no information available at all. This leaves 916 components.

Of the remaining 916 components, 419 have been ordered previously by IMS based on article number. An important side note here is that the IMS article numbers are still fairly new. Previously, article numbers were mostly specified just by whether they were 'make' or 'buy' parts. Of the 497 components that have not previously been ordered (as far as can be seen based on article number), 219 components are make parts. These are parts (in this case specified by article type 'sheet metal' or 'machining'), that must be made by a supplier based on the technical drawing from IMS. As these were usually specified by article number 'make parts – type' in the ERP system, there is no accurate data present. Recently however, the purchase department has started to use article numbers for these make parts as well. This could in the future lead to more accurate data for lead time analysis.

### 2.3.2 Molder suppliers

The components outlined in Section 2.3.1 can be linked to suppliers. These suppliers were either specified in the BOM by the engineers or found in the ERP system based on historic order data for the article number or the name of the component. Here it is important to note that there are certain components (for example of type 'fasteners') that can be ordered at the manufacturer itself, or at a wholesale supplier. This causes some components to have multiple alternatives for suppliers. When ordering, the supplier choice is made by the purchaser based on the circumstances, mostly based on their experiences. However, generally the price at the wholesaler is higher and the lead time is slightly shorter. Also, if more components can be ordered at the wholesaler, this decreases the total number of orders and therefore order cost.

For the 'machining' make parts, it is not yet possible to definitively determine which supplier will produce what part for IMS, as this requires a procurement process and is judged based on quotations. For this reason, a list of the most used suppliers for make parts was created, and these are ranked on quality and price. These can then be assigned to the 'make parts'. In reality, this of course requires the expertise of the purchasers. All 'sheet metal' make parts will be produced by one supplier, as they currently only have one supplier for this. IMS is looking to add another to the portfolio. This leads to a list of 65 suppliers in total for analysis.

The number of components supplied by the same supplier is quite variable. There are a lot of suppliers that only supply a handful of components, say 1-10 components. Then there are some suppliers that supply a large number of components, up to 130 by one supplier. An overview of this can be seen in Table 3.

*Table 3: Number of components per supplier*

| Number of components | Number of suppliers to supply that number of components |
|---|---|
| 0-10 | 48 |
| 11-20 | 5 |
| 21-30 | 2 |
| 31-40 | 3 |
| 41-50 | 1 |
| 51-60 | 1 |
| 61-70 | 1 |
| 71-80 | 1 |
| 81-90 | 1 |
| 91-100 | 0 |
| 101-110 | 0 |
| 111-120 | 1 |
| 121-130 | 1 |

## 2.4 Lead times

Through the data available in the ERP system, historic lead times were analysed to specify lead times for the Molder components. Several issues complicated this. The order date in the ERP system is not always equal to the actual order date. For make parts, this is often (but not always) the date that a request for quotation was first sent. For buy parts, it is more often equal to the order date, especially when an order is placed through a webshop. Otherwise, there might be time between registered and actual order date due to waiting on quotations as well. Also, the date of receipt is not always accurate or present. Especially if changes are made to the order in the ERP system, for example in quantities. It also occurred that the order date was equal to the delivery date. These orders were excluded from the analysis.

The analysis provided estimates for the average lead time (in working days), and a standard deviation. For some suppliers these will be better estimates due to a higher number of orders. The analysis mostly showed the high variability in lead time that IMS has experienced. An example of one of their key suppliers is shown in Figure 2. The blue bars show the actual values that were extracted from the ERP system. As can be seen, even during periods of increased lead times, it occurred that the lead times were shorter. The orange line however, shows the lead times as they were perceived by IMS, according to the purchase department. The blue bars in Figure 2 show that even in the period that their lead times were exceptionally high (second half of 2021 to beginning 2023), some orders had a low lead time. This is due to the fact that they were experiencing quite some delay on the work floor due to these increased lead times. This shows a discrepancy between reality (at least according to the registered data in the ERP system) and what the impact it had on IMS. This also goes to show that actual insight and awareness of variability in procurement lead times is lacking within the purchase department.

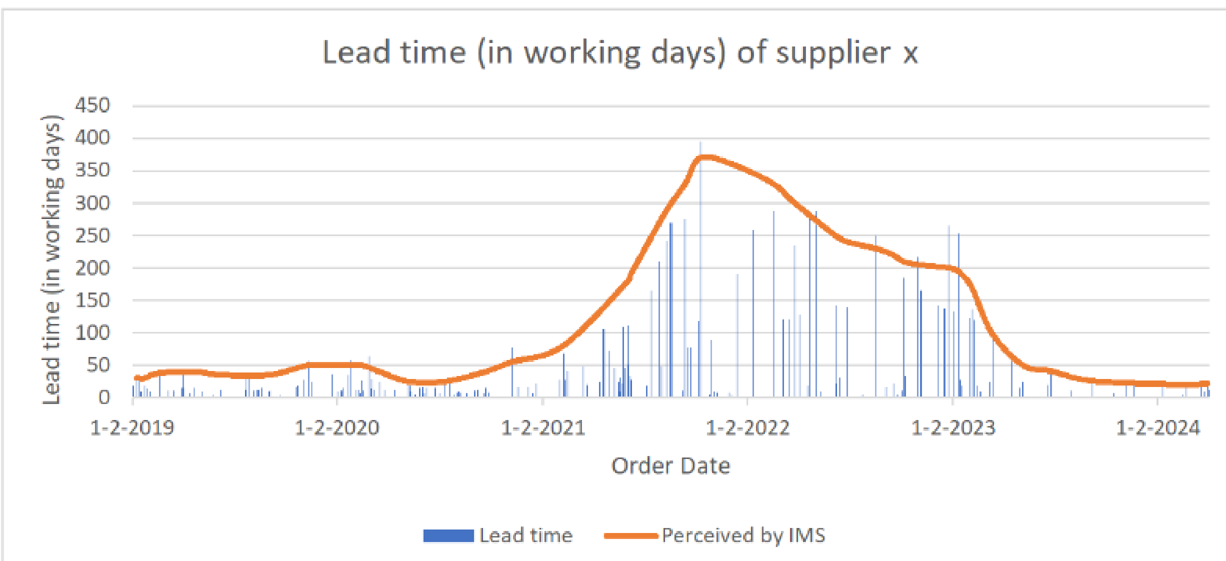



*Figure 2: Lead time (in working days) of supplier x*

Only 419 of the 917 components have been ordered previously according to the ERP systems, but the question is how accurate this data is. Also, this leaves 498 components with no historic lead time information. Of course, it would be desirable to determine a lead time estimate for every single component, but with no information these would merely be estimates, and it is questionable how useful this would be for analysis. There is slightly more order data based on suppliers. Therefore, it is possible to determine lead time averages and standard deviations for each supplier, these can be found in Appendix B. Here, it is once again important to note that it can be questioned how accurate these are due to the unreliability in data quality and inaccurate storing in the ERP system.

The characterisation of the lead times can be found in Table 4 and Table 5.

*Table 4: Characterisation of mean lead time*

| Minimum mean lead time | Maximum mean lead time | Average mean lead time |
|---|---|---|
| 5.14 | 140.10 | 27.47 |

*Table 5: Characterisation of standard deviation of lead times*

| Minimum standard deviation | Maximum standard deviation | Average standard deviation |
|---|---|---|
| 1.50 | 95.37 | 21.47 |

## 2.5 Order costs

Also, an analysis for transport and order costs was done. This mostly showed that transport costs are not always clearly defined in the orders, and they are highly variable. The purchasing department does usually also not know the transport costs in advance. In the case of make parts, it is generally based on the weight of the component, especially when they are ordered from a supplier in China. They do often provide an estimate at quotation. The complete process of sending out an order at IMS costs the company about 100 euros, in terms of overhead, employee costs, and other cost items.

For all 65 of the suppliers considered for the analysis, fixed order costs were determined. The values consist of the average value that was found after data analysis of the data in the ERP system, where transport and order costs are combined, and now just referred to as 'order costs'. The fixed order costs are assumed not to depend on order size or the number of order lines within an order. It is known that for some suppliers this is not completely accurate, but as there is no data on which this can be based, this assumption is made. The fixed order costs generally do show some indication of the geographical location of the supplier. Especially the suppliers from China have a larger fixed order cost. A complete overview of all supplier characteristics can be found in Appendix B: Supplier characteristics.

## 2.6 Conclusion

The current ordering and inventory process at IMS is not necessarily suitable for producing the HP-Molder as an OEM. There can be a lot of different orders, and this leads to inefficiency in assembly, as well as introduces holding and/or delay costs. The exact extent of this is not known, as it concerns a future direction that IMS would like to move to. It is however known that at one point the value of their inventory was well above a million in product value, and this is something that they would like to prevent.

Furthermore, there are issues regarding lead time. To combine all aspects into a simulation optimisation model to find order dates for each component that minimises costs, it is required to know how best to build such a model, what methods are available to use, and how to optimise. Chapter 3 therefore explores methods to model the assembly process, specifically for multi-item systems, methods for supplier selection, how to handle lead time uncertainty and what methods can be used to combine all these and evaluate all these dependencies.

# 3 Literature Review

This chapter explores the available theories and methods in literature. In Chapter 2, several issues were highlighted, namely the highly variable lead times and the need for a model to optimise the ordering. Section 3.1 reviews the theory on inventory management in manufacturing, specifically for assembly processes. Section 3.2 discusses theory on handling multiple suppliers. Section 3.3 describes several approaches handling lead time uncertainty. Section 3.4 discusses relevant theory on using simulation combined with optimisation algorithms as a tool for finding a solution.

## 3.1 Inventory management in assembly manufacturing processes

This section takes a closer look at inventory management, specifically for manufacturing systems. This section is meant to position this research in the literature landscape. Section 3.1.3 reviews the relevant theories specifically for assemble-to-order systems. Section 3.1.3 describes methods used for modelling an assembly process. Section 3.1.3 reviews several multi-item inventory management methods.

### *3.1.1 Assemble-to-order*

Assemble-to-order (ATO) systems consist of numerous components, often complex subassemblies, which are assembled into end products. Assembly of end products only starts once demand arises. Atan et al. (2017) review models for ATO systems with various characteristics, such as single- or multiple-period, single- or multi-item, single- or multiple end product(s), with both periodic and continuous review policies. For the case of a single period, with a single end product, and periodic-review, the most important decision is generally the component quantity to be ordered. For multi-period, with a single end product but continuous review, the main challenge is component order synchronisation. Most studies consider various demand classes, as they assume differences for service levels for different customers. For multiple end products in assemble-to-order systems, difficulty increases significantly, as both component allocation and component inventory decisions should be optimised.

Optimal solutions for assemble-to-order systems mostly only exist for systems with fairly simple settings. Atan et al. (2017) also review approximation methods for (large-scale) ATO systems. Examples of these are algorithms combined with queueing theory, a decomposition algorithm, for various settings of demand, lead time, and other characteristics. Especially for systems with a high number of components and/or end products it becomes increasingly difficult to develop computationally efficient methods. Because of this, optimisation-based genetic algorithms and simulated annealing are also used.

Atan et al. (2017) furthermore mention that ATO systems are common for low-volume high-tech systems, where continual engineering changes often occur. Since lead times of key components are often relatively long, late engineering changes can be expensive as it could make (pipeline) stock obsolete. However, this problem has received limited attention in literature.

### 3.1.2 Modelling the assembly process

Modelling an assembly system in inventory management is often done with the use of multi-echelon models (Sbai & Berrado, 2022). In a multi-echelon assembly system, a 'stage' has one or multiple predecessors, and one successor. A stage can be seen as a physical location or any activity, such as for example an assembly step. Sbai & Berrado (2022) review several multi-echelon inventory management policies in assembly systems. An important factor of multi-echelon inventory management is that it accounts for the interdependencies of the different stages. Multi-echelon inventory management is concerned with multiple stock locations.

Axsäter (2006) considers a multi-stage assembly network, which features several end-products which should be delivered to the end customer at a certain time. A consequence of not meeting this deadline is a delay cost. Furthermore, if components are delivered too early, this results in holding costs. An assembly step can only start if all preceding operations have finished. Such delays only result in delay costs if they result in delay for the end-product. As the final due date is known, starting times of assembly steps can be deduced from this. However, the assembly steps have a stochastic duration. The purpose of the model is to optimize the starting times of assembly steps. For a multi-stage network however, this can only be done approximately. Therefore, a simulation is used to determine starting times.

Ould-Louly & Dolgui (2001) study an assembly system with one end-product that contains several types of components. The replenishment lead times of components are random variables, and customer demand of the end product is constant. They propose a Markov model to measure indicators such as average holding cost and stockout probability.  They assume orders are only placed at the start of each period, and unsatisfied customer demands are backordered and must be satisfied during the following periods. With this model, they determine inventory positions for each component. A disadvantage of this model is that it does not account for dependencies between different components.

### 3.1.3 Multi-item inventory management

A review of multi-item inventory management shows that the most common direction is coordinated ordering policies (Minner, 2003). For example, Van Eijs (1994) researches the possibility of reduction in order costs when coordinating replenishments in multi-item systems. This approach considers the interaction between ordering and transportation decisions, by determining whether the order size should be enlarged, to reduce costs.

Proth et al. (1997) consider a cyclic assembly system that manufactures numerous end products. They propose an optimization model to formulate a component delivery schedule that minimizes the total inventory and backlogging costs. They first formulate a production schedule according to a fixed policy, and then determine a set of control variables. As the resulting problem formulation is quite complex, they use a simulation and apply a stochastic gradient-descent algorithm to solve the problem.

Minimizing the total costs (such as set-up and inventory costs) for a multi-item capacitated lot-sizing problem for over multiple periods is mathematically complex. Maes & Van Wassenhove (1988) review the existing heuristic approaches used to solve these types of problems. Most optimal methods require extensive computational power, and often only have limited applicability to practice. They conclude that the selection of a heuristic depends largely on the specific problem and its characteristics. Furthermore, it also depends on the solution that is sought after. For example, finding a near-optimal solution is not always better than finding a feasible solution, especially if a feasible solution already yields considerable cost reduction.

This all goes to show that solving multi-item problems is quite complex, and often a global optimum is out of reach due to the large solution space. However, there do exist some relatively simple heuristics that yield good results. An example of this is the multi-item lot sizing heuristic by Chan & Chiu. They consider a multi-product dynamic lot sizing problem, in which N products have to be produced over T periods, and due to major setup costs, coordinated production is interesting. To determine lot sizes in a multi-product, multi-period system, while minimising costs, they propose an extension of the single-product one-way eyeballing heuristic. This heuristic groups components with a common major set-up cost together, i.e. from the same supplier or mode of transportation. During initialisation, all components are produced. The heuristic then iteratively checks for each period whether the costs for introducing an extra order for each component outweigh the costs of not ordering. A worked-out example can be found in Chan & Chiu (1997). This heuristic is simple to use and provides good results even though it is not exact.

## 3.2 Multiple suppliers

As a way to combat disruptions in the supply chain, supply chain managers can choose to use multiple sourcing as opposed to single sourcing, which is inflexible and leads to dependence on a single supplier. Svoboda et al. (2021) review the literature on multiple supplier inventory control models and provide a typology. They show that lead time uncertainty is a commonly observed phenomenon in practice, but they are only researched in 17% of publications.

Another aspect of inventory management is the selection of suppliers. The selection and maintenance of component suppliers is one of the most important aspects of the purchasing department (Weber et al., 1991). There are multiple reasons that support either having a few or multiple suppliers (Minner, 2003). In the case of expensive product design and considering the costs of supplier development, it is more beneficial to have one supplier. Furthermore, having one supplier means that the purchasing volume at that one supplier is higher, which gives the option of negotiating for quantity discounts and other agreements (Minner, 2003). However, companies are often afraid of becoming too dependent of the supplier in the case of single sourcing, and associate this with risks. The idea is that variability in lead time, supply disruptions or quality can be combatted with the availability of multiple suppliers. A strategy that goes together with the reduction of the supplier base is Just-In-Time (Minner, 2003).

(Alfares & Turnadi, 2018) propose a model for the lot sizing supplier selection problem (LS/SS) in the case of multiple items, multiple suppliers and multiple time periods. Their model also considers shortages, transportation costs, and quantity discounts. As their model includes a large number of realistic characteristics, it makes the model more applicable to practice, but also more difficult to solve. They therefore propose the use of two heuristics to provide a solution; a modified version of the Silver-Meal heuristic and a genetic algorithm (GA) heuristic.

Thevenin et al. (2022) conducted a case study during the Covid-19 pandemic that shows the need for companies to have purchase planning methods that are robust to varying and uncertain lead times. To prepare themselves for supplier lead time uncertainty, and prevent disruption, companies can use techniques such as diversification, multi-sourcing and safety lead times. Their study is focused on supplier selection, with the use of a robust optimization model, a row and column generation algorithm and several heuristics. The results of their study show that when there is no uncertainty at all, a buyer would select just a single supplier, with a lower total cost. However, as soon as any uncertainty arises, diversification should happen.

## 3.3 Handling variability in lead time

As is well known, inventory control is important for companies to keep track of, as this is needed to match supply and demand. It should ensure the appropriate availability of materials to fulfil customer demand but should not be too high as it could lead to unnecessary capital tied up in inventory. What complicates this, is the uncertainty in the factors to be matched, i.e. supply and demand. Classic MRP approaches follow from the assumption that demand and supply lead times are known and deterministic. In reality however, this often does not hold up, and production processes are affected by various types of uncertainty, such as in demand or supply (Ayala et al., 2024). Safety lead time is a measure to combat the variability in supply, as component lead times are rarely forecasted accurately. Ayala et al. (2024) perform a case study to investigate the effect of different safety lead time calculations. They focus on demand variability.

Lead time can refer both to the time between the release of an order to the shop floor and the delivery to the customer, or the time between an order to a supplier and the receipt of the item (Pahl et al., 2007). Often, lead times are treated as static input data, but lead times are one of the most important properties to consider in production planning and supply chain management (Pahl et al., 2007), and the effect that their variability can have, is often not considered. Nielsen et al. (2017) note that lead times have only received limited interest in literature, despite their importance in the performance of a supply chain. In the cases where stochastic lead time is considered, simulation can be used (Nielsen et al., 2017). Eppen & Martin (1988) research the safety stock settings in the case of stochastic lead time and demand and consider a case in which both parameters are unknown. They assume that the distribution of supplier lead times can be estimated with historical data, even with a large number of SKUs. They state that it should be possible to find a good lead time distribution estimate by aggregating lead times for a supplier over classes of common products.

Dolgui & Prodhon (2007) have performed a survey of methods for supply planning with uncertainties in MRP environments. Literature is most often concerned with demand and lead time uncertainty. The demand uncertainty arises from the fact that not all demand is known in advance, and the lead time uncertainty comes from the fact that actual lead time can differ from planned lead time. The aim of safety stocks is to minimise the shortage and holding costs, or to maintain an appropriate service level, shortly mentioned in Section 3.3.1. Safety lead time is based on the same idea, but instead works with time, this is further explored in Section 3.3.2.

### *3.3.1 Safety stock*

Safety stock is a well-known measure used to prevent stockouts. This safety stock measures for some uncertainty in demand and supply. It is defined as the average level of net stock right before a replenishment order arrives (Silver et al., 2017). For more information on safety stock, the reader can consult Silver et al. (2017).

### *3.3.2 Safety lead time*

Whybark & Williams (1976) show how simulation can be used to research the effects of safety stock and safety lead time against the quantity and timing uncertainty of demand and supply. The outcome of this research shows that safety stock is better for protecting against quantity uncertainty and safety lead time is better for timing uncertainty. However, they only researched equal safety lead times for all components. Also, they solely investigated with simulation, there was no optimisation of safety lead times.

Hegedus & Hopp (2001) confirm the result of Whybark & Williams (1976) for an assembly system specifically for purchased components from suppliers and with deterministic demands. In this assembly system, jobs cannot start until all components in the job are received. The biggest disruption to this system is delays caused by late supplier deliveries. Hegedus & Hopp (2001) develop a model to maintain a feasible service level with minimum inventory carrying cost. They have in this case defined the service level as the percentage of the jobs that start timely. Furthermore, they assume that jobs can be started earlier, if all the components are available when another job cannot be started yet. Their research consists of a combinatorial optimization method to research different settings and scenarios.

Dolgui & Prodhon (2007) conclude that the number of studies concerning lead time uncertainty is quite low as compared to the number of studies on demand uncertainty, especially for multi-level products or assembly systems, as the components can be interdependent, and this complicates the problem further. Dolgui & Ould-Louly (2002) more specifically research planned lead times under lead time uncertainty for a single-level, multi-item dynamic multi-period planning problem. Lead time is a random variable with a known distribution, and each item type has its own distribution. The unit holding cost per period and unit backlogging cost per period are assumed to be known. They formulate an approach using a Markov chain and showcase a numerical example with two components needed for assembly, which shows that an optimal solution can be found in some particular cases. They emphasise that further research is needed for the general case.

Kampen et al. (2010) study the effectiveness of using safety lead time and safety stock as a measure to combat both unreliable demand information and supply variability in a multiple product situation. They have performed a simulation study that investigates the trade-off between safety lead time and safety stock and their benefits. Their research shows that in the case of variability in supply, safety lead time yields a higher performance.

Hopp & Spearman (1993) performed research regarding setting appropriate lead times for the purchasing of components in assembly systems with stochastic delivery lead times. They perform their research under the assumption that assembly time is only a minor part of flow time, and therefore ignore this time in their models. They furthermore assume that assembly cannot be performed earlier than planned and assume that demand is known before parts are ordered. Their model aims to minimise inventory carrying costs subject to a service level constraint, due to the case company's concern about tied-up money in inventory.

Yano (1987) also researches stochastic procurement lead times, but in two-level assembly systems, with the objective of minimizing holding and tardiness costs. The research was also inspired by Whybark & Williams (1976) who indicated that safety time is preferred to safety stock when the timing is uncertain. They consider the 'problem' for each assembly run to be when to either produce or procure the components and when to begin assembly.

## 3.4 Simulation

A simulation is used to investigate possible trade-offs and the effects of certain choices. The advantage of a simulation is that different scenarios and the effects of certain choices can be tested, without having to try them in reality. Because of the complexity of production companies and their supply chains, analytical models are not the most suitable, as they do not allow important details and can contain too many simplifications (Byrne & Heavey, 2006). Simulation models, however, provide a degree of flexibility with the ability to incorporate stochastic elements (Abo-Hamad & Arisha, 2011). Simulation models are also an effective way to analyse multiple scenarios and to test theories before implementing them in reality (Gallego-García et al., 2021).

Ammar et al. (2015) use a simulation model for a multi-level assembly system. Their study is concerned with determining optimal order release dates of components in order to minimise the sum of average inventory holding costs for components and average backlogging and holding costs of the end-product. Their focus is on the uncertainty of supply lead times. The system has one end-product, of which demand for each period is known. They incur a unit inventory cost for each component, and a unit inventory holding and backlogging cost for the end-product. The supply lead times are assumed to be independent random discrete variables with known probability distributions. A Monte Carlo simulation is then used to analyse three different scenarios. A Genetic Algorithm is subsequently used to determine planned lead times.

Chauhan et al. (2009) consider an assembly system with one end-product. This end-product contains $n$ components, of which there is no safety stock. These components have no safety stock due to fear of price volatility or obsolescence due to quick technological improvements. The final product can only be assembled if all required components are available. They therefore define the assembly starting time as the maximum of all required components' delivery dates. Probability density functions are used to calculate the probability that a component is on time. They calculate inventory cost for keeping components in stock until assembly start time, and average backlogging cost if the end-product is finished later than the due date. To solve this problem, they start with a Monte Carlo simulation to evaluate the costs of a solution set. They then use simulated annealing to randomly select a component and increase or decrease the current ordering time and evaluate the costs. They evaluate ten different cases, for three to twelve components.

Gallego-García et al. (2021) performed a study on considering risks such as uncertainty in suppliers' behaviour, and used a simulation study. For this study, Gallego-García et al. (2021) simulated several scenarios, based on the reliability of the supplier (reliable or non-reliable) and the level of disruption (non-existing, low or high). With this, they devised three scenarios, and they ran their simulation with five different Procurement Order Quantities (POQs) for each of the scenarios. This way, the effects of the different POQs can be analysed through the use of KPIs.

### *3.4.1 Simulation optimisation*

In the case of a large solution space, it is computationally intractable to analyse every possible solution. Therefore, simulation is often used to evaluate the different configurations to optimise the model, this is known as simulation-optimisation.

Abo-Hamad & Arisha (2011) research various simulation optimisation methods specifically for supply chain applications. They explore the four main methods of simulation optimisation; gradient-based methods, meta-model-based methods, statistical-based methods and meta-heuristics models. In the case of a high-dimensional and discontinuous solution space, or qualitative decision variables, meta-heuristics are used to find potential solution points (Bianchi et al., 2009). Bianchi et al. (2009) also show that meta-heuristics are a good way to apply to combinatorial optimization problems under uncertainty. The search of a meta-heuristic is guided through the balance of 'exploration' and 'exploitation' (Abo-Hamad & Arisha, 2011)

#### *3.4.1.1 Local search*

A local search algorithm iteratively tries to find a better solution by considering neighbour solutions. An example of a local search algorithm is the so-called 'greedy hill-climbing' approach (Dechter, 2003). This algorithm tries to improve the solution by considering all neighbour solution and accepting the best one if it improves the current solution. It terminates if no improvement is found, or if a maximum number of iterations is reached. Local search does not guarantee an optimal solution, but generally returns a pretty good solution in a reasonable computational time.

#### *3.4.1.2 Tabu search*

Tabu Search is an improved, more intelligent version of the local search method (Glover & Laguna, 1999), first coined by Fred Glover (1989). It is an extension of local search, as it also allows moves that provide a worse solution value than the best found so far, and in that way tries to escape local optima. Furthermore, the search is constrained. Tabu Search constrains its search by putting certain neighbourhood moves on the 'tabu list'. If moves are on this tabu list, they are prohibited (Glover, 1989). A solution remains on the list until an expiration date has been reached. In the case of intermediate- and long-term memory, the tabu list will also contain solutions that are not allowed to be visited due to specified characteristics, such as solutions that contain specific attributes.

#### *3.4.1.3 Simulated Annealing*

An example of a meta-heuristic, and perhaps one of the most well-known options, is Simulated Annealing. It uses an initial solution as a starting point, which is often chosen randomly. From there, it generates a ‘neighbour solution’. If this solution is better, it is chosen as the ‘new solution’. If the neighbour solution is worse, it is only accepted with a probability. The acceptance probability is influenced by the ‘temperature’ (Chopard & Tomassini, 2018). The temperature decreases with the number of neighbours proposed, and the acceptance probability is related to the temperature. By also allowing worse solutions, Simulated Annealing tries to prevent getting ‘stuck’ in a local optimum. To implement Simulated Annealing, one needs to make several key decisions. These include the starting temperature T(1) and the final temperature T(Q) (Brusco, 2014). The starting temperature needs to be high enough to allow enough exploration. How quickly the temperature decreases, is decided by the ‘cooling rate’. Furthermore, the length of the Markov chain decides how many solutions are explored at each temperature.

## 3.5 Conclusion

As Atan et al. (2017) show, it becomes increasingly hard to find an optimal solution if the number of components and assembly steps increase. They also show that there is a large number of methods that can be used, and mention simulation as one of them. As Axsäter (2006) also showed, simulation is a good way to study the interdependencies in an assembly system such as at IMS. To combat lead time uncertainty, safety lead time is a common measure. This is also confirmed by the result of Whybark & Williams (1976) who also use a simulation model to find appropriate settings. Therefore, this seems like a good starting point, since the assembly process can be modelled as a simulation, and the lead times can be simulated. Then also the effects of safety lead time can be investigated using simulation. Maes & Van Wassenhove (1988) note that it is not always better to find an optimal solution for multi-item systems, as this could significantly improve computational efforts. First, a simulation model will be used, which will simulate the effects of ordering components at certain dates and evaluating the associated costs. These order moments will then be optimised using a optimisation method. As Section 3.4.1 showed, there are several methods to do this, but generally the quality of a solution goes up with computation time. The effects of this are studied in Chapter 5.  Chapter 4 provides the design of the simulation model, the simulation optimisation algorithms, and the neighbour generation which will be used to optimise a starting solution.

# 4 Model design

This chapter details the design of the simulation model. Section 4.1 provides the assumptions made in order to construct the model. Section 4.2 details the model outline. Section 4.3 shows how clusters were made in order to decrease the size of the solution space. Section 4.4 gives the corresponding mathematical model formulation. Section 4.5 describes the penalty cost setting. Section 4.6 introduces the 'base' solutions from which optimisation can start. Section 4.7 concludes this chapter.

## 4.1 Assumptions

As it is impossible to model reality exactly, seven assumptions were made to simplify analysis, these are listed in this section.

1. Assembling of a subassembly can only start when all required components have been received and if it is allowed according to planning. Furthermore, the sequence of subassemblies is given, and subassembly times are deterministic.
2. Each component is assumed to have one supplier.
3. Each component is only ordered once.
4. If multiple components are ordered from a supplier at the same day, this is assumed to be one order at that supplier.
5. If orders from different suppliers are placed on the same day, the employee costs are only incurred once.
6. The lead time distribution from a supplier is always the same, regardless of which component.
7. Each component has a fixed order quantity per machine.

Assumption 1 follows from the way of working at IMS. They prefer not to start assembly until all components within that subassembly have arrived. Because plannings are made in advance, and ensure the availability of machine builders, it is not possible to start earlier than the planning. As it is currently not possible to know all supplier choices for the components, and as the main goal is to find out when which component should be ordered to minimise total costs, each component is assumed to have one supplier, as assumption 2 states. Alternative suppliers are left for further research. Assumption 3 follows from the desire to limit the number of orders. Multiple orders of one component are therefore not allowed.  For sake of simplifying analysis, and to ensure efficiency and avoiding additional order costs, multiple component orders at one supplier on the same day are combined into one order. Assumption 5 is due to the fact that for efficiency in the purchasing department, it is better to have these on one day, as it reduces the need for switching between different activities for a purchaser. Assumption 6 results from a lack of available data. The simulation uses a Gamma distribution, as a Normal distribution introduces the possibility of negative lead times. The mean and standard deviation of each supplier were used to calculate the shape and scale parameters ($\alpha$ and $\beta$) of the Gamma distribution. The mean and standard deviation were calculated based on all available historical lead times of a supplier.

Assumption 7 excludes the determination of order quantities from the model. As quality is not considered and only one machine (or parallel building of multiples of this machine) is considered, it is less important to determine the order quantities and analysis focusses instead on the determination of order dates.

## 4.2 Model outline

The simulation model simulates the ordering and assembly process at IMS. The purpose of the model is to find optimum order dates for all components, while minimising the overall costs. An order of a component is simulated by drawing a lead time value from the supplier specific lead time distribution. The simulation model evaluates all relevant costs that are incurred due to early or late deliveries (holding costs versus penalty costs), and the influence this has on the rest start dates of all steps of the assembly process.

The objective is to minimise overall costs. The overall costs include holding costs for all components that had to be held in inventory, order costs, and an overall penalty cost if the complete machine is too late.

The Molder assembly process consists of 32 different subassemblies, that are built in a sequential manner. 15 of these subassemblies can be done in parallel, at various steps, as these subassemblies also must be assembled together before the next step can start. The complete assembly process is therefore narrowed down to 17 steps. A flowchart of the subassembly sequence can be found in Appendix E: Subassembly sequence. As all durations of building each subassembly are known and deterministic, each step in the assembly process can be given a 'preferred' starting date according to the planning. Also, a step cannot start if the previous step (so all subassemblies in that step) is not finished. The actual starting dates of subassemblies depend on the arrival dates of components. If a subassembly starts late, due to late components, then the rest of the assembly process is also delayed. Components that were on time, will now have more holding costs, as they are suddenly needed later. But as the assembly process is delayed, there are also penalty costs incurred. The model calculates the costs by tracking component arrival dates. It does so for the assembly of one end product, namely the HP-Molder. The optimisation model then tries to find the best order dates to minimise total costs. Within one iteration, a neighbour solution is created, by changing the order dates of clusters. This is then replicated a number of times, in which each replication consists of drawing new lead times. A flowchart of the simulation optimisation model can be found in Appendix D: Simulation optimisation flowchart. The settings for the number of replications are determined in Chapter 5.

## 4.3 Creating clusters

As there are 914 components, and all 914 could potentially be ordered at different dates, the search space for the optimisation algorithm is very large. Hypothetically, even with a simple local search algorithm, in which one iteration evaluates every component twice (moving the order date earlier or later), this leads to 1828 operations, for which all subassembly start dates have to be re-evaluated based on component arrival dates. Also, this would have to be done for a high number of evaluations, due to the high number of components. This is therefore not computationally tractable. The decision is made to divide the components into different clusters. This is also closer related to reality. An additional reason for this, is that there are no individual component lead time distributions, but only supplier lead time distributions. For the clustering, it is therefore decided to make these based on suppliers. It does not make sense to do it based on subassembly, as a subassembly also contains components from different suppliers. As was shown in Chapter 2, there are a lot of suppliers that supply a small number of components and a few suppliers that supply a large number of components.

To create clusters in an informed way, inspiration was taken from Chan & Chiu (1997), who used a heuristic to form clusters in a multi-item lot sizing problem as discussed in Section 3.1.3. The heuristic is not immediately applicable, as there are no minor set-up costs, and the heuristic assumes that each component is produced/ordered before the first period. However, the basic idea from this article is used to form clusters for each supplier, through an iterative way. For this calculation, the mean lead time of a supplier is used for calculation. The heuristic was slightly modified, as the idea from Chan & Chiu (1997) worked well for suppliers that supply components that are needed at only two to five different subassembly steps. However, there are suppliers that supply components for up to 14 different subassembly steps, and for those suppliers, also typically suppliers with lower order costs, this approach introduced a lot of different order dates. As this research attempts to limit the number of orders, and provide some structure in when to order, it was decided to limit the number of orders per supplier to five. This is also more workable in practice. Also, this approach ignores quite some options and focusses heavily on the first subassemblies.

Therefore, the heuristic was slightly modified and does not iteratively go through the subassembly steps. Instead, in each iteration it introduces a next order that divides the steps somewhat equally. Still, the first iteration orders everything for the first subassembly, as it is preferred to have components arrive on time, the next iteration introduces a second order, but for the second half of the subassembly steps. To clarify, an example is shown in Table 6. In this scenario, supplier y supplies components that are needed in subassembly step 3, 4, 5, 10, 11, 12, 14, and 15. In iteration 1, only one order is placed which should arrive at the date that subassembly step 3 starts. In iteration 2, a second order is created, which supplies the second half of the subassembly steps. In iteration 3, a third order is created, such that each order supplies one third of the subassembly steps, and so on.

*Table 6: Cluster creation example*

| Subassembly step | 3 | 4 | 5 | 10 | 11 | 12 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|
| Iteration 1 | Order all components | | | | | | | |
| Iteration 2 | Order for 3, 4, 5, 10 | | | | Order for 11, 12, 14, 15 | | | |
| Iteration 3 | Order for 3, 4 | | Order for 5, 10, 11 | | | Order for 12, 14, 15 | | |

As the number of subassembly steps for which the supplier provides components is not always divisible by the number of orders, the exact placement of the order can differ a bit, as can also be seen in Iteration 3. The placement of the order is also evaluated for different steps, as this can be influenced by the number of components to arrive at their step, or high component values and therefore high holding costs. So, for example, for iteration 3 it is evaluated if having orders to arrive at 3, 5 and 12 is better than ordering at 3, 10, and 12 for example. In this case, iteration 4 has a higher cost, therefore the heuristic terminates, and the best configuration of iteration 3 is selected. For this supplier, that leads to 3 clusters to arrive at subassembly step 3, 5, and 12. The heuristic is formalised in pseudocode in Figure 3. As the heuristic requires some logical thinking, it is easier to explain in pseudocode than in a mathematical model formulation.

```
'initialisation

'- place one order, which should arrive at the first subassembly step
'- set order costs equal to the supplier order costs times one
'- calculate holding costs for all components needed later than the first subassembly step
'- calculate total costs

'2. incrementing the number of orders
'- increment the number of orders by one
'- number of evaluations is 1

'3. assign orders
'- assign each order to one of the subassembly steps, such that each step
'  supplies ~(number of steps/number of orders) steps

'4. evaluate costs
'- set order costs equal to number of orders times supplier order costs
'- for each order calculate the holding costs for all components needed
'  later than when the order arrives
'- calculate total costs
'- if number of evaluations is less than 3, go to step 3 to try a different configuration,
'  increment number of evaluations.
'- if number of evaluations is 3, and costs are higher than costs of (number of orders-1) then
'  go to step 5, otherwise go to step 2

'5. termination
'- set number of clusters equal to number of order dates of best costs
```

*Figure 3: Pseudocode of cluster heuristic*

The heuristic leads to 119 clusters in total, which are each specified by the combination of a supplier and an order date. It is important to note that in the calculation of these cluster creations, the penalty costs are left out. This is due to the fact that by only considering one supplier, the calculations only concern an isolated part of the problem. However, the complete problem and all dependencies are still investigated in the simulation optimisation model, and the cluster creation is just a way to decrease the solution space. The clusters formed with this heuristic serve as input for the initial solutions, further elaborated on in Section 4.6. The complete overview of all clusters can be found in Appendix F: Final clusters.

## 4.4 Model formulation

This section details the complete mathematical model formulation of the simulation optimisation model.

Decision variables:

- $x_{tc} = \begin{cases} 1 \; if \; cluster \; c \; i \; is \; ordered \; at \; time \; t \\ 0 \; otherwise \end{cases}$

The simulation evaluates all costs associated with the assembly process, based on when each cluster is ordered.

Auxiliary variables:

- $o_s$: number of orders placed at supplier $s$
- $s_k$: actual start date of subassembly $k$ $(dependent \; on \; possible \; delay)$
- $r_i$: actual required date of component $i$
- $a_i$: arrival date of component $i$
- $l_c$: lead time of cluster $c$ (drawn from supplier-specific distribution by simulation)
- $e$: end date of complete assembly (final product)

General model parameters:

- $H$: fixed holding cost rate per day as fraction of the component value
- $M$: delay costs per day delay of the final product
- $J$: required end date of final product
- $G$: fixed employee costs of placing orders on an order date

Sets:

- $T$: set of all order dates (dates on which orders are placed)
- $I$: set of all components
- $S$: set of all suppliers
- $K$: set of subassemblies
- $C$: set of all clusters
- $I_k$: set of all components in subassembly $k$, $I_k \subset I$
- $I_s$: set of all components ordered at supplier $s$, $I_s \subset I$
- $I_c$: set of all components in cluster $c$, $I_c \subset I$
- $C_s$: set of all clusters associated with supplier $s$, $C_s \subset C$

Component-specific parameters:

- $V_i$: value of component $i$
- $S_i$: supplier of component $i$
- $Q_i$: order quantity of component $i$
- $D_i$: date that component $i$ is required according to original planning

- $F_i$: the subassembly that component $i$ is required first in

Supplier-specific parameters:

- $B_s$: fixed order cost of supplier $s$
- $\mu_{lead,s}$: mean lead time of supplier $s$
- $\sigma_{lead,s}$: standard deviation of lead time of supplier $s$

Subassembly-specific parameters:

- $P_k$: start date according to original planning for subassembly $k$
- $W_k$: duration of subassembly $k$ (in working days)

Objective function:

$$Min\ Z = \underbrace{\sum_{s \in S} B_s * o_s + \sum_{t \in T} t * G}_{1} + \underbrace{\sum_{i \in I} H * V_i * (D_i - r_i)}_{2} + \underbrace{M\ * (e - J)}_{3} \tag{1}$$

Equation (1) shows the objective function of the simulation optimisation algorithm.

1. Order costs: for each supplier, the order costs amount to the number of times an order is placed at a supplier multiplied by the supplier-specific order costs, plus the number of different order dates multiplied with the employee costs for ordering
2. Holding costs: for each component, the holding costs are calculated by multiplying the holding cost with the component value and the number of days it was too early for actual assembly
3. Machine delay costs: for the complete machine, the delay costs are multiplied with the number of days too late

Constraints:

- Arrival date of a component:

$$a_i = \sum_{t \in T} x_{tc} * (t + l_c)\ \forall i \in I_c, \forall c \in C \tag{2}$$

Equation (2) shows the calculation of the arrival date of each component. It equals the order date of the cluster that it is in, plus the lead time of that cluster.

- Start date of the first subassembly:

$$s_1 = \max\,(\max_{i \in I_1}(a_i), P_1) \tag{3}$$

The first subassembly can start if all components in the subassembly have arrived and if it is allowed according to planning. The calculation is shown in Equation (3). So, the start date is the maximum of those two factors.

- Start date of a subassembly:

$$s_k = \max\left(\max_{i \in I_k}(a_i), P_k, \mathrm{s}_{\mathrm{k-1}} + W_{k-1}\right) \ \forall k \in K, k > 1$$

(4)

Equation (4) shows the calculation of the start date of a subassembly. A subassembly can only start if all components in the subassembly have arrived, if it is allowed to start according to planning, and if the previous subassembly is finished. So, the actual start date is the maximum of these three factors.

- Ordering each cluster once:

$$\sum_{t \in T} x_{tc} = 1 \ \forall c \in C$$

(5)

Due to the assumptions, each cluster is limited to one order. This constraint ensures that. The calculation is shown in Equation (5).

- End date of assembly process:

$$e = s_K + W_K$$

(6)

The end date of the assembly process is the start date of the last subassembly plus its duration, as shown in Equation (6).

- Determining when a component is actually required:

$$r_i = \min_{k \in K : i \in I_k} (s_k) \ \forall i \in I$$

(7)

Equation (7) shows how to calculate the date that a component is actually required. This is equal to the minimum starting date of all subassemblies that component $i$ is featured in.

- Determining the number of orders placed at a supplier

$$o_s = \sum_{t \in T} \min\left(1, \sum_{c \in C_s} x_{tc}\right) \forall s \in S$$

(8)

Equation (8) shows how to calculate the number of orders (on distinct dates) that were placed at a supplier. As it is possible due to the optimisation algorithm that two clusters from one supplier are ordered at the same date, the number of orders placed at a supplier is not necessarily equal to the number of clusters associated with that supplier. Therefore, for all dates, the number of orders placed at that supplier is equal to the minimum of 1 and the number of clusters that are ordered at that date. This ensures that the number of orders that are counted is either 0 or 1.

## 4.5 Holding versus penalty costs

The penalty costs for a day of delay in production should be in proportion to the holding costs. This is done by balancing the penalty costs of one day of delay to the costs of holding all components in stock for one day times a certain factor. The setting of this parameter for the base scenario from which experimenting is done can be found in Chapter 5.

## 4.6 Base solutions

This section explains the Base Solutions, which the optimisation algorithms will use as a starting solution to improve on. All of these Base Solutions will also be used by the simulation to evaluate costs.

### *4.6.1 Base Solution 1: Deterministic lead time assumption*

This Base Solution uses the assumption that all lead times are deterministic. The idea is to provide a benchmark, that shows that lead time is decidedly not deterministic and shows the importance of considering this. In this scenario, each cluster is ordered the average lead time before the cluster is required. The clusters are formed according to the modified heuristic, which means there are 119 clusters.

### *4.6.2 Base Solution 2: 'Smart' solution*

The idea behind this 'smart' Base Solution is to start from a more informed idea of when it is smart to place orders. That is why with this Base Solution, the lead time of every cluster is set to be the average lead time of the supplier of that cluster plus twice the standard deviation. So, each cluster gets assigned the order date of the subassembly step they should arrive at minus the average lead time plus twice the standard deviation. This Base Solution therefore also uses the clusters that follow from the clustering heuristic. The idea of this Base Solution is to account for the different steps of the assembly process into account. Namely, a component that is only required late in the assembly process, does not have to arrive before the start of the assembly process. In fact, it is likely preferred that this component arrives later.

### *4.6.3 Base Solution 3: Start assembly*

The idea of this Base Solution is to have all components arrive (or attempt to) at the date that the first subassembly step starts. The idea behind this Base Solution is to investigate the importance of accounting for the different steps in the assembly sequence. This means that each supplier is only ordered from once, and the order date corresponds to the date of the first subassembly step minus the average lead time plus twice the standard deviation. In this Base Solution, all components are desired to arrive at the start of the assembly process, so at the first subassembly step. This therefore corresponds to 65 clusters, one for each supplier.

## 4.7 Conclusion

This chapter shows the design of the simulation optimisation model. The model is used to experiment with different numbers of order moments, as well as assigning components to different order moments. As placing an order always costs money, and there could be an advantage to combining orders from one supplier, it is important to investigate the effects of the order dates. The simulation model itself is used to evaluate these costs, whereas the optimisation algorithm is used to find the improved settings for the decision variables, i.e., the order dates for each component, based on the resulting costs. Chapter 5 will provide an analysis of the results of the simulation optimisation model.

# 5 Analysis of results

This chapter will provide an analysis of the results of the simulation optimisation model. The simulation results are shown in Section 5.1. Section 5.2 provides the optimisation results. Section 5.3 details the sensitivity analysis.

## 5.1 Simulation

This section details the simulation results. Section 5.1 discusses the simulation model and its results. Section 5.2 discusses the optimisation results. Section 5.1.3 provides a sensitivity analysis.

### *5.1.1 Verification and validation*

Three simulation experiment runs have been performed, each with 10000 replications. These three experiments are derived from the three base solutions. The results are discussed in Section 5.1.3. This section explores the verification of the simulation. This means checking that there is no unexpected behaviour, as well as things that should not be allowed. For example, it is checked that subassemblies do not start any earlier than they are allowed to, i.e. all components within that subassembly should have arrived and the previous step needs to be finished. This holds for all results. Furthermore, the lead time values should reflect the distributions. Over the total 30000 replications (10000 per run), the average of all drawn lead times was calculated for each component, and this corresponded roughly to the averages of the suppliers corresponding to those components. Validating the model is harder, since the real life data is not currently available and the model can therefore not be compared to reality. However, in the future this should be possible.

### *5.1.2 Parametrisation*

This section discusses the parameter settings which will be used as a Base Scenario, which all three Base Solutions will use. The values can be found in Table 7.

*Table 7: Parameter settings initial simulation scenario*

| **Parameter** | **Setting** |
|---|---|
| Penalty costs per day delay | 31332.9 |
| Lead time distributions | Gamma distributions as calculated from data |
| Number of replications | 10000 |

The penalty costs per day of delay of the final product are determined to be three times costs of holding all components in stock for one day. The idea of this is to balance the penalty and holding costs, as that is where the most important trade-off in this case lies. A higher setting of the penalty costs makes the penalty costs too dominant compared to the other costs. This means that one day of delay of the final product results in penalty costs of 31332.9 euros. The lead time distributions for the Base Scenario are the gamma distributions as determined from the lead time data. The characterisations of these can be found in Chapter 2.

One simulation run consists of 10000 replications. Within a replication, each cluster is 'ordered' by drawing a lead time from the lead time distribution corresponding to the supplier of that cluster. Then, the arrival date of each cluster is calculated, and starting dates of assembly steps are calculated. From there, all costs can be calculated. The 10000 replications are considered to be enough, as the average difference in costs compared to other runs with a 10000 replications is about 2%. Further increasing the number of replications would also increase computational time without a significant increase in accuracy.

### 5.1.3 Results

The simulation has been run with the three different Base Solutions as explained in Section 4.6. The idea of this is that these are the starting points from which optimisation is run, and the costs of these simulation runs provide some initial insight for improvement. The average over these 10000 replications can be found in Table 8.

*Table 8: Base Solution simulation results over 10000 replications*

| | Base 1: Deterministic | Base 2: Smart | Base 3: Start |
|---|---|---|---|
| Average Total Cost (in thousands) | 5324 | 2603 | 2058 |
| Average Order Cost (in thousands) | 12.02 | 13.12 | 7.36 |
| Average Holding cost (in thousands) | 1070 | 936 | 982 |
| Average Penalty Cost (in thousands) | 4241 | 1654 | 1069 |
| Average Days too late (in working days) | 135.37 | 52.79 | 34.12 |

It is obvious that the scenario with the deterministic lead time assumption has the highest costs, and this also makes sense, as the scenario does not account for lead time variability, even though it is clear it exists. This scenario highlights the importance of accounting for the lead time variability. For the other two scenarios however, it is interesting to note that the scenario where all components should arrive at the start of assembly has lower total costs than the smart solution. It does make sense that the penalty costs and order costs for the smart solution are higher, as there are more clusters and therefore more orders and components are planned to arrive later. It also makes sense that the holding costs in the second scenario are lower, as components arrive closer to the date they are needed on, than in Base Solution 3. The fact that the third scenario, where all components are desired to arrive at the first subassembly step performs better than the scenario that accounts for the different steps, is due to the fact that as soon as one component is delayed, the whole assembly process is delayed. Base Solution 3, in which all components should arrive at the first step, can therefore be seen as the most cautious option out of the three. This can also be seen in the slightly higher value for the average holding costs, as well as the lower average days of delay. As the penalty costs outweigh all other costs, the most cautious scenario performs the best in this case. However, as the total assembly process is meant to take only 58 days, there is still room for improvement. Even in Base Solution 3, on average, final assembly is still 57% too late.

Furthermore, it is important to note that the order costs are only a small fraction of the total costs in each scenario, so in terms of costs there is not a lot of improvements to make. However, the limiting of the number of orders comes from the desire to introduce more structure in the ordering process at IMS.

The high variability of lead times plays a significant role in the resulting costs. This can also be seen in the boxplot in Figure 4. This shows the values that the Total Costs have taken (in thousands) over the 10000 replications for each Base Solution. This shows that Base Solution 2 and 3 clearly outperform Base Solution 1, but even Base Solution 2 and 3 sometimes show high values, only due to lead time variability.

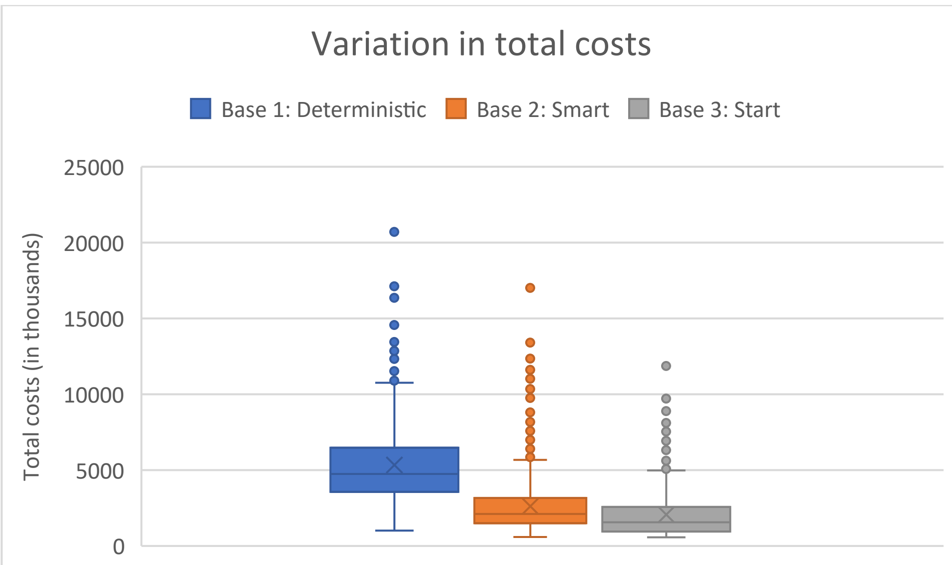



*Figure 4: Influence of lead time variability on Total Costs*

Another example of this is the days of delay of the final product, shown in Figure 5. For each Base Solution, this shows the minimum and the maximum number of days that the final product was delayed over the 10000 replications. This shows that with the relatively simple idea of Base Solution 2 and 3 it is possible to have just one day of delay for the final product. However, it is also possible to have more than a year of delay, which is of course not desirable. Lowering the variation in lead times is researched in the sensitivity analysis in Section 5.3.

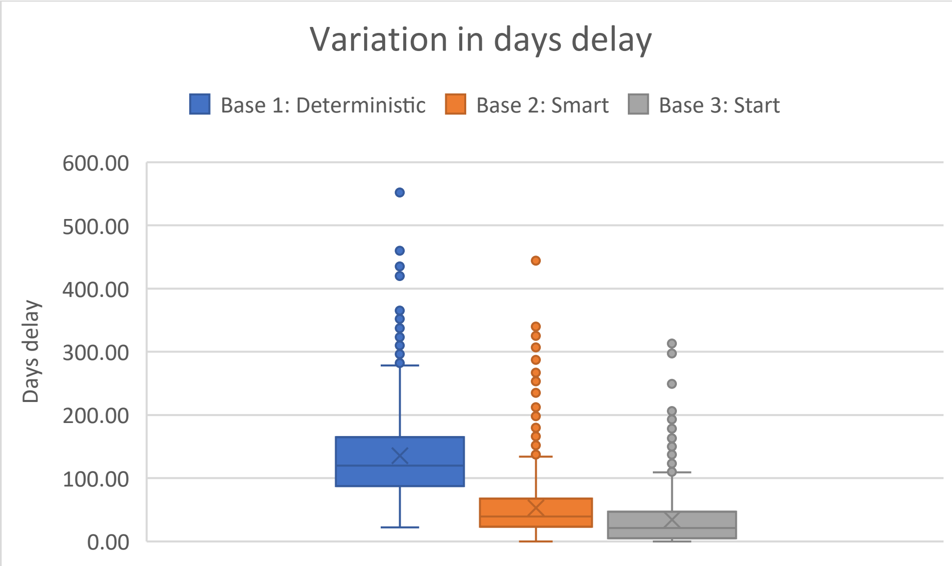



*Figure 5: Variation in days of delay for the final product*

As the initial results showed that there was quite some delay still, more cautious runs are also performed, by incorporating more safety lead time. Therefore, Base Solution 2 and 3 are performed again, but with extra safety lead time, by ordering even more standard deviations earlier. These results can be found in Table 9.

*Table 9: Results of ordering even earlier*

| | Base 2: Smart | | | | | Base 3: Start | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 2 stdevs | 3 stdevs | 4 stdevs | 5 stdevs | 6 stdevs | 2 stdevs | 3 stdevs | 4 stdevs | 5 stdevs | 6 stdevs |
| Average Order Costs (in thousands) | 13 | 14 | 14 | 15 | 15 | 7 | 8 | 8 | 8 | 8 |
| Average Days delay | 52.79 | 26.27 | 12.30 | 4.61 | 1.98 | 34.12 | 14.04 | 7.20 | 2.30 | 1.65 |

The results show that there is a ‘tipping point’ concerning the number of standard deviations used as safety lead time. From 2 to 3 the total costs still decrease, as well as from 3 to 4. After that, the total costs increase again. This is the same for Base Solution 2 and 3. The tipping point comes from balancing the holding and penalty costs. While the penalty costs decrease for each extra standard deviation, the holding costs of course increase. This can also clearly be seen in Figure 6.

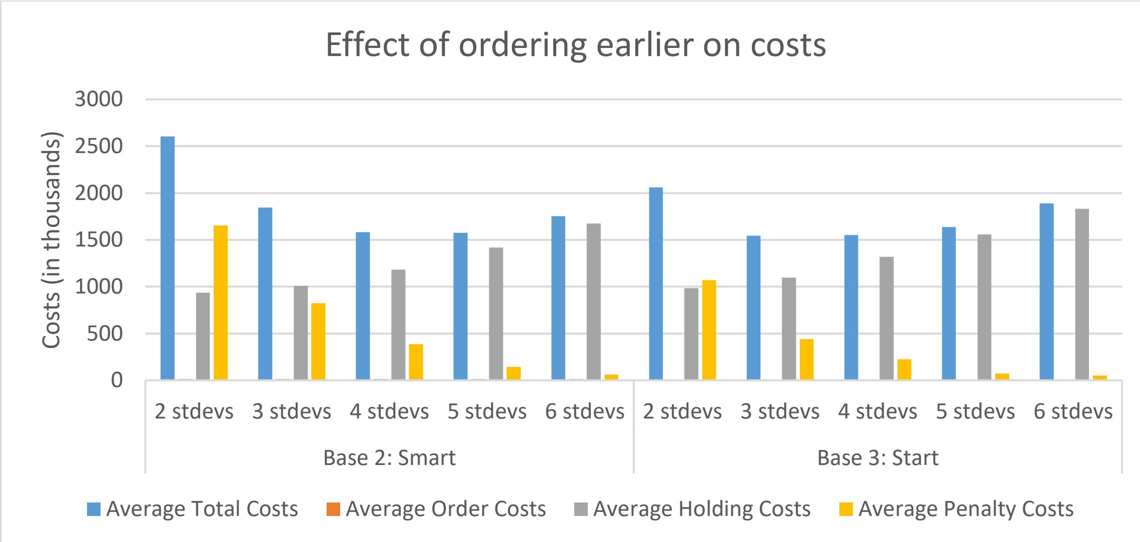



*Figure 6: Graph displaying more cautious ordering*

Some insight into what this means in terms of clusters, can be found in Table 10. These are the results over 10000 replications of Base Solution 2 in which each cluster is ordered the average lead time plus four times the standard deviation before it is required. These are all clusters that are needed late in the assembly sequence, namely step 15. These all have a high holding cost, in part due to relatively high component value, but partly because they are needed late and a delay is likely to occur earlier in the subassembly sequence and the components in these clusters have to be held on stock. The maximum number of days of delay caused by the clusters is also shown.

*Table 10: Insight into clusters of Base Solution 2, 4 standard deviations*

| | Step cluster is needed in | Total component value | Average holding cost of all components in cluster | Max days delay caused by cluster |
|---|---|---|---|---|
| Cluster 1 | 15 | 1519.22 | 25414.42 | 44 |
| Cluster 2 | 15 | 3048.55 | 51263.90 | 32 |
| Cluster 3 | 15 | 1392.77 | 14911.82 | 22 |

Eight out of the ten clusters with the highest holding cost have a total component value well above the average per cluster, so the high holding costs can be mostly ascribed to that. However, that means there are two clusters with a relatively low average component value, but a high holding cost. These are both clusters that are needed late in the assembly process. The mean plus four times the standard deviation is too high for these clusters, as it is quite likely a delay has already occurred earlier in the assembly process, and these components can therefore arrive later. Therefore, it would make sense to have a lower safety lead time for these clusters. Section 5.2 explores the possibilities for optimising these results further.

Delay in the subassembly sequence is generally caused by one cluster, due to a high lead time realisation for that cluster. In terms of penalty costs, if you were to have this delay, it is most likely preferable to have it occur early on in the assembly sequence, as all components needed later are then ‘allowed’ to arrive later. However, if it is just one cluster that arrives really late, and all other clusters arrive at reasonable dates, this introduces a lot of holding costs.

## 5.2 Optimisation results

The idea of the optimisation algorithm is to change the order dates of clusters, and to investigate the effects of this on the costs. As the high lead time variability plays a big role, moving the order date of just one cluster by just one date is not enough to see any significant difference in objective value. Therefore, it is necessary to change the order dates of multiple clusters at once. As the initial solution used is Base Solution 2 with 4 standard deviations as safety lead time, the optimisation algorithm focuses on decreasing order costs, as is the main cost element in the solution. Base Solution 2 allows for more flexibility, as the clusters are already more spread out. Within one iteration, the algorithm selects the 30 components with the highest holding costs, and then selects all clusters which contain these 30 components. As the holding costs are the issue, all order dates of these clusters are moved to a later date, by one week (5 working days). Then, the model draws lead times for all components for 10000 replications. The number of replications needs to be this high, otherwise all surrounding solutions are basically the same, and the algorithm is unable to find any improvements. Using a lower number of replications increases computational speed but makes the results of the algorithm too dependent on ‘good’ lead time values. An overview of the parameter settings can be found in Table 11.

*Table 11: Parameter settings optimisation*

| **Parameter** | **Setting** |
|---|---|
| Penalty costs per day delay | 31332.9 |
| Lead time distributions | Gamma distributions as calculated from data |
| Number of replications | 10000 |
| Initial solution | Base Solution 2, 4 standard deviations |
| Move order date | By a week |

The algorithm converges quickly, generally after about 5 iterations, in which each iteration moved about 10 clusters. These experiments do show that the initial solution is quite good already, but the high lead time variability prevents calling it an optimum. It is therefore more accurate to say that these solutions are in the neighbourhood of the optimum given these lead time settings. The lead time settings are an interesting topic for sensitivity analysis, this will be discussed in Section 5.3.

The outcome of the optimisation can be found in Table 12. The results are quite similar, and show once again why a local search algorithm with a lower number of replications did not produce any satisfactory results, as the lead time variability poses a difficulty.

*Table 12: Optimisation results*

| | Optimisation of Base 2: 4 stdevs | Base 2: 4 stdevs |
|---|---|---|
| Average Total Costs (in thousands) | 1476 | 1582 |
| Average Order Costs (in thousands) | 15 | 14 |
| Average Holding Costs (in thousands) | 1109 | 1183 |
| Average Penalty Costs (in thousands) | 352 | 385 |
| Average days delay | 12.29 | 12.30 |

As to be expected, the optimisation shows a decrease in holding costs, as that is what the algorithm focussed on. There is also a slight decrease in delay and therefore penalty costs, however this is insignificant and due to the variation in lead time. The most impactful on this decrease seems to be one specific cluster, as this was moved four weeks later than the initial date. The reason for this is that this cluster contains a quite expensive part, which therefore introduced high holding costs when it was ordered according to the same rule as all other clusters. Other clusters that were moved are mostly clusters that are needed in the last part of the assembly process. As there is always some delay, clusters that only contain components that are needed late are likely to be needed later than planned. Therefore, these clusters can also be ordered with a lower safety lead time. Furthermore, moving these clusters did not impact the delay significantly.

Table 13 shows how the clusters that were moved correspond to the different steps in the subassembly sequence. It shows that mostly the same clusters were moved, and some were not moved at all. It also shows that for almost all steps clusters were moved. However, there is a slightly higher number of clusters moved that are needed later in the subassembly sequence. This is due to likely delay earlier in the process, as explained earlier. It is also interesting to see that for step 5 a relatively high number of clusters was moved. This could be explained by the fact that delay already happens before that, and also because step 4 is the first step in which more subassemblies are built in parallel. This therefore increases the possibility of delay.

*Table 13: Cluster moves per step in subassembly sequence*

| Step in subassembly sequence | Number of clusters moved |
|---|---|
| 1 | 1 |
| 2 | 1 |
| 3 | 2 |
| 4 | 2 |
| 5 | 5 |
| 6 | 2 |
| 7 | 2 |
| 8 | 2 |
| 9 | 2 |
| 10 | 4 |
| 11 | 3 |
| 12 | 2 |
| 13 | 2 |
| 14 | 3 |
| 15 | 11 |

## 5.3 Sensitivity analysis

This section explores the sensitivity of various settings. Section 5.3.1 explores different settings for the lead time distributions. Section 5.3.2 explores the effects of limiting the number of orders on costs.

### *5.3.1 Lead time variability*

As the lead time distributions are based on limited data, it is unknown how accurate these are in reality. To explore if this has a large influence on the results of the analysis, this section will explore different settings for the lead time distributions. To decrease the variability, each standard deviation is multiplied with a factor. Therefore, the average lead time will remain the same, the variability will just be smaller.

Figure 7 shows the effect of lower lead time variability on total, holding and penalty costs. Table 14 shows the order costs and the days of delay of these solutions. The factors used were 0.8, 0.5 and 0.3.

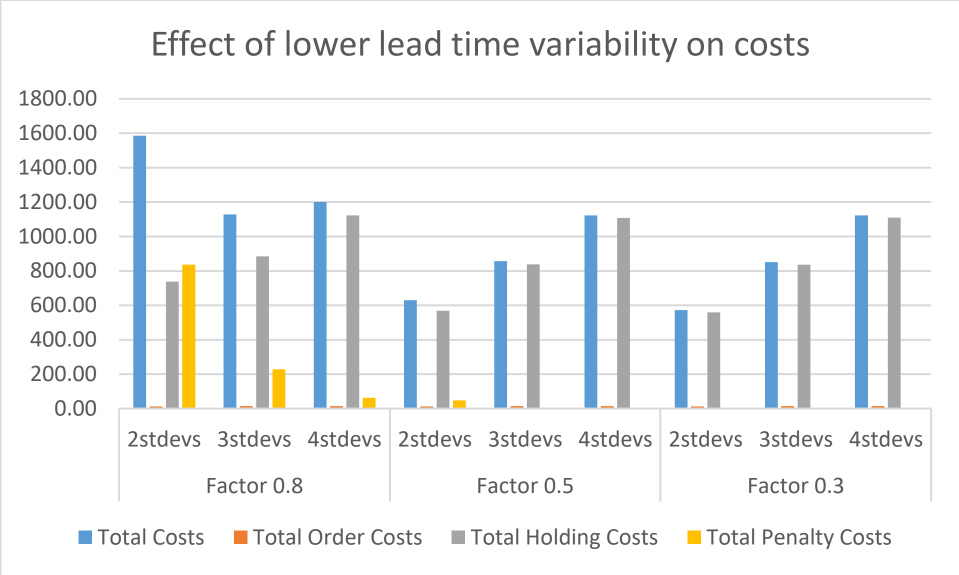



*Figure 7: Graph displaying the effect of lower lead time variability on costs*

It can be seen that even if the lead time variability is just 80% of the variability in the Base Scenario, using just two standard deviations as safety lead time results in total costs comparable to using four standard deviations in the Base Scenario. Also, using three standard deviations is clearly the better option in this case, and more likely an even better option lies in between two and three standard deviations, as the holding costs far outweigh the penalty costs in the case of 3 standard deviations. Also, the difference in days delay decreases quite significantly from two to three standard deviations.

Furthermore, for factor 0.5 and 0.3, it is clear using two or three standard deviations is far too conservative, as the holding costs are by far the dominant cost component. This does result in minimum days of delay.

*Table 14: Table displaying effect of lower lead time variability on order costs and days of delay*

| | Factor 0.8 | | | Factor 0.5 | | | Factor 0.3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2stdevs | 3stdevs | 4stdevs | 2stdevs | 3stdevs | 4stdevs | 2stdevs | 3stdevs | 4stdevs |
| Average Total Order Costs (in thousands) | 13.12 | 14.42 | 13.92 | 13.12 | 14.42 | 13.92 | 13.12 | 14.42 | 13.92 |
| Average Days delay final product | 26.67 | 7.29 | 2.00 | 1.54 | 0.09 | 0.02 | 0.00 | 0.00 | 0.00 |

As it is quite likely that the lead time distributions calculated from the data are too conservative, and influenced by outliers and inaccuracies in the data, it is interesting to investigate the simulation optimisation algorithm with all standard deviations multiplied by a factor 0.8. Therefore, the simulation optimisation algorithm is run using an initial solution of Base Solution 2 with three standard deviations and a lead time variability of 20% lower than in the Base Scenario. The result of this can be seen in Table 15.

*Table 15: Results of simulation optimisation with lower lead time variability*

| | Optimisation result | Base Solution 2: three standard deviations, 0.8 lead time variability |
|---|---|---|
| Average Total Costs | 1109 | 1128 |
| Average Order Costs | 14 | 14 |
| Average Holding Costs | 1005 | 885 |
| Average Penalty Cost | 89 | 228 |
| Average Days delay | 2.84 | 7.29 |

It can be seen that there is a decrease in total costs, however it is not that much. It is more interesting to see that the average holding costs did increase, even though clusters with high holding costs are the focus of the optimisation algorithm. This is due to the clusters that are selected to move. Clusters earlier on in the subassembly sequence, with high component values, are also selected to move, especially if their lead time are more variable. Due to the variability and the high component values, this can result in high holding costs. If the order dates of these clusters are moved to a later order date, this can introduce quite some holding costs for clusters later in the subassembly sequence. Also, clusters with a higher number of components are sometimes selected, as this also results in a higher value and therefore more holding costs, even if they are required earlier on in the process. In short, to further optimise the solution, the algorithm would need to be more 'educated' to select appropriate moves, to possibly improve from this likely local optimum.

If the lead time variability is completely removed, the problem, and therefore the solution become much simpler. Each cluster should just be ordered the average lead time before it is required. As the variability is removed, the lead time is simply the average lead time. To test the optimisation algorithm, Base Solution 2 with one standard deviation is used as initial solution. To ensure that the optimisation algorithm reaches the optimum, the search is slightly adjusted. Within one iteration, the algorithm evaluates moving the order date of each cluster by a day earlier and a day later, and selects the best one. Replications are not necessary in this case. If the move is kept at a week, it is likely that the optimum cannot be reached. The results can be seen in Table 16.

*Table 16: Results with no lead time variability*

| | |
|---|---|
| Total Costs | 33888 |
| Total Order Costs | 12022.0127 |
| Total Holding Costs | 21865.65109 |
| Total Penalty Costs | 0 |
| Average Days of delay | 0 |

It can be seen that the penalty costs and days of delay are 0, as they should be since it is known exactly when to order each cluster. The main cost component is still the holding costs, which is the consequence of the decision to cluster. If components were not to be clustered, the solution would change. This can be seen in Table 17. Here the holding costs are lower, whereas the order costs are higher.

*Table 17: Results without clusters*

| | |
|---|---|
| Total Costs | 30012 |
| Total Order Costs | 19578.94 |
| Total Holding Costs | 10432.78 |
| Total Penalty Costs | 0 |

In terms of order dates, this introduces 11 additional order dates.

### 5.3.2 Limiting the number of orders

As it is the desire of IMS to introduce more structure to the ordering and inventory process, it is also interesting to investigate the effect of introducing a fixed number of order dates. All clusters should be ordered at one of these dates.

The optimisation of Base Solution 2 leads to 87 order dates. This is quite a high number, higher even than the 40 separate order moments as estimated by the purchasing department in Chapter 2. However, there are also order dates that are on consecutive days, and also many dates that fall in the same week. The difference of 1-4 days is most likely negligible, especially with the high lead time variability. Therefore, all of these order dates are compiled into 'order weeks', meaning that an order will be placed in this week. This results in 40 different weeks. For the sake of the model, the order date is then set to be the Monday of that specific week.

These 40 different weeks are put into the simulation model as order dates. Each cluster is then assigned to the order date that is closed to the order date for that cluster from the simulation optimisation results. This already eliminated the number of order dates further down to 36. The results of this can be found in Table 18. Clearly, the order costs went down. For the rest, the results are actually quite comparable. The holding costs went up a bit, as the order dates are less directly 'catered' to the clusters, but this seems to work well for delay and therefore penalty costs. It seems that limiting the order dates still introduces some cautiousness and is able to combat the lead time variability slightly.

*Table 18: Results of 36 order dates compared to results of optimisation*

| | 36 order dates | Optimisation results Base Solution 2 |
|---|---|---|
| Average Total Costs (in thousands) | 1500 | 1476 |
| Average Order Costs (in thousands) | 9 | 15 |
| Average Holding Costs (in thousands) | 1179 | 1109 |
| Average Penalty Costs (in thousands) | 311 | 352 |
| Average Days delay | 9.94 | 12.29 |

In the interest of further limiting the number of order dates, the 36 order dates were further brought down to 10 order dates. This was done by picking 10 order dates from the 36 order dates, such that each of these 36 order dates is within 5 weeks of one of the selected order dates. Table 19 shows these results.

*Table 19: Costs of 10 order dates*

| | 10 order dates |
|---|---|
| Average Total Costs (in thousands) | 1596 |
| Average Order Costs (in thousands) | 6 |
| Average Holding Costs (in thousands) | 1120 |
| Average Penalty Costs (in thousands) | 462 |
| Average Days delay | 14.733 |

The total costs are higher and the order costs are lower, compared to 36 order dates, as is to be expected. The holding costs are lower, while the holding costs are higher. The limiting of the order dates seems to lead to more clusters being ordered later, hence the increase in penalty costs. As 75 out of a 119 clusters are ordered at a later date, the holding costs have decreased. On average, a cluster is about 8 working days away from the cluster date given by the simulation optimisation algorithm.

## 5.4 Conclusion

This chapter investigates the results of both the simulation and the simulation optimisation. By evaluating the different Base Solutions, it is clear that Base Solution 3 performs the best, as it is the most cautious in the initial scenario. The results itself are not that good yet, as even with Base Solution 3, the final assembly is on average still delayed by 58%. As expected, analysis showed that being more cautious results in better solutions. The best result for Base Solution 2 and 3 is to order each cluster the average lead time plus four times the standard deviation of the lead time. Due to the high lead time variability, the simple local search algorithm cannot provide any large improvements, which does show that already the initial solution is in the neighbourhood of an optimum, and the improved solution is just slightly better. By analysing which clusters were moved, it is clear that using four standard deviations as lead time is less suitable for clusters that are needed late in the assembly sequence, as well as clusters with a high component value and/or high lead time variability. The results do show that the simple approach of using 'logical' safety lead time already provides good results. It also shows that clusters are quite reliant of order dates of other clusters, as changing all clusters by the same safety lead time showed more impactful effects. For sensitivity analysis, the lead time variability was investigated, as well as the limiting of the number of order dates. This showed that even if the lead time variability is just reduced by 20%, this has a significant impact on costs. In fact, using three standard deviations as safety lead time is then a far better option. Also, the effect of limiting the number of orders was investigated. As IMS wants to better structure their ordering and inventory, having less dates on which orders should be placed is preferred. This analysis showed that cutting the number of order dates in half provides acceptable results. Limiting the number of order dates to just 10, increases costs again but would provide overview in the purchasing department.

# 6 Conclusion and recommendations

This section details the final chapter of this report. Section 6.1 gives the final conclusions. Section 6.2 provides the recommendations to IMS that follow from this. Section 6.3 discusses the limitations of this research and the opportunities for further research that remain.

## 6.1 Conclusions

This research aimed to answer the main research question "How can IMS best structure their ordering and inventory processes to realize their OEM goal and minimise holding, ordering, and penalty costs?". This research question arose from the core problem that IMS experienced high inventory costs and lacked the structure in the ordering and inventory system. The need to solve this arose from their desire to become an OEM for their HP-Molder. Analysis into the current situation showed this lack of structure in their current way of working, but with the shift to becoming an OEM the desired way of working is not yet certain. Further analysis showed a very large supplier base, as well as a high number of components within a machine. The literature review provided insights into inventory management for assembly manufacturing systems, but especially for multi-item inventory management, as this is needed for the large number of components within the HP-Molder. It also reviewed ways of handling variability in lead times. The most applicable of these methods seemed to be the concept of safety lead time, rather than safety stock. This concept can be used to combat the variability in lead times. By using a simulation optimisation model, the effects of different order dates were investigated.

This led to the following conclusions:

6. Using a safety lead time of the average lead time plus four times the standard deviation of lead time provides the best result when using one common 'rule of thumb' for all clusters.
7. The effect of lead time variability complicates the search for an optimal solution. The number of replications needed to accurately search neighbour solutions is too high.
8. Some clusters benefit from a more 'targeted' approach than one rule of thumb for the safety lead time. These are clusters that are needed later on in the assembly sequence, clusters that have a high lead time variability and clusters with a high component value. These clusters should have a lower safety lead time, using generally between 3-3.5 standard deviations.
9. Lower lead time variability reduces costs quite significantly.
10. Limiting the number of order dates to 10 is possible, if IMS is willing to sacrifice lower costs for more overview in the purchasing department.

## 6.2 Recommendations

The insights that follow from the analysis of several approaches and settings, led to the following recommendations for IMS:

1. Create planning based on safety lead times

To improve the efficiency and effectiveness of the purchasing department, the purchasing department should make a planning using the average lead time plus four times the standard deviation as safety lead time. For clusters late in the assembly process, as well as clusters with highly variable lead times and high components values, the safety lead time should be slightly lower, between 3 and 3.5. When deciding on order dates, attention should be paid to combining order dates if they are reasonably close. This makes the planning less chaotic and the purchasing department more specific. This planning could lower the pressure that the department sometimes feels. As the engineering department is often pushy about orders and constantly asking for orders and updates, having a planning introduces more structure. The engineers can then also be referred to this planning when they have questions. As it is likely that in reality the lead times are less variable than assumed for the model, it is important to regularly evaluate the planning, and update lead times for components accordingly.

2. Registering lead time data

The first recommendation to IMS is to put more effort into correctly logging order data into the ERP system. Because of the way this is currently organised, quite some data analysis was needed in order to calculate lead times. For example, an order date does not always refer to the actual order date. Also, the date of receipt is not always accurate. For example, if the logistics employee is not present for a few days, generally all packages are left until he is back. The date of receipt in the system does therefore not reflect the correct date, but the day that he returned. As the quality and lack of data heavily influenced this research, it is important to have a better understanding of the lead times to incorporate safety lead times. If these registered dates were more accurate, the lead time distributions would be more accurate, and the value of the solution would better represent reality.

Furthermore, this research used lead time distributions for suppliers, and not a lead time distribution for each component. In reality, it is known that for some suppliers the lead times for different components are quite different, and partial deliveries also occur. By having a lead time distribution for each component, the research could also focus on specific components. For example, which components should be kept on stock.

3. Reduce lead time variability

Next to having better insight into lead times, it would be beneficial for IMS to bring down lead time variability, especially for 'untrustworthy' suppliers. A possible way to do this, is to have stock at suppliers, or to introduce more agreements with suppliers they often order from. Although, having stock at suppliers could possibly just move the problem. Another way they could do this, is to extend the floor stock classification to more components. Even though all components that are currently classified as floor stock in the ERP system have been left out of the scope, there are some components that are ordered at the same suppliers that supply floor stock components. IMS could also look into standardising some of these components or building designs around such components. This could make stock for specific components more attractive.

4. Decreasing supplier base

IMS could also investigate decreasing the supplier base. This does not mean that they have to single-source everything, as that would make them too dependent, but having a few trustworthy suppliers with a solid partnership, this could also improve lead time and/or lead time variability. As Minner (2003) showed, a reduction of the supplier base often goes together with the introduction of a Just-In-Time strategy. This could work well if lead time variability goes down, because introducing Just-In-Time together means less holding costs, but also a lower probability of delay if the variability is not too high.

## 6.3 Limitations and further research

This research had quite some limitations. Most of them were associated with the lack of appropriate data. Therefore, a lot of assumptions had to be made, which is also important to keep in mind when considering the results of this research. This section discusses both the limitations and the possibilities for further research that result from these limitations.

### *6.3.1 Limitations*

This section details the limitations of this research.

- The lack of available data, and also the quality of the data imposes a limitation. This goes for the lead time data, but also ordering and penalty costs. For some components, also values had to be estimated, and it was not possible to provide a lead time for each component. This limits the direct value of the research, as the solutions are dependent on these values. However, the simulation and simulation optimisation methods could be performed again if more accurate measures are provided. Order costs and minimum order quantities also had to be estimated for some suppliers.
- The decision to cluster components is also a limitation, as it limits the solution space. It might very well be that there are now components within a cluster that require a different safety lead time than the other components in that cluster. Instead of first clustering and then setting order dates from safety lead times, this could also be done the other way around. Also, the heuristic for creating clusters only considered ordering and holding costs, and not penalty costs. The penalty costs might impact the cluster creation significantly.
- The simulation optimisation was just done with a relatively simple heuristic based on local search. This could have been extended and compared to other 'more sophisticated' methods to research the effect of a method on the solution. Possibly, these methods are able to evaluate more options. However, it is likely that the solution itself does not change that much, as order dates of clusters quite heavily depend on order dates of order clusters.

- The setting of values such as the penalty costs and holding costs rate were done based on estimates, as IMS has no clear values for these. The values of cost settings quite heavily influence the results of the simulation optimisation.
- Quality issues were left out of scope, as the data was limited. Quality issues however have quite a significant impact on the lead times, as rejected deliveries introduce extra lead times.
- Contracts with suppliers were also left out of scope. For some suppliers this means that the model does not account for quantity discounts.
- The research did not investigate the effect of ordering certain components at the wholesaler instead of from the manufacturer. For some components an assumption had to be made for which supplier to order from.
- In practice, it might be possible to ask a supplier to speed up deliveries, which the model does not account for. Therefore, the results could possibly be seen as a 'worst-case' solution.
- The subassembly sequence is assumed to be deterministic. However, it seems likely that the building involves some stochasticity, due to for example unforeseen circumstances.

### 6.3.2 Further research

Quality is definitely something that should be taken into account for further research. It is something that IMS has issues with quite regularly, but it was left out of the scope as there was not enough data about it. Introducing more uncertainty about data to the model is not that efficient, therefore the focus was now only on deciding when to order. Also, there are some components that need several production steps at different suppliers. For example, components that need to be milled at a specific supplier, and subsequently need to be lapped or polished at a different suppliers. A total journey of such a component can take up to 10 weeks. IMS arranges transport and planning between these different suppliers, but this takes up quite some time from the planner at the purchasing department, so this could also be looked into next.

Also, the selection of alternative suppliers is an interesting are for further research. IMS has quite some suppliers that can supply the same type of component, and often has to choose between suppliers there. In most cases, they go to a specific supplier, but this also reduces their partnerships with some other suppliers, as for instance they only come with 'urgent' orders. The selection is also interesting for components that can either be ordered from a wholesaler or the manufacturer. For these components there is a trade-off between order costs and lead time variability. For these components, the simulation optimisation algorithm could also be run with different selected suppliers.

The research could also be extended by considering multiple production cycles, and optimising both the order moments and order quantities. This could especially be interesting if the OEM path turns out to be as promising as IMS is hoping for. Then the question of which components to keep on stock also becomes more interesting.

It could also be researched what would happen if the building of the machine involves stochasticity. It is interesting to see how this would additionally impact the selection of order dates.

Furthermore, the value of the penalty cost should be researched. This is now based on an estimate, and not varied. However, the value of the penalty cost likely has significant effects on the solution. This can be done by running the simulation optimisation for various values of the penalty cost, and investigating how it affects the solution.

The limited order dates scenario could also further be researched, by using simulation optimisation to determine what the best order dates are, and which components should be ordered when.

# 7 Bibliography


Abo-Hamad, W., & Arisha, A. (2011). Simulation Optimisation Methods in Supply Chain Applications: A Review. *Irish Journal of Management*, *30*, 95–124. https://www.researchgate.net/publication/215642410_Simulation_Optimisation_Methods_in_Supply_Chain_Applications_A_Review

Alfares, H. K., & Turnadi, R. (2018). Lot sizing and supplier selection with multiple items, multiple periods, quantity discounts, and backordering. *Computers & Industrial Engineering*, *116*, 59–71. https://doi.org/10.1016/j.cie.2017.12.019

Ammar, O. Ben, Marian, H., & Dolgui, A. (2015). Supply planning for multi-levels assembly system under random lead times. *IFAC-PapersOnLine*, *48*(3), 254–259. https://doi.org/10.1016/j.ifacol.2015.06.090

Atan, Z., Stegehuis, C., Ahmadi, T., de Kok, T., & Adan, I. (2017). Assemble-to-Order Systems: A Review. *European Journal of Operational Research*, *261*. https://doi.org/10.1016/j.ejor.2017.02.029

Axsäter, S. (2006). Planning order releases for an assembly system with random operation times. In C. T. and T. B. and S. J. M. and G. S. B. Liberopoulos George and Papadopoulos (Ed.), *Stochastic Modeling of Manufacturing Systems: Advances in Design, Performance Evaluation, and Control Issues* (pp. 333–344). Springer Berlin Heidelberg. https://doi.org/10.1007/3-540-29057-5_14

Ayala, R., Mula, J., Poler, R., & Díaz-Madroñero, M. (2024). A proposal of analytical formulations to calculate safety lead times under demand variability. A case study. *Ain Shams Engineering Journal*, *15*(9), 102902. https://doi.org/https://doi.org/10.1016/j.asej.2024.102902

Bianchi, L., Dorigo, M., Gambardella, L. M., & Gutjahr, W. J. (2009). A survey on metaheuristics for stochastic combinatorial optimization. *Natural Computing*, *8*(2), 239–287. https://doi.org/10.1007/s11047-008-9098-4

Brusco, M. J. (2014). A comparison of simulated annealing algorithms for variable selection in principal component analysis and discriminant analysis. *Computational Statistics & Data Analysis*, *77*, 38–53. https://doi.org/10.1016/j.csda.2014.03.001

Byrne, P. J., & Heavey, C. (2006). The impact of information sharing and forecasting in capacitated industrial supply chains: A case study. *International Journal of Production Economics*, *103*(1), 420–437. https://doi.org/https://doi.org/10.1016/j.ijpe.2005.10.007

Chan, G. H., & Chiu, K. S. (1997). A simple heuristic for multi-product dynamic lot sizing problems. *Computers & Operations Research*, *24*(10), 969–979. https://doi.org/10.1016/S0305-0548(97)00010-5

Chauhan, S., Dolgui, A., & Proth, J.-M. (2009). A continuous model for supply planning of assembly systems with stochastic component procurement times. *International Journal of Production Economics*, *120*, 411–417. https://doi.org/10.1016/j.ijpe.2008.11.015

Chopard, B., & Tomassini, M. (2018). An introduction to metaheuristics for optimization. In *Natural Computing Series* (pp. 1–226). https://link.springer.com/book/10.1007/978-3-319-93073-2

Dechter, R. (2003). chapter 7 - Stochastic Greedy Local Search. In R. Dechter (Ed.), *Constraint Processing* (pp. 191–208). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-155860890-0/50008-6

Dolgui, A., & Ould-Louly, M.-A. (2002). A model for supply planning under lead time uncertainty. *International Journal of Production Economics*, *78*(2), 145–152. https://doi.org/10.1016/S0925-5273(00)00180-8

Dolgui, A., & Prodhon, C. (2007). Supply planning under uncertainties in MRP environments: A state of the art. *Annual Reviews in Control*, *31*(2), 269–279. https://doi.org/10.1016/j.arcontrol.2007.02.007

Eppen, G. D., & Martin, R. K. (1988). Determining Safety Stock in the Presence of Stochastic Lead Time and Demand. *Management Science*, *34*(11), 1380–1390. https://doi.org/10.1287/mnsc.34.11.1380

Gallego-García, D., Gallego Garcia, S., & García-García, M. (2021). An Optimized System to Reduce Procurement Risks and Stock-Outs: A Simulation Case Study for a Component Manufacturer. *Applied Sciences*, *11*, 10374. https://doi.org/10.3390/app112110374

Glover, F., & Laguna, M. (1999). Tabu search I. In *ORSA Journal on Computing* (Vol. 1). https://doi.org/10.1287/ijoc.1.3.190

Glover, F. W. (1989). Tabu Search - Part I. *INFORMS J. Comput.*, *1*, 190–206. https://api.semanticscholar.org/CorpusID:5617719

Hegedus, M., & Hopp, W. (2001). Setting procurement safety lead-times for assembly systems. *International Journal of Production Research*, *39*(15), 3459–3478. https://doi.org/10.1080/00207540110061625

Hopp, W., & Spearman, M. (1993). Setting Safety Leadtimes for Purchased Components in Assembly Systems. *IIE Transactions*, *25*, 2–11. https://doi.org/10.1080/07408179308964272

Kampen, T., Van Donk, D. P., & Zee, D. J. (2010). Safety stock or safety lead time: Coping with unreliability in demand and supply. *International Journal of Production Research*, *48*, 7463–7481. https://doi.org/10.1080/00207540903348346

Maes, J., & Van Wassenhove, L. (1988). Multi-Item Single-Level Capacitated Dynamic Lot-Sizing Heuristics: A General Review. *Journal of the Operational Research Society*, *39*(11), 991–1004. https://doi.org/10.1057/jors.1988.169

Minner, S. (2003). Multiple-supplier inventory models in supply chain management: A review. *International Journal of Production Economics*, *81–82*, 265–279. https://doi.org/https://doi.org/10.1016/S0925-5273(02)00288-8

Nielsen, P., Michna, Z., Sørensen, B., & Do, N. A. D. (2017). Lead Times – Their Behavior and the Impact on Planning and Control in Supply Chains. *Management and Production Engineering Review*, *8*, 30–40. https://doi.org/10.1515/mper-2017-0015

Ould-Louly, M.-A., & Dolgui, A. (2001). A Dynamic Single-Stage Multi-Item Inventory Control Model. *IFAC Proceedings Volumes*, *34*(8), 73–78. https://doi.org/https://doi.org/10.1016/S1474-6670(17)40797-X

Pahl, J., Voß, S., & Woodruff, D. L. (2007). Production planning with load dependent lead times: an update of research. *Annals of Operations Research*, *153*(1), 297–345. https://doi.org/10.1007/s10479-007-0173-5

Proth, J.-M., Mauroy, G., Wardi, Y., Chu, C., & Xie, X. (1997). Supply Management for Cost Minimization in Assembly Systems with Random Component Yield Times. *Journal of Intelligent Manufacturing*, *8*, 385–403. https://doi.org/10.1023/A:1018506232008

Sbai, N., & Berrado, A. (2022, July). *A literature Review on Multi-echelon Inventory Management Policies: Case of Assembly Systems*. https://www.researchgate.net/publication/364129832_A_literature_Review_on_Multi-echelon_Inventory_Management_Policies_Case_of_Assembly_Systems

Silver, E. A., Pyke, D. F., & Thomas, D. J. (2017). *Inventory and Production Management in Supply Chains* (Fourth Edition). Taylor & Francis Group.

Svoboda, J., Minner, S., & Yao, M. (2021). Typology and literature review on multiple supplier inventory control models. *European Journal of Operational Research*, *293*(1), 1–23. https://doi.org/https://doi.org/10.1016/j.ejor.2020.11.023

Thevenin, S., Ben-Ammar, O., & Brahimi, N. (2022). Robust optimization approaches for purchase planning with supplier selection under lead time uncertainty. *European Journal of Operational Research*, *303*(3), 1199–1215. https://doi.org/https://doi.org/10.1016/j.ejor.2022.03.029

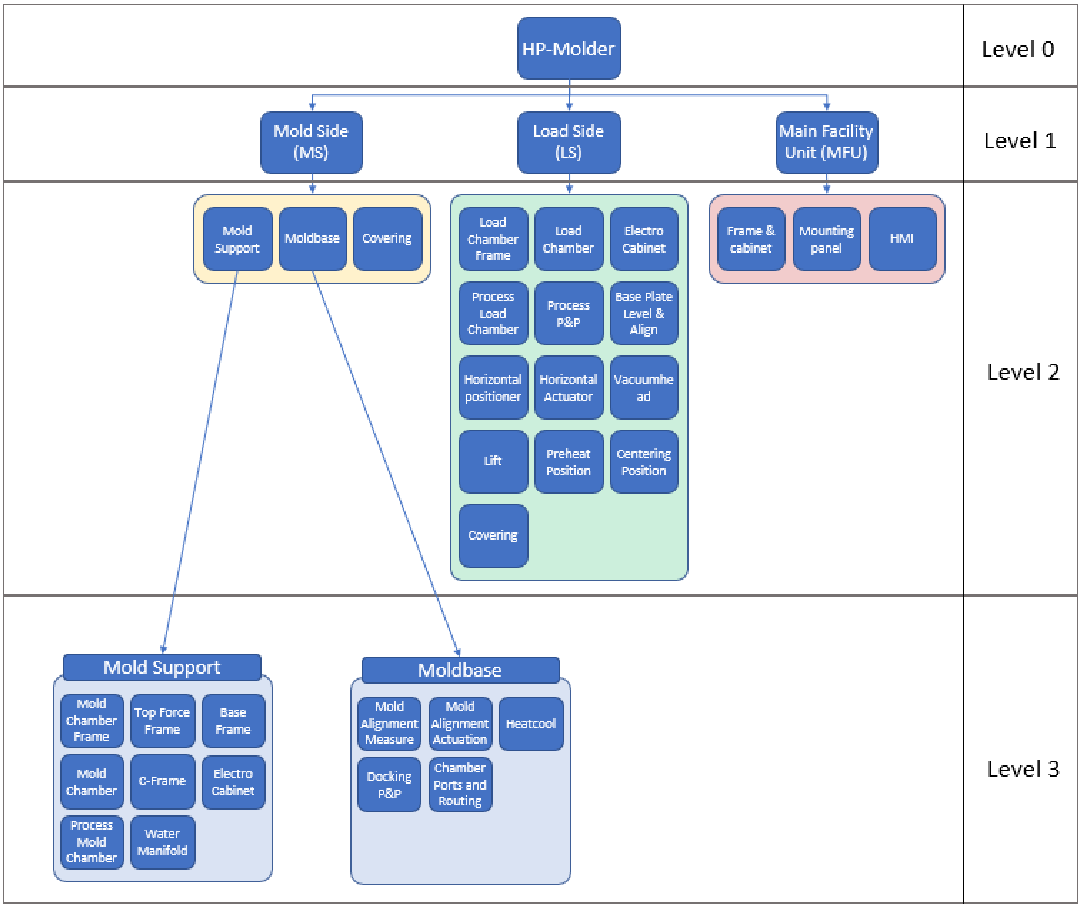
Van Eijs, M. J. G. (1994). Multi-item inventory systems with joint ordering and transportation decisions. *International Journal of Production Economics*, *35*(1), 285–292. https://doi.org/10.1016/0925-5273(94)90094-9

Weber, C. A., Current, J. R., & Benton, W. C. (1991). Vendor selection criteria and methods. *European Journal of Operational Research*, *50*(1), 2–18. https://doi.org/10.1016/0377-2217(91)90033-R

Whybark, D., & Williams, J. (1976). Material Requirements Planning Under Uncertainty. *Decision Sciences*, *7*(4), 595–606. https://doi.org/10.1111/j.1540-5915.1976.tb00704.x

Yano, C. A. (1987). Stochastic Leadtimes in Two-Level Assembly Systems. *IIE Transactions*, *19*(4), 371–378. https://doi.org/10.1080/07408178708975409

# Appendix A: Molder subassemblies




*Appendix A: Molder subassemblies*

The complete machine is Level 0, which then consists of three subassemblies at Level 1. All these subassemblies also contain subassemblies, which are then Level 2, and so on. All subassemblies shown (on Level 2 and 3) are steps in the assembly process.

# Appendix B: Supplier characteristics

| Suppliers | Mean lead time | Standard deviation of lead time | Order costs |
|---|---|---|---|
| Supplier 1 | 24.333 | 15.714 | 15.000 |
| Supplier 2 | 8.269 | 12.058 | 10.163 |
| Supplier 3 | 46.996 | 57.032 | 29.670 |
| Supplier 4 | 27.521 | 13.115 | 144.176 |
| Supplier 5 | 140.100 | 95.370 | 0.000 |
| Supplier 6 | 20.307 | 19.619 | 42.870 |
| Supplier 7 | 11.047 | 18.146 | 14.938 |
| Supplier 8 | 75.125 | 73.237 | 0.000 |
| Supplier 9 | 53.478 | 49.281 | 0.000 |
| Supplier 10 | 5.331 | 4.923 | 5.922 |
| Supplier 11 | 33.946 | 24.182 | 147.525 |
| Supplier 12 | 11.714 | 7.025 | 50.000 |
| Supplier 13 | 86.400 | 46.146 | 100.000 |
| Supplier 14 | 30.224 | 13.327 | 580.000 |
| Supplier 15 | 19.197 | 27.324 | 21.917 |
| Supplier 16 | 26.105 | 13.483 | 0.000 |
| Supplier 17 | 20.109 | 10.108 | 0.000 |
| Supplier 18 | 13.847 | 10.339 | 23.550 |
| Supplier 19 | 17.009 | 12.323 | 31.540 |
| Supplier 20 | 12.500 | 6.054 | 75.880 |
| Supplier 21 | 19.524 | 16.629 | 18.320 |
| Supplier 22 | 19.009 | 20.307 | 19.139 |
| Supplier 23 | 122.429 | 52.137 | 65.000 |
| Supplier 24 | 10.227 | 14.725 | 9.171 |
| Supplier 25 | 6.626 | 14.882 | 10.078 |
| Supplier 26 | 14.630 | 12.633 | 20.776 |
| Supplier 27 | 14.000 | 0.100 | 0.000 |
| Supplier 28 | 29.930 | 24.821 | 20.667 |
| Supplier 29 | 18.759 | 25.549 | 20.368 |
| Supplier 30 | 14.524 | 8.677 | 11.133 |
| Supplier 31 | 24.111 | 9.527 | 0.000 |
| Supplier 32 | 21.821 | 10.051 | 650.000 |
| Supplier 33 | 81.200 | 65.372 | 0.000 |
| Supplier 34 | 46.956 | 26.680 | 0.000 |
| Supplier 35 | 16.364 | 8.337 | 0.000 |
| Supplier 36 | 17.256 | 14.944 | 14.176 |
| Supplier 37 | 6.767 | 5.903 | 20.000 |
| Supplier 38 | 23.798 | 32.087 | 10.406 |
| Supplier 39 | 30.244 | 25.598 | 50.000 |
| Supplier 40 | 55.832 | 22.428 | 0.000 |
| Supplier 41 | 16.028 | 12.481 | 11.033 |

| | | | |
|---|---|---|---|
| Supplier 42 | 50.310 | 43.870 | 0.000 |
| Supplier 43 | 23.060 | 23.165 | 31.757 |
| Supplier 44 | 26.886 | 35.372 | 0.000 |
| Supplier 45 | 19.011 | 14.243 | 13.500 |
| Supplier 46 | 20.636 | 13.188 | 0.000 |
| Supplier 47 | 32.961 | 19.523 | 0.000 |
| Supplier 48 | 7.917 | 19.311 | 5.221 |
| Supplier 49 | 5.489 | 2.125 | 25.000 |
| Supplier 50 | 6.500 | 1.500 | 6.950 |
| Supplier 51 | 21.483 | 30.333 | 20.000 |
| Supplier 52 | 19.826 | 20.064 | 25.250 |
| Supplier 53 | 61.250 | 63.164 | 34.750 |
| Supplier 54 | 26.908 | 20.937 | 51.460 |
| Supplier 55 | 20.014 | 13.833 | 39.396 |
| Supplier 56 | 22.667 | 13.320 | 19.000 |
| Supplier 57 | 13.652 | 21.827 | 2.460 |
| Supplier 58 | 11.359 | 14.272 | 17.115 |
| Supplier 59 | 26.163 | 12.319 | 17.944 |
| Supplier 60 | 7.834 | 9.150 | 22.334 |
| Supplier 61 | 20.000 | 7.439 | 0.000 |
| Supplier 62 | 8.065 | 7.682 | 24.400 |
| Supplier 63 | 17.557 | 16.766 | 47.500 |
| Supplier 64 | 6.846 | 6.024 | 15.000 |
| Supplier 65 | 25.137 | 14.053 | 0.000 |

*Appendix  B: Supplier characteristics*

# Appendix C: Quality ratings

| **Make part supplier** | **Quality rating** |
|---|---|
| Make part supplier 1 | 4 |
| Make part supplier 2 | 3.3 |
| Make part supplier 3 | 4 |
| Make part supplier 4 | 4.3 |
| Make part supplier 5 | 4 |
| Make part supplier 6 | 4.5 |
| Make part supplier 7 | 3.8 |
| Make part supplier 8 | 5 |
| Make part supplier 9 | 5 |
| Make part supplier 10 | 4.5 |
| Make part supplier 11 | 4 |

*Appendix C: IMS quality ratings for make part suppliers*

A score between 1 and 5 is given to each supplier, mostly based on past experiences and an estimate. These scores can be seen in Appendix C.

# Appendix D: Simulation optimisation flowchart

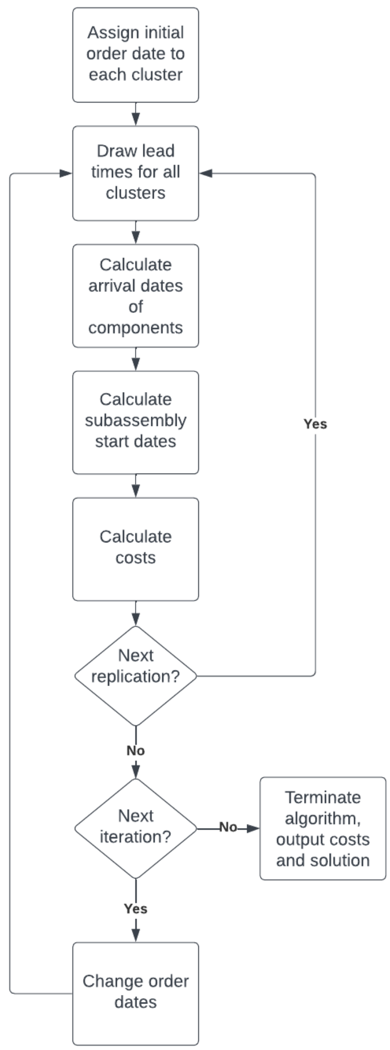
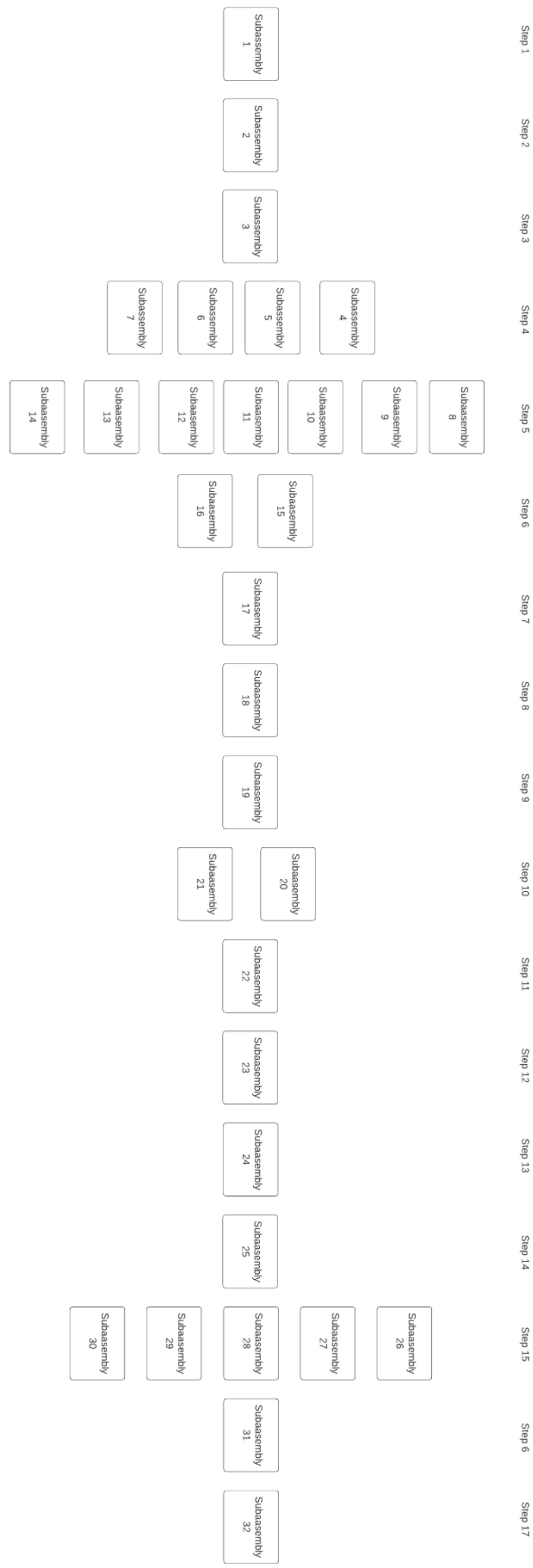



*Figure 8: Flowchart of simulation optimisation model*

# Appendix E: Subassembly sequence



# Appendix F: Final clusters

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | Number of clusters |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Supplier 1 | | | | 1 | | | | | | | | | | | | | 1 |
| Supplier 2 | | | | | | 1 | | | | | | | | | | | 1 |
| Supplier 3 | | | | | | | 1 | | | | | | | | | | 1 |
| Supplier 4 | 11 | | | 17 | | | | 13 | | | 11 | | 32 | | | | 5 |
| Supplier 5 | | | | | | 5 | | | | | | | | | | | 1 |
| Supplier 6 | 1 | | | | | | | | | | | | | | | | 1 |
| Supplier 7 | 29 | | | | 31 | | | | | 49 | | | 21 | | | | 4 |
| Supplier 8 | | | | | | 2 | | | | | | | | | | | 1 |
| Supplier 9 | | | | | | | | | | | | | | | 2 | | 1 |
| Supplier 10 | | | | | 4 | | | | | | | | | | | | 1 |
| Supplier 11 | | | | | | | | | | | 1 | | | | | | 1 |
| Supplier 12 | | | 1 | | | | | | | | | | | | | | 1 |
| Supplier 13 | | | | 1 | | | | | | | | | | | | | 1 |
| Supplier 14 | 7 | | | | 17 | | | | | 5 | | 4 | | | | | 4 |
| Supplier 15 | | | | | 1 | | | | | | | | | | | | 1 |
| Supplier 16 | 2 | | | | 3 | | | | 3 | | | | | 2 | | | 4 |
| Supplier 17 | 1 | | 3 | 6 | | | 5 | | | | 6 | | | | | | 5 |
| Supplier 18 | 4 | | | | 2 | | | | | | | | | | | | 2 |
| Supplier 19 | | | | | | | | | | | | | | | 3 | | 1 |
| Supplier 20 | | | | | | 1 | | | | | | | | | | | 1 |
| Supplier 21 | | | | | | | | | | | | | | | 1 | | 1 |
| Supplier 22 | | | 5 | | | 2 | | | | | | | | 6 | | | 3 |
| Supplier 23 | | | | | 1 | | | | | | | | | | | | 1 |
| Supplier 24 | | | | | | 5 | | | | | | | | | | | 1 |
| Supplier 25 | | | | | | 3 | | | | | | | | | | | 1 |
| Supplier 26 | | | | | | | | 1 | | | | | | | | | 1 |
| Supplier 27 | | | | | | | | | | | | | | | 1 | | 1 |
| Supplier 28 | | | | | 2 | | | | | | | | | | | | 1 |
| Supplier 29 | | | | | | | | | | | | | | | 1 | | 1 |
| Supplier 30 | 5 | | | | | | | | | | | | | | | | 1 |
| Supplier 31 | | | | | | | | | | 4 | | | | | | | 1 |
| Supplier 32 | | | | | | | | | | | | | | | 2 | | 1 |
| Supplier 33 | | | 3 | | 5 | | | | | 1 | 6 | | | | | | 4 |
| Supplier 34 | 1 | | | | 7 | | | | 4 | | | | | | | | 3 |
| Supplier 35 | | | | | | | | | | 2 | | | | | | | 1 |
| Supplier 36 | 12 | | | | | 1 | | | 32 | | | | | | | | 3 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Supplier 37 | | | | | | | | | | | 1 | | | | 1 | | 2 |
| Supplier 38 | | | | | 2 | | | | | | | | | | | | 1 |
| Supplier 39 | 4 | | | 3 | | | 3 | | | | | | | | 5 | | 4 |
| Supplier 40 | 3 | | | 8 | | | | | | 4 | | 2 | | | | | 4 |
| Supplier 41 | | 4 | | | | | | | | | | | | | | | 1 |
| Supplier 42 | | | | | | | | | | | 2 | | | | | | 1 |
| Supplier 43 | | | 3 | | 9 | | | | | | | | | | 13 | | 3 |
| Supplier 44 | | | 1 | | | | | | | | | | | | | | 1 |
| Supplier 45 | | | | | 3 | | | | | | | | | | | | 1 |
| Supplier 46 | | | | | | 3 | | | | | | | | | | | 1 |
| Supplier 47 | | | 14 | | | | | | | | 2 | | | 15 | | | 3 |
| Supplier 48 | | | 2 | | | | | | | | | | | | | | 1 |
| Supplier 49 | | | | | | | | | | | | | | | 1 | | 1 |
| Supplier 50 | | | 4 | | | | | | | | | | | | | | 1 |
| Supplier 51 | 2 | | | | | | | | | | | | | | | | 1 |
| Supplier 52 | 3 | | | 38 | | | | 10 | | | | | | | 5 | | 4 |
| Supplier 53 | | | | | | 2 | | | | | | | | | | | 1 |
| Supplier 54 | | | | | | 3 | | | | | | | | | | | 1 |
| Supplier 55 | | | | 43 | | | | 10 | | | | | | | 14 | | 3 |
| Supplier 56 | | | | | 1 | | 2 | | | 1 | 2 | | | | 4 | | 5 |
| Supplier 57 | | | | | | | | | | | | | | | 1 | | 1 |
| Supplier 58 | | | | 7 | | | | | | | | | | | | | 1 |
| Supplier 59 | | | | | | | | | | | | | | | 1 | | 1 |
| Supplier 60 | | | | | | | | | | | | | | | 4 | | 1 |
| Supplier 61 | | | | | | | | | | | | | 1 | | | | 1 |
| Supplier 62 | | | 10 | | 15 | | | | | | | | | 9 | | | 3 |
| Supplier 63 | | 44 | | | | 18 | | | | | | | | 12 | | | 3 |
| Supplier 64 | | | | | | 2 | | | | | | | | | | | 1 |
| Supplier 65 | 17 | | | | 49 | | | | | 43 | | | | | | 9 | 4 |
| | | | | | | | | | | | | | | | | | 119 |

*Appendix D: Final clusters*

The number specifies the number of components from that supplier, which should arrive at that subassembly step. Any non-empty cell therefore constitutes a cluster.