Exploring improvement opportunities for the Master Production Schedule

Graduation Thesis

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Preface

Dear reader,

You have opened my graduation thesis for the Bachelor's programme Industrial Engineering and Management at the University of Twente. This research was performed at Demcon Production, the production department of its parent company, the Demcon Holding. Over the course of half a year, I have learned a lot about the history of Demcon, the current way of working of Demcon Production and, of course, the subjects covered in this thesis.

I would like to thank my supervisor Gino Heijnsdijk for supervising me. He was more than helpful in supervising not only the research I performed but also in formulating the report in front of you as we speak. Gino gave me the freedom to explore the processes of Demcon Production while at the same time providing guidelines I needed to continue. Due to the COVID-19 pandemic, most of this research had to be performed from home. Gino ensured that I still got to know the company even though I was not able to visit it.

Additionally, I would like to thank the other employees of Demcon that took the time to answer my questions, even when far more pressing matters were at hand.

Lastly, I would like to thank my UT supervisors Derya Demirtas and Engin Topan for helping me, from start to finish, in realising this report. Both provided valuable feedback and were always willing to think along.

Daan Peters

Management summary

This research explores opportunities for improvement within the Master Production Schedule. The conclusions and recommendations made can be used as a starting point for a continuous improvement project for the whole Manufacturing Resources Planning.

Background

Demcon is an engineering company located in Enschede. Its production department, Demcon Production (DP), was established in 2005. Due to its roots in project-wise engineering, DP's supply chain is not designed as a production company and due to the rapid growth in demand, no time has been taken to evaluate and change this way of working. As a consequence, the company is struggling with keeping up with the demand and often fails to deliver on time, negatively affecting its service level. Over 2019, 35.3% of the products were delivered too late, leaving significant room for improvement.

The mentioned growth is expected to continue and DP wishes to keep up with the increasing demand. In order to manage this expansion of production practices, the current process is researched.

Problem identification & Method

The whole production process, from receiving order to finishing product, has an impact on the delivery date of the product. Multiple problems within this process have been identified, from which one is chosen: the Master Production Schedule (MPS). The MPS is an overview of when and in what quantities production should start in order to meet the promised delivery dates. The schedule should therefore be properly designed to avoid lateness and thus keeping up the service level. To help DP with designing their MPS, this thesis will explore opportunities for improvement within the MPS and its main input: demand. As a result, three main subjects are covered in this thesis: Master Production Schedule, Analysing past demand and Demand forecast accuracy.

Master Production Schedule

The MPS is the first step in any production process and therefore forms the basis for all subsequent phases, such as the Material Requirements Planning (MRP) and Capacity Planning. The MPS should thus be feasible and reliable. The impact of changes in the MPS is called schedule instability, which can cause issues in later phases. These issues might affect the ability to deliver on time and therefore, a stable schedule is preferred. To create a more stable schedule, multiple techniques were found in literature. Based on these techniques, some recommendations are made. One option is to implement frozen periods in which no adjustments can be made to the schedule. An alternative is using slushy periods, in which only adjustments can made to the timing or the quantity of the orders. This can be used as a restriction for clients when they order products at DP. Additionally, this can be used as a commitment for placing orders for materials/parts at suppliers. This might enable more reliable delivery of materials or even shortened lead times, as either the timing or the quantity is already known to the supplier. Other ways of reducing schedule instability is using safety stock and safety lead times.

Another aspect of the MPS is the way the schedule is created. Computing power can be used to find a (near-to-)optimal schedule. Therefore, a list of scheduling methods found in literature is addressed and compared. Based on these comparisons, the requirements for a suitable scheduling method are formed. A scheduling technique for DP should focus on decreasing the lateness of products and must be flexible so that it can easily adapt to schedule changes. Further research is required before choosing or designing a suitable scheduling technique.

Analysing past demand

The main input of the MPS is the demand. When designing the MPS, it is important to know what characteristics are of the demand DP is dealing with. Therefore, some characteristics of demand are researched. As part of understanding the different types of demand, an Excel-based tool has been created to compare and statistically test the demand data against a selection of probability distributions. As limited data is available data is available, the results might be skewed. However, the conclusion can be drawn that using the normal distribution to model the demand is acceptable. The other probability distributions selected appear to be unfit for modelling demand of the different products. Another way of using the tool is to model the delivery times of suppliers, which should help with determining the previously mentioned safety lead times.

Demand forecast accuracy

The products DP manufactures are complex and often require items with very long lead times. To provide shortened lead times for DP's clients, these clients deliver forecasts. Based on these forecasts, DP makes purchasing and production decisions. However, these decisions bring substantial (financial) risks as the actual orders have not yet been placed. An Excel-based tool was created to evaluate the accuracy of the forecasts delivered by the clients. It was found that the accuracy of products significantly differ, which in combination with the relatively little data (only 12 months) makes it difficult to draw general conclusions. However, it can be concluded that, even though the forecasts delivered by the clients significantly differ from real-life demand, the forecasts are more accurate than the forecasting techniques selected for comparison. Additionally, it is found that, based on a few products, the forecasts two months in advance are most accurate, even more accurate than the forecast delivered one month in advance.

Keywords: Master Production Schedule; Schedule instability; Schedule nervousness; Demand forecast accuracy;

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1. Introduction and problem statement

In this chapter, some background information on the company and the motivation behind this research will be given. Subsequently, the problem will be identified and explored, resulting in the research questions this thesis will answer.

1.1. Demcon Production

Demcon Production B.V. is part of the Demcon Holding group. Established in 1993, Demcon started as a mechatronic engineering firm. Over the course of 26 years, Demcon has been expanding rapidly, finally growing into the Demcon group. Demcon group is a coordinated set of independent companies. With a total of over 700 employees in its six locations worldwide, Demcon group has identified four areas of specialisation. These so-called business units are:

- *High-tech systems*
  Demcon develops high-tech systems for various markets and purposes, from single production machines to tools produced in series.
- *Medical systems*
  Through product development and production, Demcon aims to contribute to better and more efficient medical care. From decreasing the invasiveness of surgeries to manufacturing hearing aids, Demcon affects many lives.
- *Robotic systems*
  From medical robots to drones, Demcon is specialised in mobile and autonomous robotic systems. The systems are deployed in various fields such as maintenance, cleaning, and safety.
- *Optomechatronic*
  With Demcon's unique knowledge in the field of optical systems and precision inspection, Demcon develops optomechatronic systems for several high-tech markets, such as space travel.

In general, each project includes the development and prototyping of a single product or system. However, in the early 2000s, more and more clients asked for the possibility of Demcon to produce multiple items. This mainly happened to the medical systems business unit. As a consequence, the Demcon Holding decided to start producing products in 2005. This production takes place at Demcon Production B.V..

Demcon Production (from now on referred to as DP) is specialized in manufacturing complex and high-tech products and systems. The company's deliverables range from prototyping to complete supply chains. DP follows a make-to-order principle, meaning that it only produces products after the order has been received.

1.2. Motivation for research

Demcon Production has been rapidly growing ever since its establishment in 2005 and they do not intend to stop here. The number of clients and the number of products and systems they order are ever-growing and DP is determined to keep up with the expected growth. The managing director of DP has therefore decided to look into the whole process, the Manufacturing Resources Planning (also known as MRP II), in order to make the upscaling of the department possible.

1.3. Problem statement

Due to its rapid growth, DP is struggling with delivering its products on time. Of all products that had a promised delivery date in 2019, 36% of the products could not be delivered before or on the promised delivery date. This problem will become even more relevant when the demand will increase in the future and is, therefore, the main problem DP is facing at the moment.

DP is ambitious and is planning to grow, but before doing so, it needs to solve the problem at hand. Due to the COVID-19 pandemic, DP has not yet taken the time to formulate a clear goal for its service level. Therefore, one (ambitious) goal is proposed: having 90% of the products delivered on or before the promised delivery date. Of the 10% of products that are delivered late, 75% cannot be more than one week late.

Meeting more promised delivery dates is mainly important for a few people, the problem owners. The managing director at DP is responsible for all the processes. His goal is to increase revenue and consequently increase the profit DP is making. As a production department, the revenue DP makes is highly dependent on the number of products it manufactures. To increase the number of products, customers must be satisfied with DP's service level: the extent that DP is meeting their promised delivery dates. The managing director of Demcon Production is, therefore, the problem owner of the action problem described.

Combining all this information, the action problem can be defined as follows:

How can DP increase the service level of orders?

1.4. Problem cluster

To solve the identified action problem, the problem has to be investigated. What is causing the problem? How are the different problems related to each other? Only once these questions have been asked and answered, one will find the root of the action problem: the core problem(s) (Heerkens & Van Winden, 2017). To find out what the underlying problems for the late delivery of products are, a problem cluster has been designed (see Figure 1). The core problems are indicated in

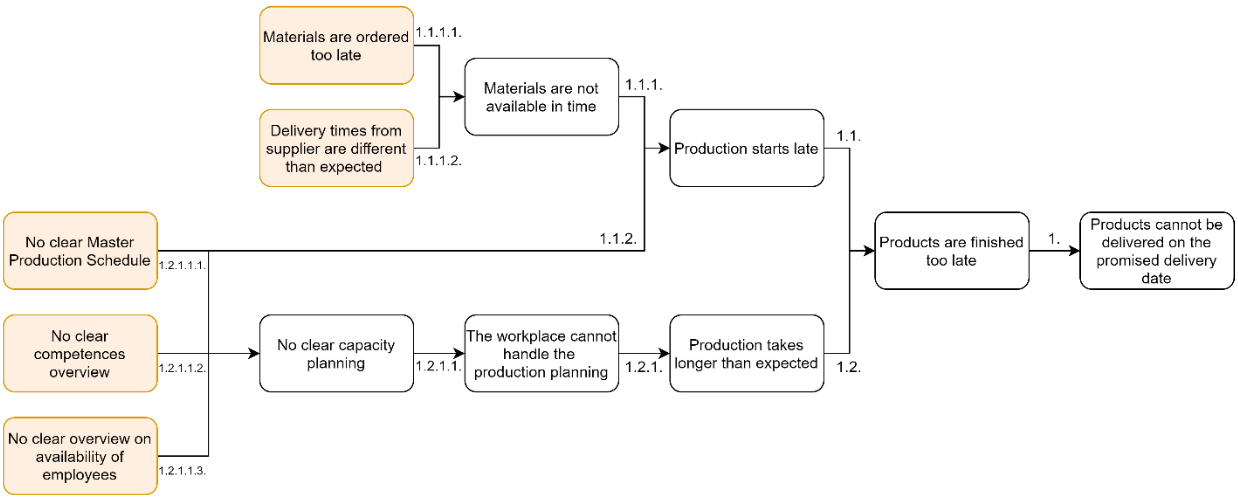


Figure 1 - Problem Cluster

All causational relationships are indicated with arrows. Each relationship will be briefly explained below.

1. A product can only be delivered after it is finished. If a product is finished too late, DP cannot meet that promised delivery date.

1.1. When production starts later than planned, products will consequently be finished later than planned.
   1.1.1. Production can only start when all materials and required parts are available. When these are not available at the moment when production should have started, a delay is created.
      1.1.1.1. Materials and parts are ordered too late, causing them to not be available when the production should have started.
      1.1.1.2. Delivery times from suppliers are longer than expected, causing issues with realising the production planning.
   1.1.2. DP does not follow a clear production schedule. Without having such an overview, it is hard to determine when specific products should start production in order to meet the promised delivery dates.
1.2. Production sometimes takes longer than initially expected. This causes products to be finished later than planned.
   1.2.1. The capacity of the workplace is sometimes too low for the production that is planned there, resulting in longer production times.
      1.2.1.1. No clear capacity requirements planning is used by DP, resulting in capacity issues at the workplace.
         1.2.1.1.1. The Master Production Schedule is one of the inputs of the capacity planning and should therefore give a clear overview of when certain production activities should take place.
         1.2.1.1.2. One of the capacities DP is dealing with is the manpower required to produce the ordered products. The competences matrix should provide an overview of which employees can perform which tasks.
         1.2.1.1.3. The availability of the employees should be presented in such a way that it can be combined with the competences matrix.

1.5. Scope of the thesis

Within the problem cluster in Figure 1, two groups of problems can be identified, both containing different core problems (highlighted in orange). The first group of problems is focused on the material flow to and at DP. The second group of problems involves the capacity planning. Previous research has already been performed on the material flow (Wonders, 2020), suggesting the implementation of safety stocks to improve material availability.

From the identified core problems, one problem affects both the material flow and the capacity planning problem group: *No clear Master Production Schedule*. The output of the Master Production Schedule stage within the MRP II is a rough-cut production plan. This production plan answers the following question: *When should production start in order to deliver the ordered products on time?* Having a properly designed Master Production Schedule is therefore essential for delivering on time. Hence, this core problem is chosen to investigate.

More information about the MPS, the other stages within the MRP II and how they relate to each other can be found in Appendix A: Manufacturing Resources Planning.

1.6. Research design

As the MPS is the first phase of a production process, it should provide a solid base for the subsequent phases. To illustrate, the Material Requirements Planning relies on the production planning made by the MPS. If the MPS is unrealistic, this may result in infeasible purchasing plans, consequently delaying production and delivery. This research will focus on how the MPS can be improved.

Based on the previous sections, the action problem can be specified better. This leads to the main research question of this thesis:

How can the Master Production Schedule be improved to increase the service level of orders?

Figure 2 gives an overview of the inputs needed to produce a Master Production Schedule. To find opportunities for improvement, this thesis will investigate three main parts:

- **Master Production Schedule**
- **Demand**
- **Forecasted demand**

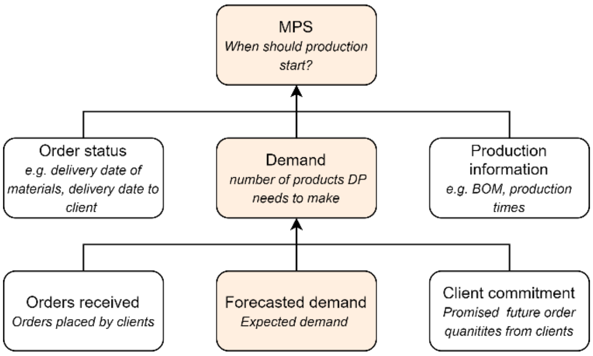


Figure 2 - Master Production Schedule inputs

To answer the main research question, some research questions have been set up, corresponding to these three subjects. Throughout this thesis, information about the research questions is gathered and analysed with the goal of answering the research questions. As demand and the demand forecasts are important inputs for the MPS, additional research will be put on improving DP's understanding of their demand.

Research question 1: What techniques can be found that help designing a solid Master Production Schedule? (Section 2.1)

This research question focuses on two things: tackling schedule instability and optimizing the production schedules. First, it will be investigated what techniques already exist to decrease schedule instability. As the MPS is the first phase of a production process, changes can have a snowball effect on the subsequent phases, e.g. a small change in the MPS might require drastic changes in the capacity planning. In literature, this effect is referred to as schedule instability, which should be minimized to create a solid base for the rest of the supply chain. A more stable schedule enables better decision making on the production planning required to avoid lateness of delivery.

Till what point in time are the employees allowed to makes adjustments to the MPS? What agreements should be made with the client to create more stability? These questions will be addressed and answered in the first part of Section 2.1.

Subsequently, an optimal way of scheduling is sought. Currently, DP creates its Master Production Schedule manually. However, with the increasing number of products DP has to produce to keep up with the demand, manually creating this production plan is becoming increasingly complex. Computing power can be used to systematically (by for example using algorithms or heuristics) create the Master Production Schedule. However, there is not one single solution in achieving this.

What factors play a role in determining when a certain production activity should be planned? What scheduling methods are available in literature? How can an algorithm or heuristic minimize lateness of deliveries? These questions will be researched and explained in the mentioned section.

Research question 2: What characteristics can be identified in demand? (Section 2.2)

Demand is the most important input for the MPS. Understanding the characteristics of this demand helps when designing a production schedule, which should be properly established to finish products on time. One of these characteristics is the probability distribution of demand. For example, in previous research into the processes of DP, the assumption was made that the demand is normally distributed, but this assumption is not well-founded. Understanding the characteristics of the demand at DP will help to substantiate these assumptions and to make well-founded decisions. Well-found decisions help with creating feasible and realistic production plans.

For this research question, the demand characteristics from different products and clients will be researched. This will not be limited to justifying the normality assumption, but will investigate possible alternative distributions as well as investigating demand patterns such as trends and seasonality.

Research question 3: How can the accuracy of the forecasts delivered by DP's clients be measured? (Section 2.3)

The products DP assembles often require parts that are manufactured by other organisations. These parts can be rather complex and delivery times can rise till over twenty weeks. For some products, DP has to wait for several weeks where assembling these parts only takes one or two weeks. Clients, therefore, have to wait a long time for their order while at the same time, DP is waiting for the product parts to arrive.

To decrease the delivery times for the clients, some of DP's clients provide their expected demand for the upcoming period. This enables DP to release purchase orders in advance for parts that have a long lead time. However, clients often tend to deviate from their initial forecasts, resulting in capacity problems. These capacity problems include not having enough skilled employees to realise the production or having a shortage or excess of parts.

As decisions are based on these forecasts, inaccurate forecasts require more adjustments in the MPS, increasing instability. For this research question, the accuracy of the forecasts provided by clients will be investigated. When the Master Production Schedule relies on the forecast data of the clients, issues might occur when the data is faulty. Once the accuracy of the forecasts is known, DP can take actions that prevent these scheduling issues. Additionally, the forecasts provided by clients will be compared to common forecasting techniques.

1.7. Deliverables

Based on the research questions in the previous section, a list of deliverables is created.

Deliverable 1: Overview of improvement opportunities within the MPS (Chapter 3)

The Master Production Schedule is a common term in the field of production companies. There are many different ways of (optimally) planning a company's production activities. Based on the literature, an overview of important factors that influence the MPS and an overview of available techniques, such as algorithms and heuristics, will be given.

Deliverable 2: Understanding demand characteristics (Chapter 4)

Insights in the different characteristics, e.g. probability distributions, of demand will be given and applied to the data available for DP's clients and products. These demand characteristics should help DP to understand what types of demand they are working with. How this knowledge can be applied in their practices will be elaborated upon as well. Additionally, a tool will be created to test data sets on certain probability distributions.

Deliverable 3: Forecast accuracy tool & findings (Chapter 5)

To evaluate the forecasts delivered by DP's clients, an Excel tool will be created and used to compare the actual demand to the forecasted demand. Additionally, findings from using the tool for different clients and products will be summarized.

Deliverable 4: KPI selection and tool for measuring service level (Chapter 6)

As the goal of DP is to improve its service level, it should be easily measurable what DP's performance is. Therefore, some KPIs have been chosen that represent the service level over a certain time frame. The calculation of these KPIs is done by the Excel tool created. If the recommendations formulated throughout this thesis are implemented, the tool provides insight in how the service level has developed.

2. Literature

Before answering the research questions, literature is gathered to explain the related concepts. This chapter is divided into three sections. Per research question, which can be found in Section 1.6, relevant literature is mentioned and explained. The findings of this literature study will be used in the subsequent chapters.

2.1. Master Production Schedule

The Master Production Schedule, in short MPS, is an overview of how much a company needs to produce and when it needs to produce it in order to meet customer demand. Inputs for the MPS are planned orders, future (e.g. forecasted) orders and both current and future availability of products. The latter includes the number of products that are in stock and the number of products that are currently in production.

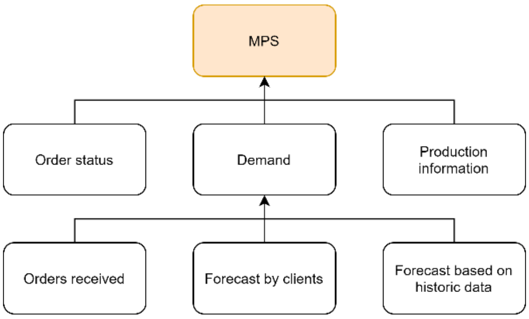


Figure 3 - MPS inputs: MPS

Based on production lead-times, the MPS gives an overview that says what products have to start production on what days. The date and the number of to-produce products are the main output of the MPS. These start-dates are the due-dates for the Material Requirements Planning (MRP), which ensures that required materials are available in time.

In the supply chain, the MPS is one of the first steps (see Appendix A: Manufacturing Resources Planning) and can have a significant impact on the performance of the rest of the processes at the company. Bakar *et al* mention the MPS as the most significant activity with regards to planning and controlling production (Bakar, Abbas, Alsattar, & Kalaf, 2017). Therefore, the MPS should be properly established to provide a solid base for the subsequent phases of scheduling.

2.1.1. Schedule nervousness/instability

Changing the Master Production Schedule might seem insignificant, but can lead to complications in subsequent stages and departments. Multiple researchers define this phenomenon to be a consequence of a nervous or unstable system. Instability and schedule nervousness thus refer to the big impact that small changes in the MPS can have on the MRP plans (Zhao, Goodale, & Lee, 1995).

Zhao & Lee (1993) introduce a formula for measuring the schedule instability:

$$I = \frac{\sum_{i=1}^{n} \sum_{k>1} \sum_{t=M_k}^{M_k+N-1} \left| Q_{ti}^{k} - Q_{ti}^{k-1} \right|}{S}$$

where *i* is the item index, *n* the number of items, *t* the period, *k* the planning cycle, Q_{ti}^{k} the scheduled order quantity for item *i* in period *t* in planning cycle *k*, M_k the beginning period of planning cycle *k*, N the length of the planning horizon and S the total number of orders in all planning cycles. (Zhao & Lee, 1993)

Throughout literature, many approaches for dampening this schedule instability have been researched. In the next section, these will be mentioned.

Decreasing schedule instability

Both Robinson *et al.* (2008) and Xie (2010) indicate that an Early Order Commitment (or Advance Order Commitment) policy can help to create a more efficient and integrated process. In such an EOC (or AOC) policy, the manufacturer releases purchasing orders in advance, providing the vendor with future order visibility. The vendor can consequently improve the efficiency of its replenishment activities. (Xie, 2010) (E. Powell Robinson Jr, Funda Sahin & Li-Lian Gao, 2008)

These commitment measures generally decrease the number of changes made in the MPS and thus provide a more stable system. Additionally, different researches indicate that a more integrated supply chain in make-to-order processes can be very beneficial for all parties involved. Some studies even claim to enable an average cost reduction of nearly 50% (when moving from a traditional to a fully integrated system) (Sahin & Robinson Jr., 2005).

A key criterion for an effective EOC, and subsequently decreasing nervousness of the supply chain, is providing a stable order schedule to the vendor. Robinson *et al.* (2008) define two ways of improving this stability: frozen period and determined schedule flexibility. More information on these approaches can be found in the following two sections.

Another recommended approach for decreasing schedule instability is to forecast beyond the planning horizon. This approach and its effectiveness greatly depend on the accuracy of the demand forecasts. (Kadipasaoglu & Sridharan, 1995)

Kadipapaoglu & Sridharan (1995) mention an additional action that aims to increase the stability of the schedule: incorporating the cost of schedule changes into the lot-sizing procedure. This incorporation should balance the cost of a non-optimal schedule with the cost of nervousness. However, the cost of changing a schedule is difficult to estimate, while the lot-sizing rule is extremely sensitive to such a cost. (Kadipasaoglu & Sridharan, 1995)

Additionally, dealing with fluctuations in demand can be done by keeping a safety stock of end-items. However, as DP follows a make-to-order policy, creating end-stock is not desired. Safety stock can also be applied to materials and other required parts. Creating safety stock for materials is also an effective way of dealing with fluctuations of lead times from a supplier. As previous research has already been conducted on safety stocks at DP, this thesis will not cover it. (Wonders, 2020)

Lastly, there is the concept of safety lead time. Safety lead time is a concept similar to safety stock, but where safety stock deals with fluctuations in demand, safety time deals with fluctuations in delivery and lead times. This technique aims to bring in an inventory of items before they are planned for production. (Armstrong, 2013)

Frozen period in MPS

A frequently mentioned mechanism for balancing schedule costs and stability is freezing a portion of the MPS. In general, lead times determine the timing of release and completion of component orders. To avoid rescheduling of open orders on a lower level, the MPS should be frozen. Within the frozen period, the production schedule cannot be adjusted, which enables stable replenishment schedules for lower-level items.

The length of the frozen period is a trade-off between the flexibility and the future order visibility. Increasing the length of the frozen period means that DP can efficiently order required parts and materials, but this decreases DP's responsiveness for new incoming orders. Zhao, Goodale and Lee (1995) identify different parameters that help determine the portion of the MPS that should be frozen. These are:

- The lead time (LT): the cumulative lead time is the time between ordering materials and finishing production of the end item. Schedules within the lead time are assumed to be frozen.
- The planning horizon (N): the number of periods beyond the lead time for which production schedules are developed in each replanning cycle.

- The frozen period (FP): the number of periods of which the schedules are implemented according to the original plan.
- The free interval: the number of scheduled periods that can still be adjusted, e.g. the planning horizon minus the frozen period.
- The frozen proportion (F): the ratio of the frozen period relative to the planning horizon. The higher this ratio is, the more stable the production schedules are, and thus the lower the nervousness is. However, the chances of stock-outs increase as well as the schedule decreases in responsiveness.
- The replanning periodicity (R): the number of periods between replanning (Zhao & Lee, 1993).

Figure 4 illustrates how the different periods relate to each other. More information on the free interval can be found under heading Free-interval flexibility. The MPS freezing parameters are influenced by the lot-sizing rule chosen (Zhao & Lee, 1993). More information about lot-sizing can be found under section Lot size.

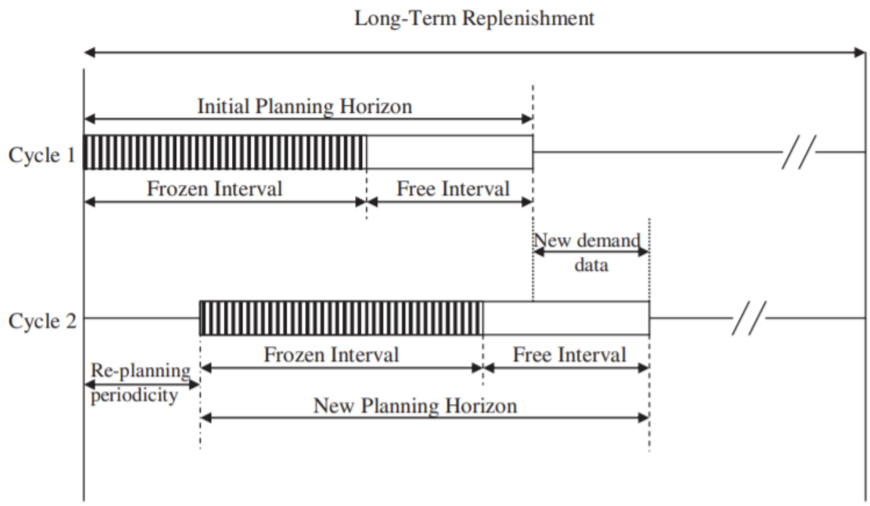


Figure 4 - Frozen period (Sahin, Narayanan, & Powell Robinson, 2013)

Kadipasaoglu & Sridharan (1995) state that while freezing is effective in reducing instability, costs increase significantly when the frozen proportion exceeds 50% of the planning horizon. Additionally, they find that the frozen period should generally be equal or longer than the cumulative lead time. (Kadipasaoglu & Sridharan, 1995)

Sahin *et al.* (2013) found and summarized findings from many articles on rolling horizon plannings. The parameters described above have a significant impact on the costs and schedule instability. For single planning layers, the instability decreases when the planning horizon increases. Another way of decreasing instability is by increasing the length of the replanning periodicity. For more information about the impacts of the mentioned parameters, consult (Sahin, Narayanan, & Powell Robinson, 2013).

More information about the parameters of the frozen period can be found in Appendix D: Frozen period.

2.1.2. Scheduling methods (sequence planning)

The MPS gives an overview of when and in what quantities products have to be finished. This output is essential for the purchasing department when determining their order-strategy. However, the MPS provides a rather general overview of what needs to be produced. The most-detailed level a MPS could take is day-to-day production requirements.

To create more detail in the planning, the production orders have to be scheduled. Previous research on the planning organisation of DP divides the creation of the production planning into four stages, as shown in Figure 5 - LOGICS Production planning. The MRP stage is not included in this figure but is described as an activity that is done parallel to the four production planning stages.

The *mijlpalenplanning* can be compared to the Master Production Schedule. As a subsequent stage towards creating the production planning, the capacity planning is mentioned. The third activity is, directly translated, the sequence planning. The *werkuitgifte* stage involves the implementation of the designed production planning to the workplace. (Arentsen & van Kaam, 2014)

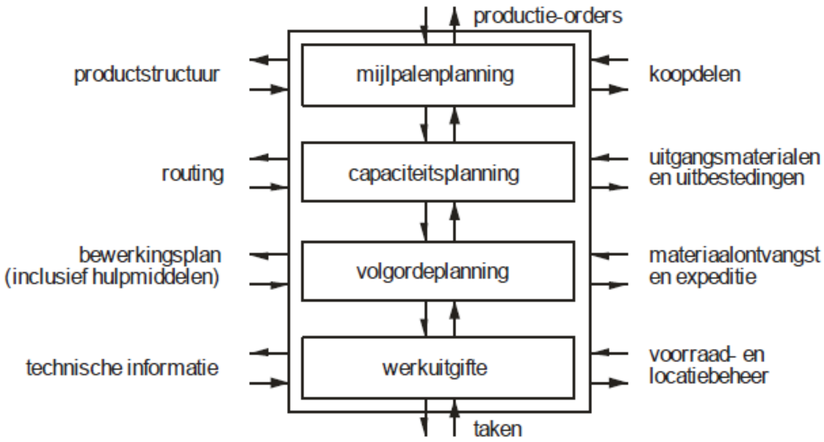


Figure 5 - LOGICS Production planning (Arentsen & van Kaam, 2014)

The four different stages are closely related as changes in one cannot only result in changes in the subsequent stages, but might require changes in previous stages. Therefore, the three stages following the MPS are important for determining the feasibility of the MPS. In this section, the focus is put on the sequence planning.

Systematically creating a sequence planning is a trade-off between finding the optimal solution and the computation time. If a problem and its objective function are properly defined, it is possible to find the optimal solution for this objective function, for example minimizing costs. Finding the sequence of four jobs that minimizes the tardiness costs is a rather simple problem and can even be done manually. Real-life scenarios are often more complex, for example finding the optimal sequence of a set of 20 jobs that can be performed on different machines and takes into account both the tardiness costs and the changeover costs. Such a problem is too time-consuming to be solved by hand and even computers might take a while to compute all possible sequences.

Scheduling techniques

To reduce the computing time, different techniques have been created. Instead of computing all possible variable sets, these techniques prematurely eliminate some suboptimal combinations of variables to reduce the total number of computations. In this section, some techniques found in literature are explained and evaluated. More details on some concepts related to the scheduling techniques and the steps taken in these methods can be found in Appendix E: Scheduling/sequencing techniques.

Total Enumeration Heuristic

The total enumeration heuristic provides a near-optimal solution in terms of minimizing makespan. The name refers to the concept of 'complete enumeration', which means that all possible solutions of a certain problem or system are calculated. This heuristic divides the problem into two subproblems: finding the optimal sequence of required operations per product and finding the optimal sequence for all products. This limits the number of computations drastically but requires a lot of computing power. It is therefore not capable of handling large size problems as the computation time of this heuristic grows exponentially for problems with more than 7 products. (Bhongade & Khodke, 2012)

NEH

The NEH heuristic, named after its researchers Nawaz, Enscore & Ham, is focused on the flow-shop sequencing problem. The heuristic starts with ordering the jobs on their makespan. The two jobs with the longest makespan are taken and the optimal sequence between these two is chosen by calculating both possible sequences. The relative order of the first two jobs is now fixed. Subsequently, the job with the third-highest makespan is chosen and the total timespan for the three possible sequences are calculated. This process is repeated until all jobs are planned. (Nawaz, Enscore, & Ham, 1983)

NEH_BB heuristic

The NEH_BB is a combination of the Branch and Bound heuristic with the NEH heuristic. This combined heuristic is designed to first find the optimal sequence of parts within a product and subsequently uses the optimal sequences to determine the optimal sequence of products.

Disjunctive heuristic

As well as the NEH_BB heuristic, the disjunctive heuristic is divided into two phases. The first decides the sequence of operations on machines for each product. Subsequently, the sequence of products is decided for minimum makespan. For the second phase, this heuristic uses the branch and bound heuristic. (Bhongade & Khodke, 2012)

Johnson's algorithm

Maybe the most classical algorithm in the field of scheduling is Johnson's algorithm. This algorithm gives the optimal solution in terms of makespan for a scenario of n jobs and 2 machines. (Allaoui & Artiba, 2009)

Travelling salesman problem

The travelling salesman problem (TSP) is a famous concept in the fields of process optimization. The goal of the problem is to find the route that minimizes the travel distance for a salesman that has to visit a set of cities. An abstract description of the TSP enables it to be applicable to many other scenarios. The cities can be depicted as nodes, where node 0 is the starting city. Shapiro (1993) considers a network with nodes 0, 1, 2, …, N, directed arcs (i, j) for all i and $j \neq i$, and associated arc lengths c_{ij}.

Now, we adjust the TSP to a single machine where the optimal route is the sequence of jobs that minimizes costs. Instead of the distance between cities, this scenario involves changeover and tardiness costs (costs for delivering late). The tardiness costs can be negative when finishing jobs earlier than the due date is rewarded.

Concluding remarks

There are several other methods of creating a sequence planning, next to the ones mentioned in this section. The aforementioned methods help us to find out what the requirements for a suitable scheduling method for DP should be. More information about this can be found in Section 3.2.

Comparing the NEH_BB, Total Enumeration and Disjunctive heuristic, we find that the latter is fastest in computing time (Bhongade & Khodke, 2012). This increases the flexibility of the heuristic as computing the heuristic after a change of the input information requires little time. It should however be noted that a rerun of the heuristic might drastically change the schedule, which would decrease flexibility. This should be taken into account when determining whether or not a rerun of the heuristic is necessary.

2.2. Analysing past demand

An important input for the MPS, or for any business process for that matter, is the demand. Understanding the characteristics of the demand you are dealing with increases the basis for decision making. Additionally, choosing the right forecasting method is dependent on some of the demand's traits.

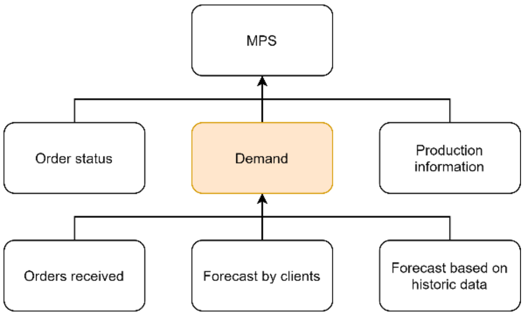


Figure 6 - MPS inputs: Demand

Demand modelling is broader than demand forecasting. A demand model takes into account the stochastic characteristics that real demand has. An accurate model can therefore be used for making calculations.

To understand what type of demand a product follows, one can look at certain characteristics. These characteristics will be addressed and explained in this section. First, some general information about the demand at DP is given.

DP is specialised in assembling and manufacturing high-end products and systems. DP's direct clients are often part of the Demcon Holding as well and therefore outsource the assembly of their products to DP. Thus, DP rarely ships its products to end-customers. Production at DP can therefore be seen as a service.

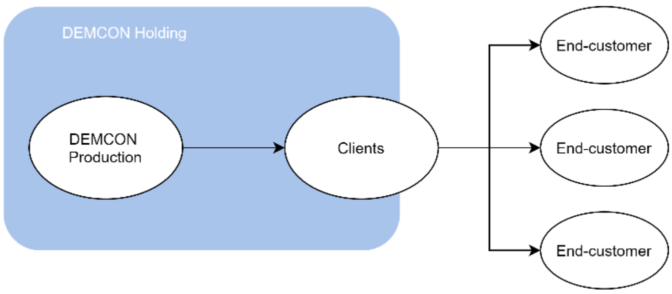


Figure 7 - DP clientele

2.2.1. Input probability distributions

Probability distributions are often used as input for simulations. However, finding a suitable or valid distribution can be challenging. Law (2013) identifies two approaches in trying to find a suitable approximation of $F(x)$:

- Fitting a standard theoretical distribution to the data

This approach requires the researcher to compare several distributions (e.g. normal, exponential, lognormal) to the data available. There are different ways to determine to what extent a certain distribution "fits" the data, such as Goodness-of-Fit tests. The main disadvantage of this approach is that for some data sets, it is simply not possible to find a fitting distribution.

- Using an empirical distribution constructed from the data
  This approach divides the data into n intervals, such that $X_1 \leq X_2 \leq \ldots \leq X_n$. The empirical distribution can subsequently be formulated as

$$F(x) = \begin{cases} 0 & if\ x \leq X_{(i)} \\ \frac{i-1}{n-1} + \frac{x - X_i}{(n-1)(X_{(i+1)} - X_i)} & if\ X_{(i)} \leq\ x \leq X_{(i+1)} \\ 1 & if X_{(n)} \leq x \end{cases}$$

Law (2013) believes that the empirical distribution is only worthwhile if no fitting theoretical distribution can be found. This is due to the disadvantage of the empirical distribution function not being able to generate values outside of the range of observed data. Additionally, the theoretical distribution provides a more compact representation of the data, smoothing out irregularities.

Finding a fitting theoretical distribution

The first activity mentioned by Law (2013) for finding the theoretical distribution that represents the data best is to find a general distribution family that appears appropriate based on the shape of the data. In this phase, one should not worry about the distribution parameters too much. To graphically evaluate the shape of the data, a histogram should be made. Additionally, one can look at a set of useful statistics. These descriptive or summary statistics provide insights into the shape of the data.

Descriptive statistics

The *mean* (μ) and the *median* ($x_{0.5}$) can be used to determine if the distribution is symmetrical. If μ and $x_{0.5}$ are (almost) equal, this indicates that the data set is symmetrically distributed. If μ is larger than $x_{0.5}$, the distribution most-likely has a longer right tail than left tail: the distribution is right-skewed.

Another way of determining skewness (*v*) is by using the following formula: $v = \frac{E[(X-\mu)^3]}{(\sigma^2)^{3/2}}$. A positive *v* indicates that the distribution is skewed to the right and subsequently, a negative *v* indicates a left-skewed distribution. When *v* equals or nears zero, the distribution is symmetrical. A skewness value that does not fall between -1.96 and 1.96 is considered to be significantly skewed. (George & Mallery, 2010)

The coefficient of variation (*cv*) can also provide useful information about the shape of a data set. If cv = 1, the data follows an exponential distribution. More information about exponential distributions can be found in section

When one or multiple suitable distributions have been hypothesized, the parameters of the distributions need to be estimated. One way to evaluate the quality of an estimator is the maximum-likelihood estimation (MLEs). For more information about MLEs, please see Law (2015).

The third and last action in approximating a suitable probability function is determining how representative the fitted distributions are. There are different tests designed that will determine if a distribution is accurate enough to represent the data.

Discrete versus continuous probability distributions

There are two types of data: discrete and continuous. Discrete data can only take certain values, e.g. only integers. Continuous data can take any value (within a certain range). First, some discrete probability distributions will be addressed, after which some common continuous probability distributions will be elaborated upon. Some distributions, e.g. the Bernoulli and Discrete Uniform distributions, are disregarded due to their irrelevance when modelling demand at DP.

Binomial (discrete)

Assume a system where every trial has two options, e.g. success or fail (e.g. 1 or 0). A binomial distribution models the number of successes in *n* trials where *p* is the probability of success in a single trial. The MLE for *p* is the number of successes divided by the number of trials. With these two parameters, we find the probability function and corresponding mass distribution as can be found below.

$$p(x) = \begin{cases} \binom{n}{x} p^x (1-p)^{n-x} & if\ x\ \in \{0,1, \dots\} \\ 0 & otherwise \end{cases}$$

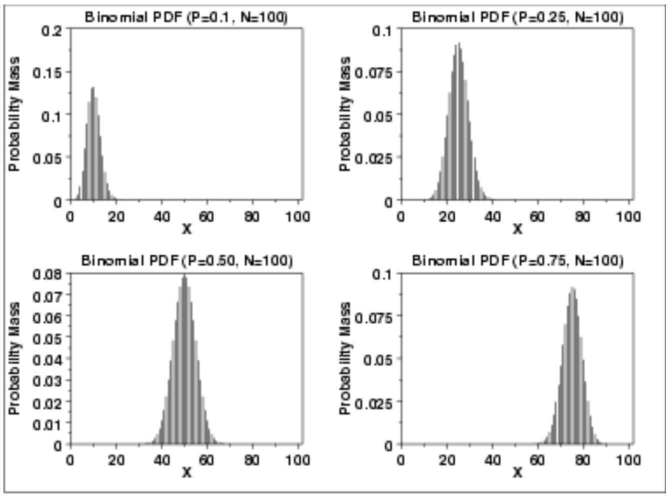


Figure 8 - Binomial distribution (Engineering Statistics Handbook, 2020)

Poisson (discrete)

A Poisson distribution has only one parameter, which is its mean value (λ). Poisson distributed data can only be non-negative integer values. The probability function and corresponding probability distribution can be found below. The MLE for λ is the mean of *n*. (Law A. M., 2015)

$$p(x) = \begin{cases} \frac{e^{-\lambda} \lambda^x}{x!} & if\ x\ \in \{0,1, \dots\} \\ 0 & otherwise \end{cases}$$

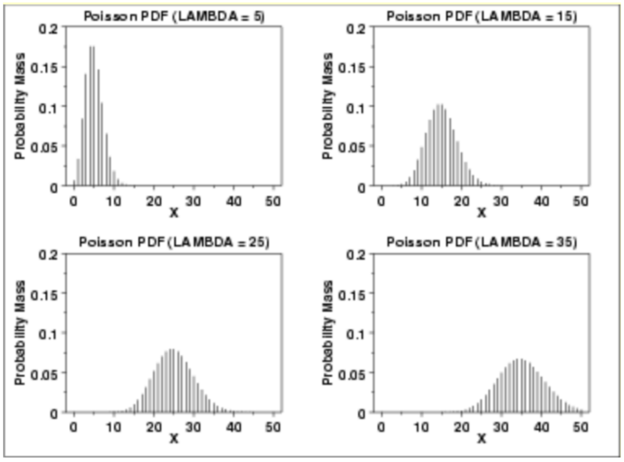


Figure 9 - Poisson distribution (Engineering Statistics Handbook, 2020)

Normal distribution (continuous)

The simplest way of forecasting the demand for the upcoming month is by looking at the mean of the previous months. If the average number of ordered products per month equal is to 50, the chance is highest that, in the upcoming month, again 50 products will be ordered. The chance of a certain number of products being ordered, denoted as $P(X = x)$ where *x* is an integer, decreases when the difference between the mean, denoted as µ, and *x* increases. In a normal distribution, this happens symmetrically, e.g. the chance of 40 products being ordered is just as high as the chance of 60 products being ordered. Thus, $P(X = \mu + x) = P(X = \mu - x)$.

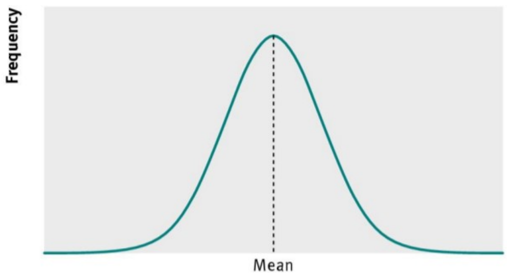


Figure 10 - Normal distribution (Sedgwick, 2012)

Demand is however rarely perfectly symmetrical. For example, looking at a mean monthly demand of 50 products, it is possible to have a demand of more than 100 products in a month, but it is not possible to have a demand of less than zero. Having more data points or more outliers on one side results in a skewed probability distribution (see Figure 11).

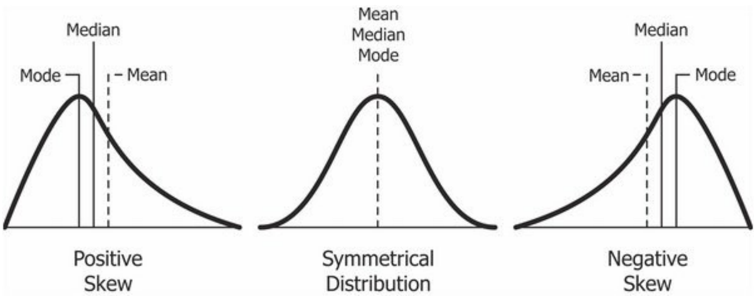


Figure 11 - Skewed normal distribution (Jain, 2018)

However, not all data sets show one smooth curve such as Figure 11. The Central Limit Theorem states that if you take a sufficiently large sample group from a population with mean µ and standard deviation σ, the distribution of the sample means will be approximately normally distributed. The rule of thumb is to have a sample size larger than 30. Thus, testing normality is especially important when working with smaller sample sizes. (UvA Wiki Methodologiewinkel, 2014)

Exponential distribution (continuous)

Demand that follows an exponential distribution can be any value between 0 and infinity. A common usage of the exponential distribution is to model the time between two successive events. The formula requires one parameter: λ, which is the average time between two successive events. The probability density function $f_x(x) = \lambda\, e^{-\lambda x}$ for x > 0 and λ > 0.

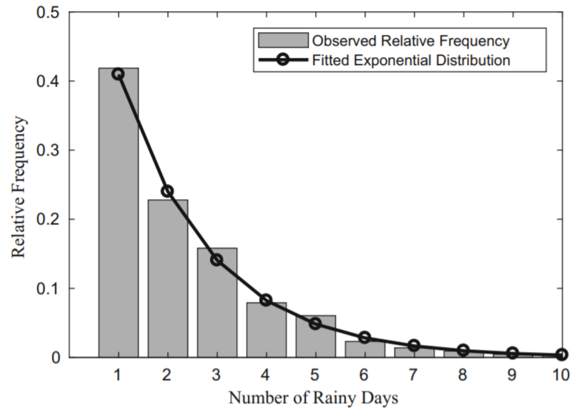


Figure 12 - Exponential distribution (Maity, 2018)

Lognormal distribution (continuous)

The lognormal distribution is a probability distribution from which the logarithmic transformation follows a normal distribution. Values within this distribution can only be positive (see Figure 13). To test a certain dataset on following a lognormal distribution, one should take the logarithmic values of the dataset and test this logarithmic dataset on normality. (Maity, 2018)

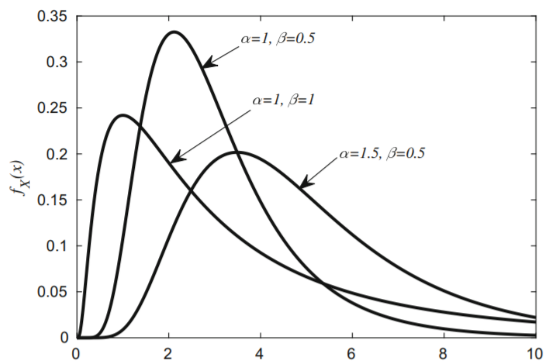


Figure 13 - Lognormal distribution (Maity, 2018)

Goodness-of-fit tests

Some common ways of testing a data set on its assumed probability distribution will be addressed below.

Q-Q plot

One way of quickly and informally testing a sample is by creating a quantile-quantile (Q-Q) plot. Quantiles are also referred to as percentiles, which are points in a dataset below which a certain proportion of the data falls. Consider a normal distribution with mean 0. Half of the data lies below 0 and half of the data lies above 0. This means that the 50th or 0.5 percentile is 0. (Ford, 2015)

In Figure 14, an example of a Q-Q plot can be found. The X-coordinates of the data points are from a normal distribution. The Y-coordinates from the data points are from the data set that is being tested. If the data points are close to the linear trend-line, one might assume that the data set is normally distributed. However, this is a rather subjective way of testing the data.

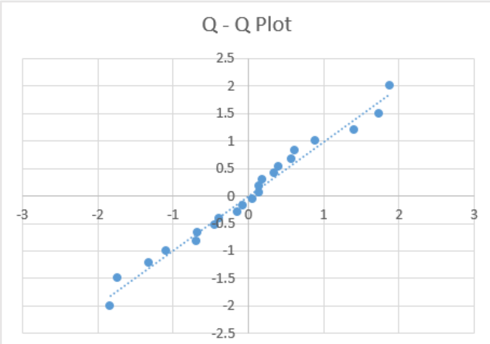


Figure 14 - Example Q-Q Plot

Chi-squared test

The Chi-squared test is the oldest goodness-of-fit hypothesis test. It formally compares a histogram to a fitted probability density function. As it uses binned data, it can be used for both discrete and continuous data. This is not a restriction but does lead to the disadvantage of the test being dependent on the bin sizes. A detailed explanation of the Chi-squared test can be found in Appendix B: Goodness-of-Fit hypothesis tests.

Shapiro-Wilk test

In terms of normality, it is especially important to test at smaller sample sizes (under thirty data points). As we are looking at the demand per month, data has to be collected for over 2.5 years to get a reasonably large sample size. This data is not always available at DP. Therefore, a test that can handle small sample sizes is required.

There are multiple statistical tests for normality. Charles Zaiontz summarizes six of these tests. The Shapiro-Wilk test is mentioned to be relatively powerful and capable of detecting small deviations of normality even for smaller sample sizes and thus, will be used in this research (Zaiontz, sd). A more detailed description of this test can be found in Appendix B: Goodness-of-Fit hypothesis tests.

The Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov test, in contrast with the Chi-square test, does not require the data to be grouped into bins. This is an advantage as no information is lost. The K-S test also tends to be more powerful than the Chi-Square test against a multitude of distributions. Law (2015) gives a method of using the K-S for datasets of which the parameters are unknown. An elaborate explanation of the test can be found in Appendix B: Goodness-of-Fit hypothesis tests. (Law A. M., 2015)

Concluding remarks

In terms of possible values that the demand at DP can take, a discrete probability distribution would be a better fit than a continuous distribution. However, some discrete distributions can be approximated by a continuous distribution. Take the binomial distribution for example. When $n*p \geq 5$ and $n*(1-p) \geq 5$, a $B(n,p)$ can be approximated by a normal distribution $N(\mu,\sigma)$, where $\mu=n*p$ and $\sigma^2 = n*p*(1-p)$. (Zaiontz, sd)

Therefore, a selection of both discrete and continuous probability distribution is made to test the available data. More information can be found in Chapter 4.

2.2.2. Trend and seasonality

"When choosing a forecasting method, we will first need to identify the time series patterns in the data, and then choose a method that is able to capture the patterns properly."
(Hyndman & Athanasopoulos, 2018)

When demand is observed over a longer period, the data seldom appears to be stationary. Hyndman & Athanasopoulos (2018) identify three common forms of non-stationarity: Trend, Seasonality and Cycles.

Trend
Within a certain data set, a trend can be defined as a long-term increase or decrease. This does not have to be linear.

Seasonality
A seasonal pattern occurs when the data is affected by seasonal factors. Ice cream is a good example of seasonality, as demand for ice cream is highest in summer and lowest in winter. Seasonality can also be identified in other time spans, e.g. day of the week. Seasonality always has a fixed and known frequency.

Cycles
In cyclic data sets, the data points increase and decrease in value, but in contrast to the seasonal time series, the frequency of these cycles is unknown. The fluctuations are often related to economic conditions. To distinguish cycles from seasonality, one can look to the duration of the non-stationarity. The duration of a cycle is usually at least two years.

(Hyndman & Athanasopoulos, 2018) (Jaynes, 2003)

Measuring time series patterns
To measure trend seasonality, data for multiple years needs to be available. For DP, not enough data is available to measure these patterns. Therefore, this thesis will not include calculations. For future research, information on these calculations can be found in Appendix F: Decomposition of time series.

2.3. Demand forecasting

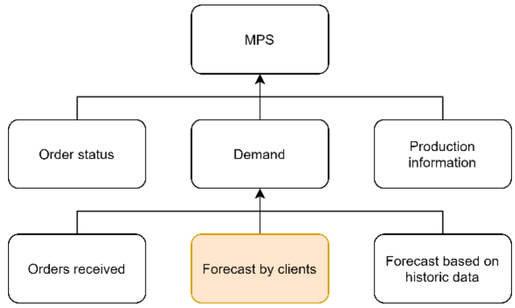


Figure 15 - MPS inputs: Forecasted demand

As Figure 15 shows, demand is an important input for the capacity planning. It is essential for a company to have a clear overview of the orders that have been received. Next to that, it can be very useful to look at the orders that have not yet been received: the demand forecast. This thesis will not focus on forecasting future demand, but forecasting techniques will be used to determine the performance of the forecasts that have been delivered by clients.

As explained in the introduction of section 2.2, DP's production can be seen as a service for its clients. The client often outsources their production to DP due to the complexness of the products and systems. As a result of this complexness, parts and other items required for the assembly of products can have rather long delivery times. Normally, the total lead time depends on both the delivery times from the supplier and the production time at DP (see Figure 16).

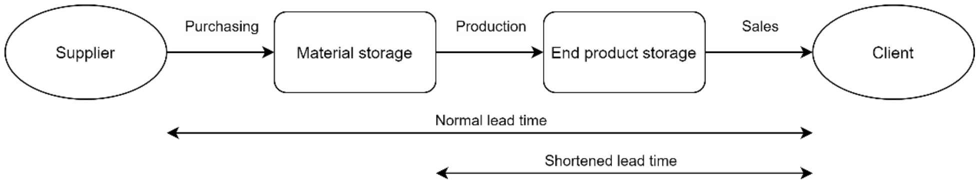


Figure 16 - Lead times

As DP's clients are not the end-customers, shortening the lead times is beneficial for both parties: the client and DP. To achieve a shorter lead time, some clients deliver forecasts to DP. Based on these forecasts, DP can order parts and materials before the actual orders are placed.

However, forecasts are always inaccurate and should therefore be evaluated (Chopra & Meindl, 2016). Calculating how accurate the forecasts used by DP are, will enable them to make well-founded decisions related to the production planning. Therefore, this section will provide relevant information for the evaluation of the forecasts.

2.3.1. Forecast accuracy

To evaluate the forecasts provided by the clients, it is important to choose a way of measuring the differences between the actual demand and the forecasted demand. There are many ways to measure these forecast errors.

There are two types of measures: scale-dependent and scale-independent measures. The first is useful when comparing datasets with similar scales. For this thesis, a scale-dependent measure will be used to compare the forecasting techniques (see section 2.3.2) to the client's forecasts. Additionally, a scale-independent measure will have to be chosen to compare results from different data sets. For example, an error of 5 items is significant for an average monthly demand of 10 items but is not too notable for an average monthly demand of 100 items. With a scale-independent measure, comparing such datasets can be done.

Scale-dependent measures

The most-commonly used scale-dependent measures will be addressed below. The forecast error (e_t) is the difference between the actual demand (Y_t) and the forecasted demand (F_t).

- *Mean Square Error (MSE)*
  The MSE is calculated by taking the mean of the squared forecast errors. Formula: $mean(e_t^2)$.
- *Root Mean Square Error (RMSE)*
  The RMSE is the square root of the MSE, giving it the same scale as the data set. Formula: $\sqrt{MSE}$.
- *Mean Absolute Error (MAE)*
  The MAE is similar to the MSE, but instead of taking the squared values, it takes the absolute values of the errors. Formula: $mean(|e_t|)$.
- *Median Absolute Error (MdAE)*
  The MdAE is the same as the MAE, but instead of calculating the mean, here the median of the absolute error values is used. Formula: $median(|e_t|)$.

The RMSE is often referred to the MSE as it on the same scale as the data itself, but both have been very popular due to their theoretical relevance in statistical modelling. A disadvantage of the MSE and RMSE compared to the MAE and MdAE is that MSE and RMSE are more sensitive to outliers. These comparisons are summarized in Table 1. (Hyndmann & Koehler, 2006)

Table 1 - Scale-dependent error measures

Scale-dependent	Formula	Advantages	Disadvantages
Mean Square Error (MSE)	$mean(e_t^2)$		- Sensitive to outliers - Not the same scale as data
Root Mean Square Error (RMSE)	$\sqrt{MSE}$	+ Same scale as data	- Sensitive to outliers
Mean Absolute Error (MAE)	$mean(\|e_t\|)$	+ Same scale as data	
Median Absolute Error (MdAE)	$median(\|e_t\|)$	+ Same scale as data	- Median might give a skewed view for data sets with few data points

Scale-independent measures

Most scale-independent measures rely on the so-called percentage errors (p_t). These are calculated by the following formula:

$p_t = 100\ e_t/Y_t$, where:

- p_t is the percentage error at time *t*
- e_t is the forecast error at time *t* ($Y_t - F_t$)
- Y_t is the actual demand at time *t*
- F_t is the forecasted demand at time *t*

Hyndmann & Koehler identify four main measures that are based on percentage errors. These are essentially the same as the scale-dependent measures, but use the percentage error (p_t) instead of only the forecast error (e_t).

- *Mean Absolute Percentage Error (MAPE)*
  Taking the mean of the absolute values of p_t: $mean(|p_t|)$.
- *Median Absolute Percentage Error (MdAPE)*
  Taking the median of the absolute values of p_t: $mean(|p_t|)$.
- *Root Mean Square Percentage Error (RMSPE)*
  Taking the square root of the average of the squared percentage errors: $\sqrt{mean(p_t^2)}$.
- *Root Median Square Percentage Error (RMdSPE)*
  Same as RMSPE, but taking the median instead of the mean: $\sqrt{median(p_t^2)}$.

A disadvantage of using percentage errors is that the measures become infinite, undefined or extremely skewed when the actual demand is equal to or nears zero. This is due to Y_t being the numerator in the equation. Additionally, the MAPE and MdAPE have the disadvantage of putting a heavier penalty on positive errors than on negative errors. This observation gave rise to a new 'symmetric' measure:

- Symmetric Mean Absolute Percentage Error (SMAPE)

$$SMAPE = mean\left(2 * \frac{|Y_t - F_t|}{|Y_t + F_t|}\right)$$

The SMAPE can be changed to SMdAPE, using the median instead of the mean. Both measures (SMAPE and SMdAPE) decrease the severity of the problems arising when Y_t nears zero, but can still arise when both F_t and Y_t near zero. (Hyndmann & Koehler, 2006) However, using both F_t and Y_t in the numerator of the equation decreases the chances of skewed SMAPE values significantly. Next to that, the symmetric measure robustly rejects outliers (Maiseli, 2019).

Table 2 - Scale-independent error measures

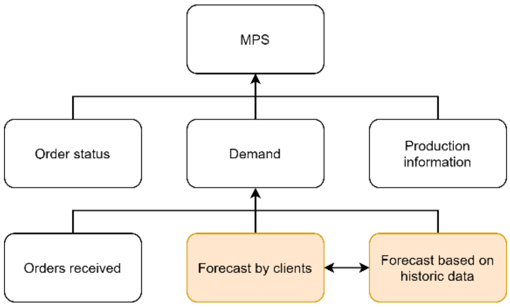
Scale independent	*Formula*	*Advantages*	*Disadvantages*
Mean Absolute Percentage Error (MAPE)	$mean(\|p_t\|)$		- problems arise when Y_t nears or equals zero - heavier penalty on positive errors
Median Absolute Percentage Error (MdAPE)	$median(\|p_t\|)$		- problems arise when Y_t nears or equals zero - heavier penalty on positive errors
Root Mean Square Percentage Error (RMSPE)	$\sqrt{mean(p_t^2)}$		- problems arise when Y_t nears or equals zero
Root Median Square Percentage Error (RMdSPE)	$\sqrt{median(p_t^2)}$		- problems arise when Y_t nears or equals zero
Symmetric Mean Absolute Percentage Error (SMAPE)	$mean\left(2 * \frac{\|Y_t - F_t\|}{\|Y_t + F_t\|}\right)$	- less sensitive to outliers	- problems arise when both F_t and Y_t near zero

Choosing error measures

As previously mentioned, it is useful to use one of the scale-dependent measures for comparing the client's forecasts to the actual demand and common forecasting techniques. Using the information summarized by Table 1, we see that the MAE and MdAE are preferred over the MSE and RMSE due to the sensitivity to outliers of the latter two. Subsequently, the decision between the Mean and the Median Absolute Error. Some clients have only recently started delivering forecasts. Due to the little data points (months), the median might give a skewed image. Therefore, the MAE will be used to measure the accuracy of a specific product or system.

For the scale-independent measures, the SMAPE calculation is chosen. As this calculation does not involve the percentage error, chances of problems occurring when Y_t nears zero are relatively low. Additionally, being less sensitive for outliers is therefore a big advantage. For a supermarket, if one customer decides to buy 200% of their standard demand, this does not influence their processes much. However, as DP's products are often only sold to one client, buying-decisions of this client directly influence the demand. Outliers are therefore not uncommon in the datasets available. Combining these two advantages, the SMAPE will be used for comparing the forecast accuracies of different products.

2.3.2. Forecasting methods



Next to comparing the forecasts that customers have delivered to the actual orders, it is interesting to see how accurate common forecasting techniques would have been. For example, if a certain forecasting technique is consistently more accurate than the delivered forecasts by the client, DP could give this feedback to the client or even choose to ignore the delivered forecasts.

There are several ways of calculating forecasts and different methods are suitable for different demand patterns. In this section, some commonly used methods are explained.

Moving average

One of the simplest forecast methods is the moving average technique. This technique assumes the demand to follow a constant model. Such a model can be noted as

$$Y_t = a + e_t$$

, where

Y_t = the demand in period *t,*

e_t = independent random deviation with mean zero*,*

a = average demand per period.

Many products can be represented by a constant model. Generally, if no trend or seasonality is expected, it is reasonable to assume a constant model.

The moving average gives an expected demand for the upcoming month, based on information from the previous periods. Let

N = chosen number of recent periods to include in calculation*,*

F_t = the forecasted demand in period *t,*

Y_t = the actual (registered) demand in period *t.*

With these variables, we can estimate the demand in period t using the moving average as follows:

$$F_t = (Y_{t-1} + Y_{t-2} + Y_{t-3} + \cdots + Y_{t-N})/N.$$

In this formula, *N* should depend on how slowly the demand (*Y*) is changing. (Axsäter, 2006)

Exponential smoothing

The result of the exponential smoothing technique is often similar to the smoothing average, whereas the forecasted are updated differently. This technique combines recent demands with previous forecasts. Letting F_t be the forecast for period *t*, the exponential smoothing technique can be depicted as

$$F_t = \alpha * Y_{t-1} + (1 - \alpha) * F_{t-1}.$$

A new input parameter is introduced, the smoothing constant (α). The value of α is either equal to 0 or 1 or in between these two integers ($0 \leq \alpha \leq 1$).

Comparing the exponential smoothing to the moving average, we see that both techniques rely on previously measured demands. However, wherein the moving average technique all periods are weighted equally, these weights exponentially decrease when going back in time in exponential smoothing technique.

Weighted average

The weighted average technique, also known as weighted moving average, is quite similar to the moving average technique. However, where the moving average technique does not prioritize more recent periods over data obtained a long time ago, the weighted average does make this distinguishment. By giving weights to data from different periods, demand for the upcoming period can be forecasted. Assuming that x_i is the chosen weight for the measured demand of period $t - i$, you can find the forecast demand using the weighted average as follows:

$F_t = \frac{x_1 * Y_{t-1} + x_2 * Y_{t-2} + x_3 * Y_{t-3} + \cdots + x_N * Y_{t-N} +}{x_1 + x_2 + x_3 + \cdots + x_N}$. (Milicer Gruzewska, 1933)

For example, a product with a rather constant demand might not want to solely forecast on the numbers of last month. Instead, it might be more interesting to look at the demand over the last few months. However, numbers from a few months ago might still be relevant but are often not as relevant as the numbers from last month. Therefore, the weighted average can be used, giving a weight of 50% to the demand from last month, 30% to the month before and 20% to two months before.

Double exponential smoothing

Double exponential smoothing, which is similar to (single) exponential smoothing, was designed to forecast products that follow a trend and include seasonality. The seasonality-aspect is disregarded as too little data is available for accurate measuring seasonality. There are different variants of this method. We will first identify the Holt-Winters double exponential smoothing method, which introduces some new variables:

- s_t = the smoothed value for time t
- b_t = the estimate for the trend at time t
- β = the trend smoothing factor ($0 \leq \beta \leq 1$)

With these variables, we find the following equations for $t > 0$:

$$s_t = \alpha Y_t + (1-\alpha)(s_{t-1} + b_{t-1})$$

$$b_t = \beta(s_t - s_{t-1}) + (1-\beta)b_{t-1}$$

The initial value of s_t, when $t = 0$, is in equal to the registered demand in the first month ($s_0 = Y_0$). Choosing the initial value of b_t is a matter of preference. One suggestion is $b_0 = Y_1 - Y_0$. To forecast beyond x_t, we use:
$F_{t+m} = s_t + m * b_t$. (Engineering Statistics Handbook, 2020)

One different calculation is the Brown's Double (or Linear) Exponential Smoothing method, which introduces some new variables: S' as singly-smoothed series, S'' as doubly-smoothed series, L_t as the estimated level at period t and T_t as an estimated trend at period t.

$$S'_t = \alpha Y_t + (1-\alpha)S'_{t-1}$$

$$S''_t = \alpha S'_t + (1-\alpha)S''_{t-1}$$

$$L_t = 2S'_t - S''_{t-1}$$

$$T_t = \left(\frac{\alpha}{1-\alpha}\right)(S'_t - S''_{t-1})$$

Using these equations, we use $F_{t+m} = L_t + m * T_t$ to find the forecasted demand for period $t + m$. The initial values for both S' and S'' can be put equal to Y_0. (Nau, 2020)

Concluding remarks

These five forecasting techniques will be used in Chapter 5 to compare forecasts based on historic data to the forecasts delivered by the clients.

2.3.3. Forecast commitment

As DP purchases long-lead items based on the forecasts delivered by clients, some financial risk is involved. If the client's forecasts are too optimistic (the expected order quantity is higher than in reality), the purchased long-lead items have already been bought, but will not be used for production. Agreements will have to be made, stating which party is financially accountable for these unused items.

Andy Tsay (1999) shows that quantity flexibility contracts can be used in (partially) solving these issues. In such a contract, the retailer (DP's clients) commit to a minimum purchase quantity. The manufacturer (DP) in his turn guarantees maximum coverage. These contracts are mentioned to be especially effective when the manufacturer relies heavily on the retailer for guidance on demand information. (Tsay, 1999)

Let $\bar{f}$ be the order forecast delivered by the client. The supplier should make a certain commitment, *C*, and decide on a production quantity, *q*. *q* can be larger than *C*, but this is a choice the supplier will have to make based on a trade-off between the financial risk of not selling the products (*q*-*C*) and a more efficient production lot-size. Subsequently, the customer must order at least $\alpha\bar{f}$, with α being contractually fixed and $0 \leq \alpha \leq 1$, unless the supplier committed to a smaller amount such that $C \leq \alpha\bar{f}$. The customer should not be forced to order more than the supplier is willing to commit. The minimum required order $d = min\{C, \alpha\bar{f}\}$.

At the beginning of the month of the aforementioned forecast, a certain demand, x, is observed. The customer tries to order *x* products, with a lower bound of *d*, thus $max\{d, x\}$. The supplier delivers $min\{max\{d, x\}, q\}$.

Example 1

Assume a client delivers a six-month rolling forecast, which mentions that the client expects to order 50 products in month 6. In month 1, DP will start looking at the items required to produce 50 products. It appears that one of the required items has a lead time of 15 weeks. Thus, in month 3, DP has to decide on the number of products it commits to. If the forecast is unchanged, DP plans to produce 50 products, the client must order α * 50 products in month 6. If α were to be 0.8, the client has to order at least 40 products.

In month 5, the client places an order of 40 products. DP will consequently purchase the remaining required items and produce 40 products.

The contract should mention what will be done with the 10 remaining long-lead items.

Example 2

DP mainly has long term clients, meaning that the clients will order the same product multiple times. This does not guarantee that the remaining products will eventually be sold/used but does significantly decrease the likelihood of creating idle stock. DP is, therefore, able to give more room for deviations to the client.

Take the scenario in Example 1. As we are nearing month 6, more and more purchasing and production decisions will have to be made by DP. As the actual orders have not yet been placed, these decisions are based on the forecasts delivered by the client. Thus, the accuracy of these forecasts becomes more important over time. Instead of having one moment in time where the commitment percentage (α) is determined, multiple percentages can be used. In the example scenario, the first percentage would be α_1 which is used at the moment the longest-lead items have to be purchased (month 3). The remaining items will be bought in month 5. α_2 should be more strict than the previous one, as more decisions will be based on this forecast.

Figure 17 gives two examples of this scenario. The left graph shows what would be the tolerated fluctuation (bandwidth) if $\alpha_1 = 0.7$, $\alpha_2 = 0.9$ and the forecast of 50 remains unchanged. The client would be allowed to order 45 to 55 products. The graph on the right has the same α-parameters, but the forecast is changed to 55 in month 4.

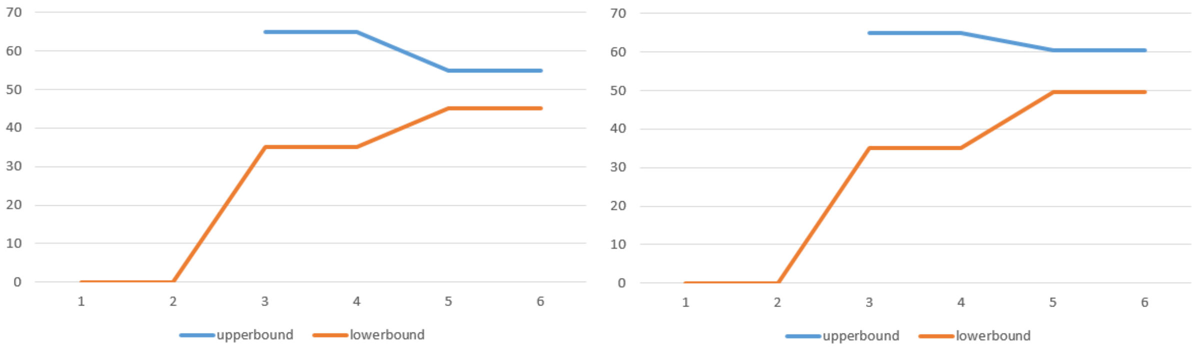


Figure 17 - Client commitment example 2

For DP, the lower bound representing the minimal order quantity of the client is more important than the upper bound. In Chapter 5.3.3, the acceptable bandwidth parameters will be investigated.

3. Master Production Schedule

This chapter is divided into two. The first section proposes techniques that should decrease schedule instability. A more stable schedule provides more time to prepare for production (as no changes will be made), which should help with sticking to production schedules and consequently delivering on time. Due to other priorities at the company, implementation of the proposed techniques and their results will not be covered in this thesis.

The second section gives an overview of what aspects of a scheduling method are most relevant for DP and what requirements such a method should have. Depending on the optimisation function chosen, having a heuristic that creates a planning can help with minimizing the number of products delivered late. The creation and implementation of a scheduling method will not be covered in this thesis.

3.1. Schedule instability

The MPS is the first step in the production planning process. It should therefore be properly organised to prevent issues during the subsequent stages, e.g. the MRP and capacity planning. The effect of the MPS on the subsequent stages is called nervousness or schedule instability and several approaches in decreasing this nervousness can be found in literature. Possible implementations of the approaches found in literature will be given below.

3.1.1. Techniques

This section proposes some techniques that, when implemented, should decrease the schedule instability.

Frozen period

The method that is mentioned most in the literature is the frozen period. One could choose to freeze a part of the MPS. Within this frozen period, no schedule changes can be made, creating a stable basis for decision making in the MRP and Capacity Planning stages.

In general, the frozen period should be at least as long as the total lead time (from ordering parts to finished product). For some of DP's products, this would mean the frozen period would be more than 20 weeks. As a lot can happen over the course of 20 weeks, not allowing changes in this planning would be impractical. The frozen period should therefore exclude the items with very long lead times. This is suboptimal as it is necessary to keep safety stocks to protect production from the variability of the orders outside the frozen period (Zammori, Braglia, & Frosolini, 2009), but is more realistic.

The length of the frozen period is dependent on the agreements made with the clients. If a standard delivery time of four weeks is agreed upon, the frozen period cannot be longer than four weeks.

Slushy zone

To further decrease nervousness, DP could start placing slushy zones. Instead of freezing both the timing and the size of the orders, a slushy order freezing only one of these. To illustrate, assume a product requires a certain part. These parts can be bought in batches of 50. Based on the forecast from DP's clients, DP can estimate when it needs to place a new order. This can be communicated to the supplier of the required parts. If the forecast of the client appears to be overestimated, and thus fewer parts were required over time, it is beneficial for DP to postpone the order. DP thus created a slushy order where the order size was fixed, but the timing of the order was uncertain. This enabled the supplier to plan and perhaps even start production before the actual order was placed.

Safety stock

As mentioned in section 2.1.1, safety stock is not elaborated upon in this thesis as previous research on the matter has already been performed (Wonders, 2020). It should however be mentioned that safety stock is a good way of decreasing schedule nervousness.

Safety lead time

Safety lead time is a concept similar to the concept of safety stock, but where safety stock deals with fluctuations in demand, safety time deals with fluctuations in delivery and lead times. Further research is recommended.

3.1.2. Suggestions for implementation

The techniques mentioned in the previous sections can be implemented in different ways. These will be covered in this section.

DP as both vendor and manufacturer

In the supply chain of supplier – DP – client, there are two separate but dependent relationships. Within the DP – client relationship, DP can be seen as the manufacturer: DP manufacturers the products that the vendors sell to the end-customer. In the supplier – DP relationship, DP is the vendor, assembling and selling the product (parts) made by the supplier.

The slushy and frozen periods can be implemented in both relationships. By using forecasts, DP already partially uses frozen/slushy orders within the DP - client relationship, but this can be structuralized more. Forecasts can be made binding by implementing the theory mentioned in Section 2.3.3, or by agreeing on a certain timing or order size.

Additionally, DP could start advance order commitments to its suppliers in combination with the slushy orders previously mentioned. More information about advance order commitments (AOCs) can be found in Section 2.1.1.

3.2. Sequence planning methods

Not all sequencing methods mentioned in Section 2.1.2 can directly be applied to DP. This section will provide an overview of what aspects of the found techniques are relevant for DP and how these techniques can be applied. For the scheduling methods, the assumption is made that materials and required parts are available.

3.2.1. Flexibility

During one of the interviews held with one of the production planners at DP, one main requirement for a scheduling method was mentioned: it should be flexible. It frequently occurs that a product needs to be repaired. This repairing job needs to be done quickly to avoid further customer dissatisfaction. The schedule should therefore be able to handle unexpected changes.

Translating this requirement to the scheduling techniques mentioned in Section 2.1.2, we find that the flexibility relates to the trade-off between finding the optimal solution and computing time of this solution. In the situation of DP, being flexible is more important than finding the perfect schedule. Therefore, scheduling techniques with higher computing times are not desired.

Having significant changes in schedules due to a rerun of the scheduling heuristic is undesired. When a unexpected production activity has to be added to the schedule, the decision has to be made on whether or not creating a new schedule is worth the change. The other option is to just add the unexpected production activity to the sequence, moving other activities to a later time. Applying costs to changing the schedule might help with making this decision.

3.2.2. Optimisation function

Different techniques aim for different optimisations. E.g., some seek to find the lowest operation time to perform the jobs (makespan) where others aim for the least costs. Makespan heuristics are most-impacted by changeover times. For the products made by DP, changeover times are relatively small and thus, basing the sequence planning on a makespan heuristic is not the best approach.

As previously mentioned, DP is struggling with delivering its products on time. A planning heuristic should therefore be focused on minimizing the lateness of products. This can be done by assigning costs to delivering late and optionally assigning rewards (negative costs) to delivering products before their promised delivery date.

3.2.3. Restrictions

Some of the techniques can only be applied to one- or two-machine systems. This restriction would be unrealistic as often more than two jobs can be performed at the same time. Ideally, the optimisation function should be applicable for N machines (workplaces), where N is an adjustable variable since different projects have different capacities.

3.3. Results

As no data on the stabilizing techniques or the scheduling methods is gathered, no results can be presented.

3.4. Discussion and conclusion

The discussion and conclusion of this chapter is divided into two sections.

3.4.1. Schedule instability

To increase the stability of the schedules, DP can increase the planning horizon and start dividing it into three parts: the frozen period, slushy period and liquid period. This means that DP is committing to a certain proportion of the production planning by freezing a part of it. Information about the (expected) demand from the client is required when freezing a portion of the production planning horizon. Advance order commitment (AOC) contracts should be set up with clients to be able to freeze realistic production plans.

Additionally, DP can start giving forecasts to its suppliers and, to a certain extent, committing to these forecasts. This might enable the suppliers to have more reliable lead times, e.g. deliver on time. Fluctuations in the lead times of supplier require changes in the production schedule and subsequently increase instability.

3.4.2. Scheduling methods

From the scheduling methods selected, the disjunctive heuristic (Bhongade & Khodke, 2012) appears to have the smallest computing time, which is preferred due to the higher flexibility. The current version of this heuristic aims to minimize the total makespan. However, this could be adjusted by replacing the makespan by the time between until the promised delivery date. E.g., products with a nearing due date would be prioritized over the products of which the due date is weeks away. This adjustment should result in fewer products being delivered after their promised delivery date.

Further research should be performed to change the optimisation goal of the disjunctive heuristic, making it applicable for DP, or to find a new heuristic which minimizes the lateness of products.

4. Analysing past demand

In this chapter, the literature found in Section 2.2 is applied to the data available at DP. Better understanding of what characteristics the demand has, might help making decisions about production plans. For example, if the standard deviation of a product's monthly demand is known, DP can calculate what risk of stock-out they take when ordering a certain amount of materials.

The available data is tested on a set of probability distributions using a tool created. Subsequently, results and conclusions are given. As not enough data is available to identify time series patterns, e.g. seasonality, this is not coved in this thesis nor the created tool.

4.1. Tool

In previous research into the safety stock levels at DP, the assumption was made that the demand of products follows a normal distribution (Wonders, 2020). This, however, might not accurately represent real-life demand. Using the literature described in Section 2.2.1, the mentioned assumption will be evaluated and an attempt to find more suitable distributions will be made.

To fit demand distributions, an Excel tool was built (Figure 18). The user must insert the data in the column on the left. This data can, for example, be the monthly demand over a certain time span. The shape of the histogram provides a first impression of the probability distribution the data follows. For the example data, the histogram suggests a normal distribution.

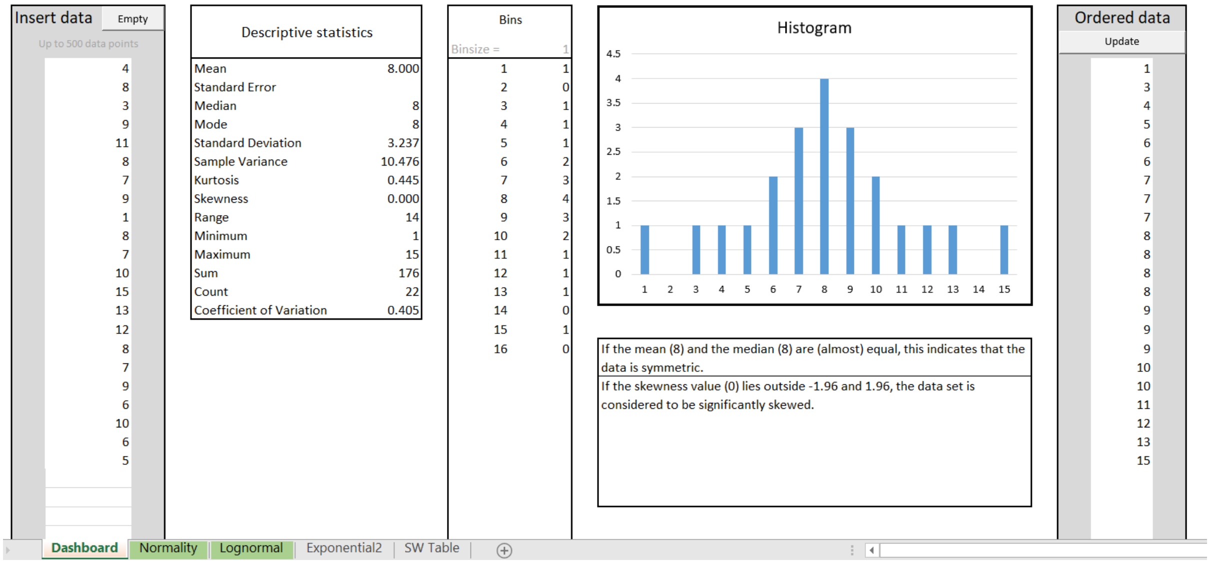


Figure 18 - Demand modelling tool

4.1.1. Normality assumption

To substantiate the assumption of normality, the sheet 'Normality' gives two ways of testing the dataset on normality (see Figure 19). Both methods of testing are explained in Section 2.2.1. The data points in the Q-Q plot follow a straight line, which indicates that the dataset indeed follows a normal distribution. The Shapiro-Wilk test provides strong evidence that the example dataset follows a normal distribution. As the p-value is higher than 0.05, the null hypothesis cannot be rejected, meaning that there is not enough evidence indicating that the dataset is significantly different from a normal distribution with the mean and standard deviation found in the descriptive statistics.

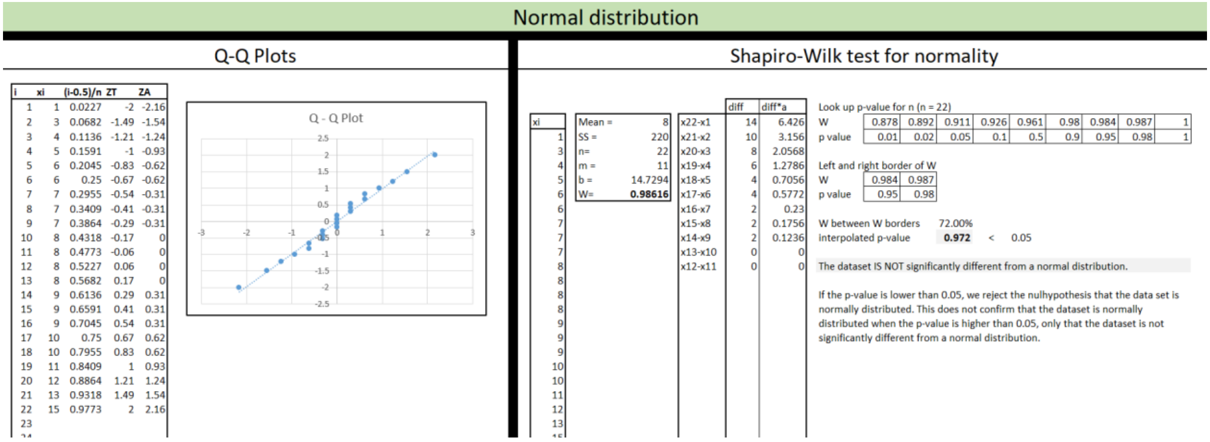


Figure 19 - Normality tests in demand modelling tool

4.1.2. Other theoretical distributions

For the other theoretical (thus non-empirical) probability distributions mentioned in Section 2.2.1, different sheets can be found. These sheets are comparable to the sheet for normality, giving a Q-Q plot and another (formal) test. For the normal and lognormal tests, the Shapiro-Wilk test is used. For the test for exponential distributions, the Kolmogorov-Smirnov test is used (Figure 20). The Chi-squared test is used for testing the datasets against the Binomial and Poisson distributions.

Lognormal distributions

The sheets for testing the dataset on log-normality is essentially the same as the sheet for normal distribution. The sole difference is using logarithmic values (LN(x)).

Exponential distribution

The Kolmogorov-Test in the created tool tests a certain dataset against the exponential distribution with a certain λ. As this parameter is unknown, the test uses the MLE mentioned by Law (2015), which is $\frac{1}{\bar{X}(n)}$, where $\bar{X}(n)$ denotes the mean value of the dataset is.

The Kolmogorov-Smirnov Test

Mean=	7.91	λ (1/mea	0.126	Tot.Max.[	0.34987

i	Order	Low esti	High est	F(X1)	Max.Dev
1	1	0	0.0455	0.11877	0.1188
2	2	0.0455	0.0909	0.22343	0.178
3	3	0.0909	0.1364	0.31567	0.2248
4	5	0.1364	0.1818	0.46857	0.3322
5	6	0.1818	0.2273	0.53169	0.3499
6	6	0.2273	0.2727	0.53169	0.3044
7	7	0.2727	0.3182	0.58731	0.3146
8	7	0.3182	0.3636	0.58731	0.2691
9	7	0.3636	0.4091	0.58731	0.2237
10	8	0.4091	0.4545	0.63632	0.2272
11	8	0.4545	0.5	0.63632	0.1818
12	8	0.5	0.5455	0.63632	0.1363

Count	n	22
Max. Deviation	Dn	0.34987
Adjusted test statistic		1.72332
Confidence	α	0.05
	1-α	0.95
Critical value	c1-α	1.094

1-α				
0.850	**0.900**	**0.950**	**0.975**	**0.990**
0.926	0.990	1.094	1.190	1.308

Conclusion
If the adjusted test statistic is lower than critical value, we accept the null hypothesis that the data is following a exponential distribution with mean 7.91.
1.72332 > 1.094
We DO reject the null hypothesis. Thus, the data IS significantly different from exponential distribution with mean 7.91.

Figure 20 - Demand modelling tool: K-S test

Binomial distribution

The binomial distribution is added to the tool due to its discreteness (e.g. values can only by integers). The sheet includes a Q-Q plot and a Chi-square test. However, the binomial distribution has the disadvantage of having no parameter similar to the standard deviation of the normal distributions.

See Figure 21. A *Bin*(100,0.5)-distribution looks similar to a *N*(50,5)-distribution. The latter can be adjusted to have a more evenly spread probability distribution. This is not possible for the Binomial distribution, thus in a system with a mean of 50, it will be nearly impossible to find the value of 10 in a Binomial distribution.

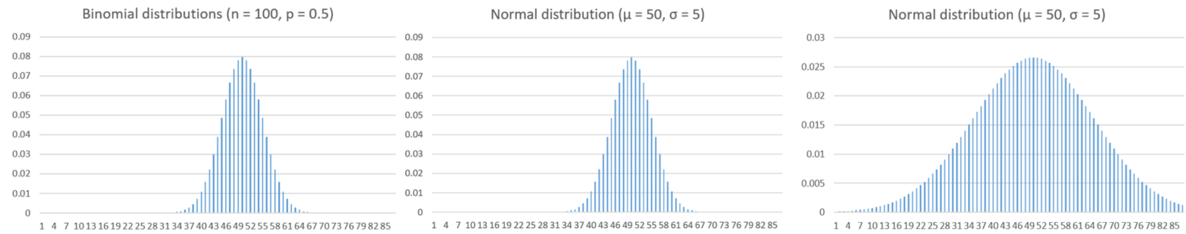


Figure 21 - Binomial versus normal distributions

Poisson distribution

Similar to the Binomial distribution, the Poisson distribution was selected on its discrete values. The sheet includes a Q-Q plot and a Chi-square test.

4.2. Results

A selection of 10 products was used in the tool. The monthly sales-orders (Dutch: *verkooporders*) of the past 12 months (August 2019 – July 2020) was gathered as input. The date that was used for reference was the date the order was placed + three weeks, which is the standard delivery time. The number of products ordered was summarized over the different sales-orders within that month. The obtained findings obtained are summarized below.

Normal

Five out of the 10 products tested had a p-value above 0.05, meaning that, with a confidence of 95%, these five products were not significantly different from a normal distribution. The data from the remaining five products strongly indicate that they are not normally distributed.

Having a closer look at the five non-normal products, we find some similarities. The datasets from all five products contain months where no products were purchased. Additionally, four out of five products only contain values between 0 and 15. The fifth product has one outlier of 124, where the other data points lie within the range 0 to 20.

In contrast, for the five products of which the null hypothesis was not rejected (and thus the data does show signs of normality), the demand lies within the range of 0 to 119 with a maximum of one zero-demand month.

Lognormal

Out of the 10 products, only three products could be tested against a lognormal distribution. This is due to the fact that such a distribution cannot contain the value 0. A zero-demand month is therefore problematic when testing a dataset for lognormality. For the three products that did not have zero-demand months, the test strongly rejected the null hypothesis that the dataset is lognormally distributed, with p-values between 0.003 and 0.005.

> ***Lognormal value of 0***
> *Lognormal values rely on the natural logarithmic value of a data point: LN(x). LN(x) gives the value with which e (Euler's number) has to be raised to get the value x ($e^{LN(x)} = x$). As it is impossible to find a value for which e (or any number for that matter) raised by that value equals zero, LN(x) is undefined. In other words, there is no value x for which $e^{x} = 0$ is true.*

Exponential

The K-S accepted the null hypothesis of only three out of the 10 selected products. In other words, the test of only three products suggests that the data was exponentially distributed. When inspecting the demand data of these three products, we find that these products are low-demand products with an overall monthly maximum of 13 ordered products. The low demand in combination with the limited amount of data might give a biased view of the distribution.

A possible fourth exponentially distributed product-demand can be found if the outlier mentioned in the normality section is disregarded. The test statistic decreases from 1.53384 to 0.94774, suddenly becoming lower than the critical value of the K-S test. This change results in no longer rejecting the null hypothesis.

Binomial

The Chi-square test is highly dependent on the number of bins chosen. A lower number of bins (three or less) often fails to reject the null hypothesis. For the binomial, none of the 10 selected datasets accept the null hypothesis with a total of bins higher than 5, thus all data sets show a significant difference from a binomial distribution.

Poisson

Only one out of the ten data sets tested accepted the null hypothesis using a number of bins higher than 5. The remaining nine products reject the null hypothesis, indicating a significant difference from a Poisson distribution.

Summary

Ten products were tested on the five selected probability distributions. The table below lists these ten products and indicates whether or not the goodness-of-fit tests found reason to assume that the probability distribution was suitable: 'yes' when the test could not reject the null hypothesis, 'no' when the null hypothesis was rejected.

Table 3 - Summary results of demand modelling tool

PRODUCT	NORMALITY	EXPONENTIAL	LOGNORMAL	BINOMIAL	POISSON
1	Yes	No	No	No	Yes
2	Yes	No	No	No	No
3	Yes	No	-	No	No
4	Yes	Yes	-	No	No
5	Yes	No	No	No	No
6	No	No	-	No	No
7	No	Yes	-	No	No
8	No	Yes	-	No	No
9	No	No	-	No	No
10	No	Yes when excluding outlier	-	No	No

The tests performed for product 4 indicate that the data could be both normally and exponentially distributed. Looking at Section 2.2.1, this is hard to believe as the probability density function significantly differ from each other. Figure 22 shows how the data points are distributed. The shape of the histogram explains why both tests failed to reject the null hypothesis that the data is significantly different from the mentioned distributions. However, when more data is collected, it is expected that the demand will start to look more like a normal distribution and that the K-S test will reject the null hypothesis.

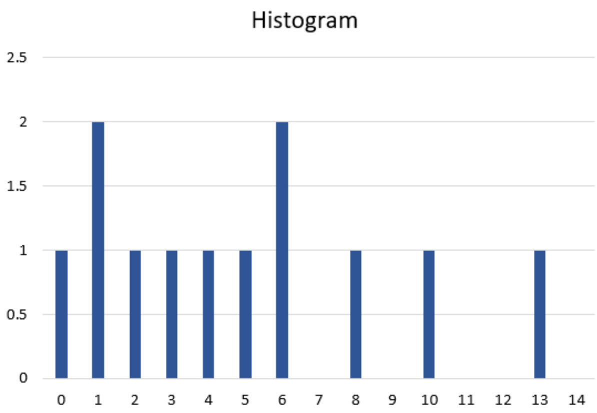


Figure 22 - Histogram product 4

4.3. Discussion and conclusion

The results summarized in Table 3. are based on one-year data. This is a limitation as one outlier can make a significant difference, as observed in the previous section on the results of the K-S test for exponential distributions. The limited available data is a limitation for finding a probability function that accurately represents real-life demand. Nevertheless, some conclusions can be drawn, explained per probability function below.

4.3.1. Conclusion per distribution

Normal distribution

First, disregarding the mentioned limitations, it can be concluded that the low-demand products do not follow a normal distribution, whereas products with a higher monthly demand do show clear signs of normality. For half of the products, the datasets did not show significant differences from a normal distribution. This means that for these products, the normality assumption is, to a certain degree, acceptable to make. The products that were found to not be normally distributed had a relatively low monthly demand.

Lognormal distribution

Secondly, it can be concluded the lognormal distribution is not useful for representing the demand of DP's products, due to its inability of handling zero-demand and the rejected null hypotheses for the products without zero-demand months.

Exponential distribution

Even though the K-S test indicated that three out of the ten products follow an exponential distribution, this cannot be concluded. The products for which the K-S test accepted the null hypothesis were products with a relatively low monthly demand. Due to this low demand, the test might give a skewed view.

Binomial distribution

As a result of the Chi-square test, none of the selected products show to follow a binomial distribution. This conclusion, however, is dependent on the bin size chosen.

Poisson distribution

Only one of the selected products failed to reject the null hypothesis, which provides evidence to believe that the demand for this specific product is Poisson distributed.

4.3.2. Concluding remarks

Due to the mentioned limitations, we establish that the results drawn from the goodness-of-fit tests might be flawed. However, even when assuming that these results do accurately represent real-life demand, the test results occasionally have to be disregarded.

> *"In applying mathematics to subjects such as physics or statistics we make tentative assumptions about the real world which we know are false but which we believe may be useful nonetheless. […] the statistician knows, for example, that in nature there never was a normal distribution, there never was a straight line, yet with normal and linear assumptions, known to be false, he can often derive results which match, to a useful approximation, those found in the real world."*
> *(Box, 1976)*

Take the safety-stock calculations in previous research at DP (Wonders, 2020). To calculate safety-stock levels, a certain value for the standard deviation should be used. This can only be done when the assumption is made that the corresponding data set is normally distributed. The created tool determines to what extent such an assumption is correct to make. However, as Box (1976) states, it might still be useful to make assumptions that are known to be incorrect. The assumption of normality will have to be made regardless of the results from the tool. It is nevertheless useful to keep in mind whether or not an assumption is correct.

Probability distribution for lead times

Due to the scope of this thesis, the tool is only used on demand data. However, the tool can be used for any dataset. One example of a useful application of the tool is lead time fluctuations. Creating stock of materials is rarely desired as it costs money that could have been spent differently. In the optimal situation, materials are received on the day that they are required for production. It is however risky to assume materials will exactly be delivered on the promised delivery date, as a delay in materials delivery has direct impact on production when no buffer is included. These buffers are called safety lead times. If information on the lead times of materials is available, the tool can help with calculating how risky certain safety lead times are.

5. Demand forecast accuracy

Some clients deliver forecasts that enable DP to assure shortened delivery times. These forecasts come in different shapes and sizes, dependent on the agreements made with the clients. In this chapter, the accuracy of the forecast delivered by one client is evaluated, referred to as *Company X*. First, the methods of comparing the forecasts to the ordered products are elaborated upon, after which the tool is explained. Subsequently, the findings from the tool are shown and explained, based on which some conclusions will be drawn.

Inaccurate forecasts directly influence DP's ability to deliver on time, as multiple materials are ordered based on these forecasts. Subsequently, calculating the accuracy of the forecasts helps decision-making on purchasing plans and, when the conclusions is used as feedback to the client, might even increase accuracy.

5.1. Measuring accuracy

DP's clients often order more or fewer products than their forecasts indicated. This difference between the forecasted and the actual (ordered) demand is called the forecast error. The difference between these amounts is not enough to evaluate the forecasts from a client. Company X, for example, delivers its forecasts on a 12-month rolling-horizon basis. Therefore, a different accuracy measurement has to be used. This thesis uses the following methods of measuring forecast errors. For both measures, the following variables are used: the forecast error (e_t) is the difference between the actual demand (Y_t) and the forecasted demand (F_t).

- **Mean Absolute Errors (MAE)**
  The MAE is calculated by taking the average of the absolute values of the forecasts errors. Formula: $mean(|e_t|)$.
- **Symmetric Mean Absolute Percentage Errors (SMAPE)**
  The SMAPE is an adjustment of the MAPE. The MAPE takes the mean of the absolute values of percentage errors (p_t): $mean(|p_t|)$, where $p_t = 100\ e_t/Y_t$. Using percentage errors has the disadvantage of becoming infinite or undefined when Y_t. The SMAPE aims to resolve this problem by using the following formula: $SMAPE = mean\left(2 * \frac{|Y_t - F_t|}{|Y_t + F_t|}\right)$.

More information about error measurements and the selection of the two mentioned measures can be found in Section 2.3.1.

Regarding forecast accuracy, multiple things are interesting to look into. First, it is interesting to see how accurate the forecasts for a certain product are per month. For example, the forecasts one month in advance are important

5.2. Comparing forecast accuracy

Using the measures described in the previous section, the accuracy of the forecasts delivered by the client can be evaluated. If these forecasts appear to be inaccurate, it might be useful for DP to create forecasts themself. Many forecasting techniques have been created and evaluated over the past few decades. A selection of common forecasting techniques found in literature is made.

- The **moving average** takes the average of the past *N* months.

- The **weighted average** takes the registered demand from the past few months, but instead of taking the average, it assigns different priorities to it. Each weight has a value within the range [0,1] and all weights combined add up to 1.
- **Exponential smoothing** uses a smoothing factor ($\alpha \in [0,1]$). An α of 0 means that the forecast completely relies on last month's registered demand, whereas α=1 means that the forecast for month *t* relies on the forecast of month *t* - 1.
- **Double-exponential smoothing: Holt-Winter's method** has two smoothing factors. One smoothing factor is the same as the α from the (single) exponential smoothing method. The other smoothing factor, denoted by β, aims to identify and incorporate the trend of the data.
- **Double-exponential smoothing: Brown's method** is similar to Holt-Winter's method in terms of the goal. They both aim to incorporate trend, but the calculations are different.

More detailed descriptions of these forecasting methods can be found in Section 2.3.2.

5.3. Tool

To compare the actual orders to both the forecasts delivered by DP's clients and the forecasting methods, a tool was created. The tool contains different sheets, that evaluate the forecasts from the clients in different ways. Each method of evaluation used is addressed separately in the upcoming sections.

5.3.1. Dashboard

The dashboard of the tool compares the forecasts delivered *X* months in advance of the actual orders to the forecasting methods mentioned in the previous section. For example, X=1 refers to the forecasts made one month before the orders are placed, e.g. forecast delivered in August for September. Thus, the X=2 for September was delivered by the client in July. The sheet is divided into different segments (see Figure 27).

- Accuracy of forecasts delivered by the client (yellow segment).
    - On the right, each column shows the estimations made for that month. For example, the 37 in cell J9 indicates that in the forecast delivered by the client in July indicated that they would order 37 products in October. Some cells are empty due to missing forecasts.
    - On the left, a summary of the performances can be found. The lowest calculated error measure is automatically highlighted in green, making the best forecasting strategy easily identifiable.
- Accuracy of forecasting methods (orange segment)
    - On the left, the different techniques are quickly addressed and the accuracy performance measures are shown.
    - On the right, the results of using the aforementioned forecasting methods can be found. The numbers in the light-coloured cells in column H are input variables required for calculating the forecasts. Finding the optimal values for these input variables can be done by a press on the button on the bottom right.
- Actual demand (white segment)
    - The segment below the orange area gives the actual number of ordered products per month. These are based on the number of units mentioned on the sales orders (Dutch: *Verkooporders*).

5.3.2. Accuracy Development

A separate sheet in the Excel workbook is dedicated to showing the performance of certain X=m (where m = 1,2,3,…; see example in introduction Section 5.3.1) forecasts over time. In Figure 23, seven X=m forecasts are selected for product A. The linear trend lines indicate that the X=1 forecasts have approved a little bit over time, whereas the trend lines for X=2 and X=3 clearly show that the accuracy has deteriorated over time.

Disregarding the impact of the COVID-19 pandemic by leaving out the data for March and April (giving the client the time to adjust its forecast), it is found that all three X=x forecasts for product A have improved over time (see trend lines in Figure 24).

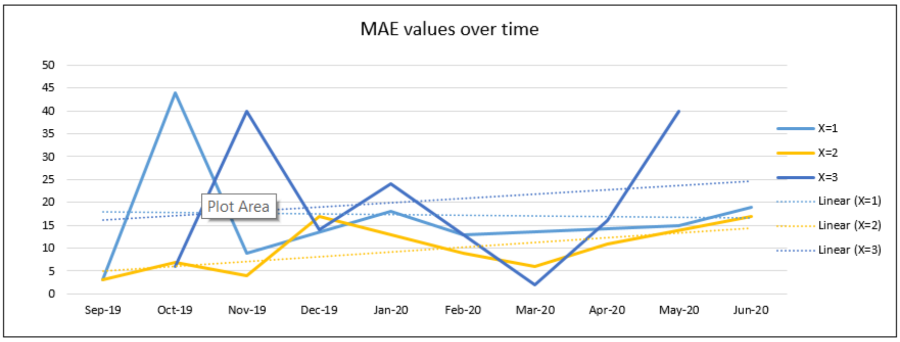


Figure 23 - Accuracy Development

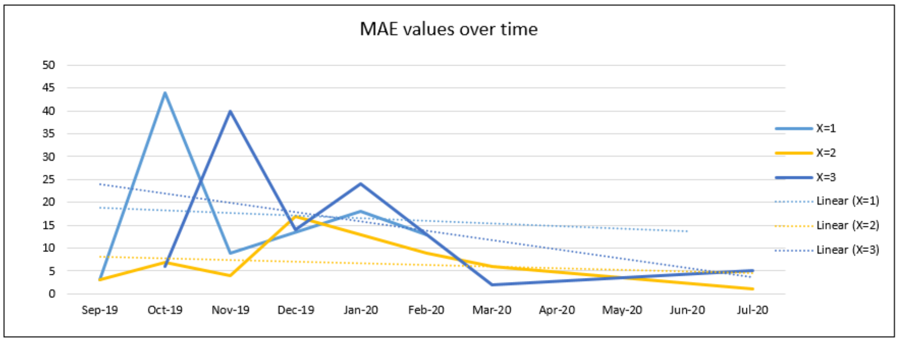


Figure 24 - Accuracy Development (disregarding COVID-19 impact)

5.3.3. Bandwidth

In general, forecasts for the near future (e.g. X=1) are more important than forecasts for the far future (e.g. X=9). This is due to the fewer purchasing and production choices relying on the forecasts for the far future. Subsequently, it is desired that the forecasts become more accurate over time (e.g. from X=9 to X=1).

For this purpose, two sheets have been added to the Excel tool, graphically showing how the accuracy of the forecast for a certain month (e.g. June 2020) have developed over time. Client commitment agreements can be made how much they can deviate from their forecasts, as mentioned in Section 2.3.3. The tool provides a graphical overview of to what extent the client adhere to this agreement (see Figure 25). The other is similar to the one found in Figure 25 but uses percentage deviations instead of absolute values.

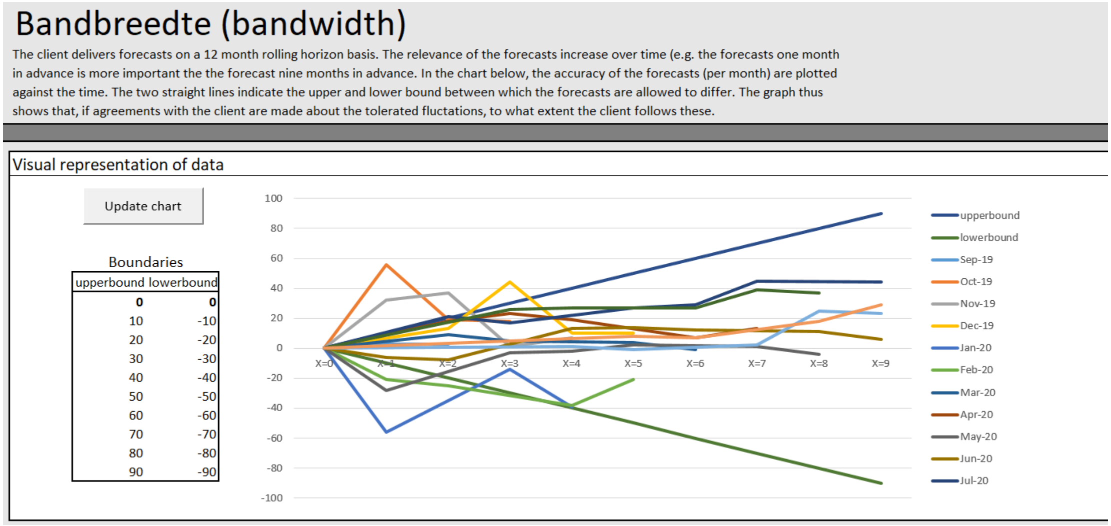


Figure 25 - Bandwidth graph from tool

5.3.4. Comparing delivered forecasts with forecasting techniques

If the forecasts delivered by the client appear to be inaccurate in representing real life demand, it is interesting to look for alternatives. Therefore, the forecasting techniques mentioned in Section 5.2 are added to the tool. A graph is added to the tool that shows how the forecasting techniques perform over time (see Figure 26). The dark brown line represents the delivered forecast from the client one month in advance.

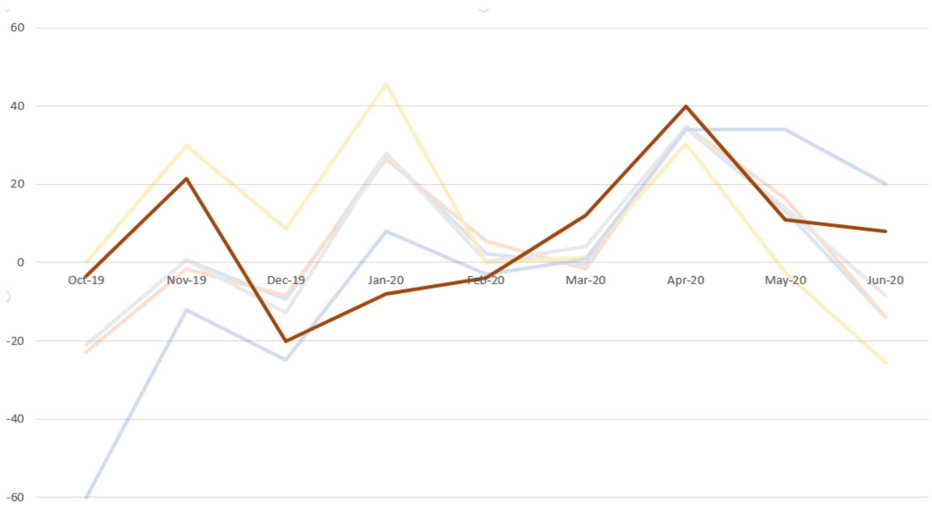


Figure 26 - Forecasting techniques accuracy

Forecast accuracy tool

Product: Make sure these two are the same product (names can differ)	
	product name from forecast
	product name from orders

The purpose of this tool is to find out how the delivered forecasts perform compared to some common forecasting techniques. In the input worksheet, you have to select the product you want to compare in both pivot tables. Subsequently, you have to press the grey button that will automatically find the optimal input variables for the forecasting techniques. The forecast with the lowest MAE value has the lowest deviation compared to reality.

	MAE	SMAPE
Forecasts delivered by client		
X=1	17.29	34.1%
X=2	9.25	14.5%
X=3	20.29	27.5%
X=4	21.43	33.5%
X=5	23.60	40.9%
X=6	13.67	24.0%
X=7	25.00	51.9%
Average last three months	14.12	23.8%
Forecasting techniques		
Weighted average	16.16	26.9%
Moving average	18.53	29.1%
Exponential smoothing	16.79	26.5%
Double exponential smoothing (Holt-Winters)	15.13	26.6%
Double exponential smoothing (Brown)	19.25	31.1%

Calculate optimal input variables (column H)

Make sure Macros are enabled.

From INPUT worksheet		Avg. difference (+/-)	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
Forecasts delivered by client												
X=1		9.57	41	75	70		23	40			16	28
X=2		4.00	41	38	75	44		36	50	45		26
X=3		8.8571		37	39	75	65		46	50	41	
X=4		4.57			45	41	40	23		46	42	47
X=5		15.60				41		40	45		46	48
X=6		11							40	34		46
X=7		25.00								40	45	
Average last 7 months			41	50	57.25	50.25	42.6667	34.75	45.25	43	38	39
Forecasting techniques (based on historic data)												
Weighted average	*1=*	0.6		38	31	62.6	49	56.2	40.6	42.8	31.2	18.2
	2=	0										
	3=	0.4										
	Total=	1										
Moving average	*N=*	3		37.25	35.17	49.33	57.00	60.33	43.00	37.33	35.00	26.33
Exponential smoothin	*α=*	*0.6*		38.00	33.80	60.92	60.97	48.99	35.79	40.72	36.69	15.27
Double exponential smoothing (Holt-Winters)	*α=*	*0.4*	38.00	31.00	46.00	47.80	40.88	31.13	32.08	28.65	13.39	7.43
	β=	*0.0*	-7.00	-7	-7	-7	-7	-7	-7	-7	-7	-7
				31.00	24.00	39.00	40.80	33.88	24.13	25.08	21.65	6.39
Double exponential smoothing (Brown)	*α=*	*0.0*	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00
			38.00	38	38	38	38	38	38	38	38	38
					38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00

Actual demand		Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
Avg.	**36.5**	**38**	**31**	**79**	**61**	**41**	**27**	**44**	**34**	**1**	**9**

Figure 27 - Forecast accuracy tool dashboard

5.4. Results

Data from multiple clients has been gathered and used as input for the tool. In this section, the conclusions of the order behaviour of one company will be addressed. Detailed results can be found in Appendix C: Forecast accuracy tool results.

One of DP's clients, from now on referred to as *Company X*, delivers its forecasts in a rolling horizon over 12 months. These predictions are updated monthly. A few of the most-sold products were used for the analysis of their forecasts errors.

Based on the available data, it is safe to say that the forecasts provided by the clients represent reality better than the forecast techniques chosen in section 2.3.2. The difference in MAE values between the best forecasting technique and the best X of the delivered forecasts was at least 30% for all selected products.

Surprisingly, the forecasted demand from two months in advance often differs less from the real demand than the forecasted demand one month in advance. Especially when the impact of the COVID-19 pandemic is disregarded, it is found that the forecasts made by the client two months in advance (X=2) are the most accurate.

When looking at the accuracy development sheet, the impact of the COVID-19 pandemic can again be identified. Figure 23 shows how the accuracy of the forecasts for product A has developed over the course of 12 months. This figure shows that the forecasts have deteriorated over the year. Figure 24, however, shows that, if we give Company X time to adjust their forecasts to the impact of the pandemic, the forecasts have gradually improved over the year.

5.5. Discussion and conclusion

The created tool evaluates how accurate the forecasts are over time. This is especially interesting for products with long lead items. Suppose it is the case that a product requires an item that has a delivery time of more than 16 weeks. The client does not want to wait more than 16 weeks for its order and therefore provides a forecast, based on which DP purchases long-lead items in advance. Financial accountability has to be determined for these items. This accountability can be with either the client or with DP. However, for both parties, it is disadvantageous to order too many or too little items. For 16-week lead time items, the accuracy of the forecast made 4 months in advance is very important.

The results mentioned above are based on data gathered over the 11 months that forecasting was done by the client (September 2019 – July 2020). The accuracy of the X=1 forecasts can thus be based on 11 data points (months), but for X=7, less forecast data is available. The accuracy measures might therefore be a little skewed, as limited data provides a smaller basis for making conclusions.

6. Service level

The previous chapters have explored opportunities that should improve the timeliness of orders. Once the proposed techniques are implemented, it is interesting to see DP's performance of delivering on time evolves. The extent to which DP delivers on time is referred to as the service level. In order to monitor this change, some Key Performance Indicators (KPIs) have to be set up that calculate DP's service level. A tool has been created to calculate the KPIs. Within this tool, the calculation of how much a certain order managed to meet the promised delivery date is calculated as follows:

> *The creation date of the ready-report of an assembly number minus the promised delivery date of this assembly number.*

Or in Dutch, as the system used by DP works in Dutch:

> *De aanmaakdatum van de gereedmelding van een assemblagenummer (verkoopregel) minus de toegezegde leverdatum van dit assemblagenummer.*

Using this way of calculating shows how the production process is able to handle the promised delivery dates. Problems with the actual picking and sending products are therefore disregarded as these are beyond the scope of this research.

6.1. Key performance indicators

To make different periods comparable, a percentage should be used instead of an absolute value. However, only looking at the percentage of products that have been delivered before the promised delivery date does not fully show how DP is performing. It is for example also interesting to see how far the products deviate from the promised delivery dates. Therefore, multiple Key Performance Indicators have been chosen:

KPI.1. Percentage of assembly numbers from which the creation date of the ready-report is before or on the promised delivery date (the difference is smaller than 0 [<u>X =< 0</u>]).

[Dutch] Percentage van assemblagenummers waarvan de aanmaakdatum van de gereedmelding voor of op aan de toegezegde leverdatum ligt (verschil is kleiner dan 0 [<u>X =< 0</u>]).

KPI.2. Percentage of assembly numbers from which the creation date of the ready-report is less than <u>one week after</u> the promised delivery date (the difference is smaller than 7 [<u>X < 7</u>]).

[Dutch] Percentage van assemblagenummers waarvan de aanmaakdatum van de gereedmelding minder dan <u>een week na</u> de toegezegde leverdatum ligt (verschil is kleiner dan 7 [<u>X < 7</u>]).

KPI.3. Percentage of assembly numbers from which the creation date of the ready-report is less than <u>14 days after</u> the promised delivery date (the difference is smaller than 7 [<u>X < 14</u>]).

[Dutch] Percentage van assemblagenummers waarvan de aanmaakdatum van de gereedmelding minder dan <u>14 dagen na</u> de toegezegde leverdatum ligt (verschil is kleiner dan 14 [<u>X < 14</u>]).

It is not beneficial for DP to finish products too early. DP could have used those man-hours to work on achieving the promised delivery dates of other orders or choose a promised delivery date that is closer to the desired delivery date from the client (see section 6.1.1). Therefore, an additional KPI is added.

KPI.4. Percentage of assembly numbers from which the creation date of the ready-report is more than 14 days before the promised delivery date (the difference is smaller than 14 [X > -14]).

[Dutch] Percentage van assemblagenummers waarvan de aanmaakdatum van de gereedmelding meer dan 14 dagen voor de toegezegde leverdatum ligt (verschil is kleiner dan -14 [X < -14]).

6.1.1. Desired delivery dates

If only the mentioned KPIs are taking into account for calculating the service level, DP can easily increase its service level by promising safer (thus later) delivery dates. However, this is not beneficial for the customer. Therefore an additional KPI has to be added. When ordering, clients indicate the desired delivery date, the date on which they would like to receive the product. Optimally, DP is able to promise delivery on this date. Therefore, the difference between these two dates is an interesting KPI.

KPI.5. The average difference (in days) between the desired delivery date and the promised delivery date.

[Dutch] Gemiddeld verschil (in dagen) tussen gewenste leverdatum en de toegezegde leverdatum.

6.2. Tool

An Excel-based tool was created to measure the mentioned KPIs. A screenshot of this tool can be found in Figure 28. The user only has to select the client or clients (Dutch: *verkooprelaties*) it wants to know (shared) performance for. This section is blurred due to confidentiality issues.

The bar graph shows how the difference between the promised and the realized delivery date has changed over the selected period. The horizontal does not represent the date of the orders but shows the performance of successive orders. This choice was taken because of the summed values of the ready-reports of the same day would inaccurately represent DP's performance.

6.3. Results

Based on the orders from which the creation date of the ready-report lies in 2019, 63.7% had a delivery date on or before the promised delivery date. This means that the remaining 36.3% were delivered too late. Most of the remaining products were delivered only one week late. 89.8 - 63.7 = 26.1% of the assembly numbers were delivered within 7 days after the promised delivery date. Another 5.5% was delivered in the week after, meaning that 100 – 95.3 = 4.7% of the total amount of products were delivered more than two weeks late.

6.4. Discussion and conclusions

Due to other priorities during the COVID-19 pandemic, DP has not yet taken the time to set a goal for its service level. The goals found in Figure 28 are based on the proposed goal mentioned in Section 1.3. However, judging from the results in the previous section, it is clear that there is a lot of room for improvement for DP's service level. If DP decides to aim for a 90% delivering on time, an additional 26.3% of the assembly orders should be delivered before the promised delivery dates.

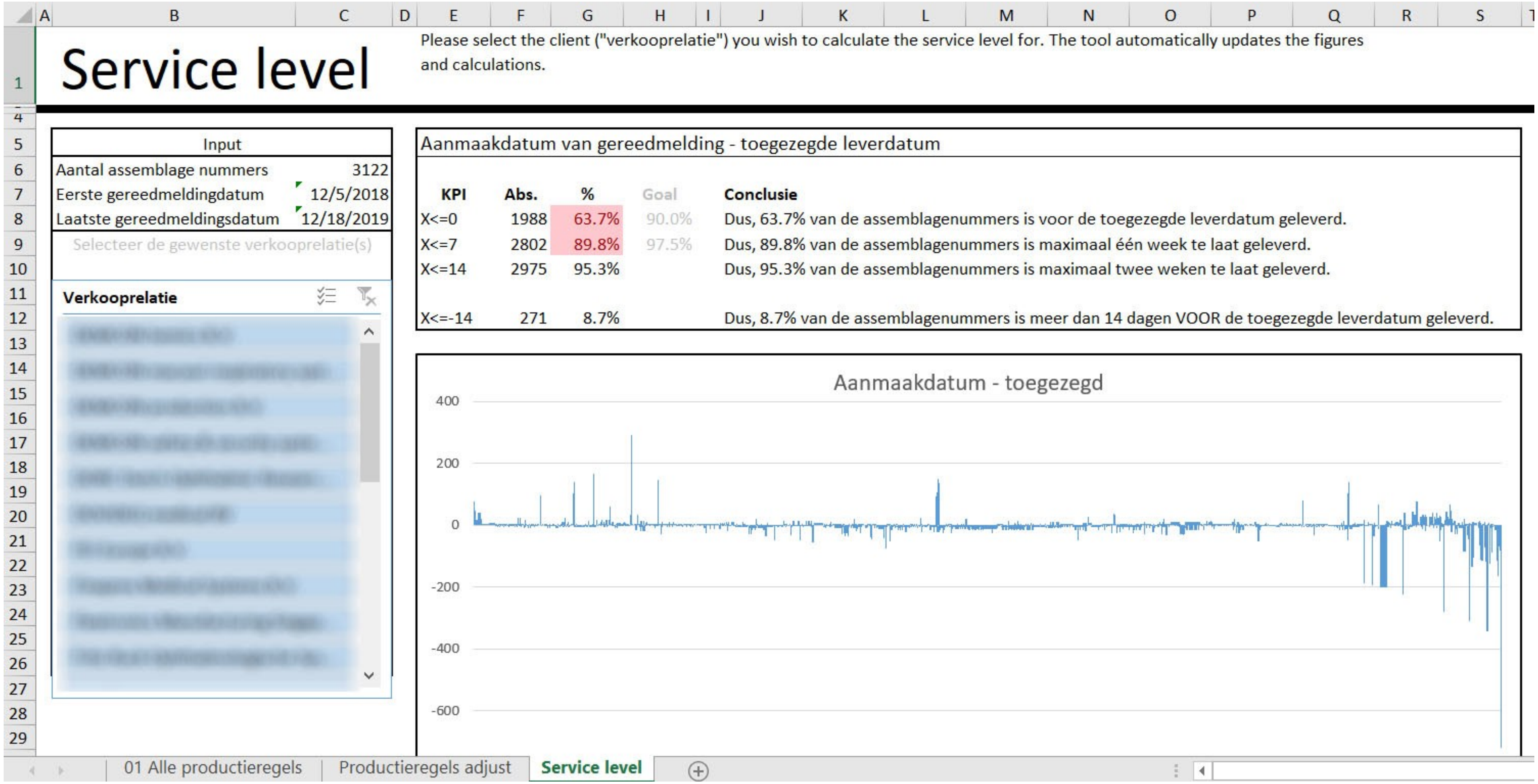


Figure 28 - Service level tool

7. Conclusions & recommendations

Based on all information gathered and obtained throughout this thesis, some conclusions and recommendations are formulated.

7.1. Conclusions

The Master Production Schedule is the first step in any production process. It determines when production activities should start in order to deliver on time. It is therefore very important that the Master Production Schedule is properly designed, which is the focus of this thesis.

As the MPS is the first step in the process of manufacturing products, changes in the MPS can cause a snowball effect: small changes requiring big adjustments in later stages. This is called schedule instability and should be avoided as further phases such as the MRP and Capacity Planning are prepared for the initial schedule and might not be able to handle the changes. To create a more stable schedule, multiple techniques were found in literature. Some of the techniques are already implemented or researched at DP, such as forecasting beyond the planning horizon and creating safety stocks. The proposed techniques that can be applied include the frozen and slushy periods, that can both be used for the purchasing and the manufacturing part of the supply chain, and safety lead times.

Additionally, a list of scheduling methods found in literature was addressed and compared. Based on these comparisons, the requirements for a suitable scheduling method are formed. A scheduling technique for DP should focus on decreasing the lateness of products and must be flexible so that it can easily adapt to schedule changes. Further research is required before choosing or designing a suitable scheduling technique.

The most important input for the MPS is the client's demand. Understanding the characteristics of this demand helps with designing a production schedule that enables delivering on time. Additionally, modelling the demand enables calculating certain production buffers, such as safety stock levels, and helps substantiating production decisions. A tool was created to model the demand data. Even though the tool does not provide one clear answer, the previously-made assumption of normality seems to be acceptable. The other probability distributions selected appear to be unfit for modelling demand of the different products DP creates and assembles.

The production performed at DP can be seen as a service to its clients. Therefore, both parties have an interest in streamlining the production activities, e.g. by decreasing the lead times. To achieve shorter lead times, some clients deliver forecasts. A tool is created that evaluates the accuracy of these forecasts. Only one year of forecast data is available, which is relatively little data for formulating well-founded conclusions. However, some conclusions can be made. It is found that accuracy significantly differs between products. This makes it difficult to draw overall conclusions. For the few products selected, the forecasts delivered two months in advance appear to be most exact. Additionally, the forecasts delivered by the clients are compared to some commonly used forecasting techniques. This clearly showed that, although the delivered forecasts are hardly accurate, they are more accurate than using the techniques forecasting based on historic data.

All findings are focused on improving the Master Production Schedule such that it provides a solid base for the rest of the production process. In the end, the explored opportunities for improvement should help with increasing the timeliness of orders and thus, increasing the service level of DP. To identify if DP is improving its service level, some KPIs have been formulated. In the year 2019, 36.3%

of the orders were delivered too late and 10.2% was delivered more than 7 days after the promised delivery date. This shows that there is definitely room for improvement.

7.2. Recommendations

The recommendations formulated in this section are based on the findings mentioned in Chapters 3 to 6, divided per chapter.

7.2.1. Master Production Schedule

Start implementing frozen and slushy periods

To decrease schedule instability, DP should start implementing a frozen period. The production schedule that is frozen can no longer be changed. This decreased the nervousness of the schedule, creating a stable supply chain.

Additionally, DP could start both accepting and placing slushy orders: orders from which only the time or only the quantity is frozen. This would help the order-receiving party to plan and possibly start production before the actual orders are placed.

Conduct further research on safety times

The concept of safety time is briefly mentioned in this thesis. Further research on this method of dealing with fluctuations in delivery times is required before implementing is made possible.

Find or design a scheduling heuristic suitable for DP

Currently, scheduling jobs is done manually. With the increasing demand that DP is expecting, creating such a schedule will take more and more time. Computing power could be used to find (near-) optimal schedules in less time. To find a suitable scheduling method, some methods found in literature have been gathered and compared. These can be found in Section 2.1.2.

7.2.2. Analysing past demand

Use tool to model lead times

The created tool also be used to model the lead times of materials. Having a probability distribution of the lead times helps with determining the safety times. For example, if 95% of the ordered materials are delivered within two weeks after the promised delivery date, the safety lead time could be set to 14 days.

7.2.3. Demand forecast accuracy

Give feedback to the client on the forecasts they deliver

The results from the created tool can be used as feedback to the clients. Creating awareness on the performance of the client's forecasts might lead to the client focusing more on the forecasts it delivers, hopefully increasing accuracy.

Ask for forecast per month

Demcon focuses on designing innovative solutions and systems for many clients. The production of these high-tech products and systems is done at DP. Due to this innovation, these products are often fairly new to the market, which subsequently means that not much data is available to analyse for these products.

To use this short timespan efficiently, capturing data should be done monthly, thus creating 12 data points per year. Some other clients deliver forecasts per quartiles.

Ask for rolling forecasts

A rolling forecast means that each period (e.g. month), a new forecast is given more multiple periods to come. For a 12-month rolling forecast, this would mean that the client provides an overview of what he is going to order each month for the upcoming 12 months.

The advantage of a rolling forecast is twofold. First, there is the advantage of having more data to analyse. One of the sheets created shows how the forecasts changed over time. Some patterns, e.g. regularly underestimating own demand, might come to light.

Secondly, using a rolling forecast might increase the accuracy of the forecasts. Take company X for example. As company X delivers a new 12-month forecast every month, they are forced to evaluate their own forecasts each month.

Make the clients commit to forecasts

Making a client fully commit to its forecast is difficult, as that would mean the client virtually places its orders multiple months in advance. However, having the client commit to a certain percentage of its forecasts should be possible. For example, the client could be allowed to be 50% off 5 months in advance (X=5). As time progresses, DP has to make more decisions regarding the production of the forecasted product. Therefore, it could be helpful to only allow a 10% deviation from the forecast one month in advance (X=1). The created tool includes two sheets graphically plotting these 'bandwidths' against the time to help DP evaluate what commitment strategy would be realistic.

Create a standard service package

At the moment, the agreements found in the contracts of DP's clients significantly differ from each other. Some clients deliver forecasts per month, some per quartile, some not at all. Some clients are financially responsible for the items purchased based on the forecasts whereas others cannot be held accountable for unused items.

DP should create one standard list of agreements that the clients are required to commit to. This creates a better overview of what agreements are made and enables DP to demand more commitment from the clients.

7.2.4. Service level

Start keeping track of the service level

The created tool should simplify the measuring of DP's service level. Keeping track of this service level creates one goal that applies to all departments within DP. Having the shared goal of increasing the service level might motivate employees to focus on obtaining this goal. A possible decrease in service level consequently shows that something went wrong.

Include an initial promised delivery date

DP produces and assembles complex products and systems of which many parts of different suppliers are required. Because of these, DP is dependent on its supplier. When a supplier is no longer able to deliver a certain part on time, the previous promised delivery date has to be revised. A new promised delivery date is communicated to the client. However, this does not accurately show DP's performance in delivering on time. To make more representative calculations of the service level, an extra date should be included: the initial promised delivery date.

7.3. Further research

This research explored opportunities for improvement within the Master Production Schedule and can be regarded as a starting point for improving the whole Manufacturing Resources Planning. In order to accomplish improvement, a number of recommendations have been formulated. Most of these recommendations formulated are ready for implementation. However, a couple of these require some extra research. For example, how long should the frozen and slushy period be? What is the optimal length of safety lead times? DP should evaluate which of the conclusions and recommendations are worth implementation and further investigation.

I wish Demcon Production good luck with their mission of creating a more production-oriented supply chain and hope that my research has contributed in accomplishing this.

Bibliography

Allaoui, H., & Artiba, A. (2009). Johnson's algorithm: A key to solve optimally or approximately flow. *Int. J. Production Economics volume 121*, 81-87.

Arentsen, A., & van Kaam, A. (2014). *Planningsstructuur voor Demcon Production.* Enschede: LOGICS bv.

Armstrong, D. J. (2013). *Using Safety Stock as an Alternative to Safety Stock.* Inventory Curve LLC. Retrieved from http://www.inventorycurve.com/uploads/Safety_Time_vs_Safety_Stock.pdf

Australian Bureau of Statistics. (2005, 11 14). *Time Series Analysis: Seasonal Adjustment Methods*. Retrieved from Australian Bureau of Statistics: https://www.abs.gov.au/websitedbs/d3310114.nsf/4a256353001af3ed4b2562bb00121564/c890aa8e65957397ca256ce10018c9d8!OpenDocument#:~:text=The%20X11%20method%20involves%20applying,'end%2Dpoint'%20problem.

Awadid, A., Nurcan, S., & Channouchi, A. S. (2019). On leveraging the fruits of research efforts in the arena of business process modeling formalisms: a map-driven approach for decision making. *Software & Systems Modeling*, 1905 - 1930.

Axsäter, S. (2006). *Inventory Control.* Lund, Sweden: Springer.

Baciarello, L., D'Avino, M., Onori, R., & Schiraldi, M. M. (2013). *Lot Sizing Heuristics Performance.* Torino.

Bakar, M. R., Abbas, I., Alsattar, H., & Kalaf, B. A. (2017). Solution for Multi-Objective Optimisation Master Production Scheduling Problems Based on Swarm Intelligence Algorithms. *Journal of Computational and Theoretical Nanoscience 14(11)*, 5184-5194. doi:10.1166/jctn.2017.6729

Bhongade, A., & Khodke, P. (2012). Heuristics for production scheduling problem with machining and assembly operations. *International Journal of Industrial Engineering Computations 3(2)*, 185-198.

Box, G. E. (1976). Science and Statistics. *Journal of the American Statistical Association, Vol. 71, No. 356.*, 791-799. Retrieved from http://mkweb.bcgsc.ca/pointsofsignificance/img/Boxonmaths.pdf

Bywater, P. (1994). *MRP II: planning for success.* Sanderson Computer Ltd.

Cadle, J., Paul, D., & Turner, P. (2014). *Business Analysis Techniques - 99 Essential Tools for Success (2nd Edition).* BCS The Chartered Institute for IT. Retrieved from https://app.knovel.com/hotlink/toc/id:kpBATETSE1/business-analysis-techniques/business-analysis-techniques

Chacuat, B. (2020, 8 8). *Mixed-Integer Linear Programming (MILP): Model Formulation.* Retrieved from McMaster University: http://macc.mcmaster.ca/maccfiles/chachuatnotes/07-MILP-I_handout.pdf

Chopra, S., & Meindl, P. (2016). *Supply Chain Management: Strategy, Planning, and Operation.* Harlow: Pearson.

Clausen, J. (1999). *Branch and Bound Algorithms - Principles and Examples.* Copenhagen, Denmark: Department of Computer Science, University of Copenhagen.

Durango-Cohen, E. J., & Yano, C. A. (2006). Supplier Commitment and Production Decisions under a Forecast-Commitment Contract. *Management Science, Vol. 52, No. 1*, 54-67.

E. Powell Robinson Jr, Funda Sahin & Li-Lian Gao. (2008). Master production schedule time interval strategies in make-to-order supply chains. *International Journal of Production Research, 46:7*, 1933-1954. doi:10.1080/00207540600957381

Engineering Statistics Handbook. (2020, 6 30). Retrieved from Double Exponential Smoothing: https://www.itl.nist.gov/div898/handbook/pmc/section4/pmc433.htm

eNotes Editorial. (2011, 11 29). *What is the difference between an algorithm and a heuristic?* Retrieved 08 08, 2020, from eNotes : https://www.enotes.com/homework-help/what-difference-between-an-algorithm-heuristic-298252

Ford, C. (2015, 8 26). *Understanding Q-Q Plots*. Retrieved from University of Virginia Library: https://data.library.virginia.edu/understanding-q-q-plots/

Gao, X., & Li, Z. (2006). Business process modelling and analysis using UML and polychromatic sets. *Production Planning & Control, 17:8*, 780-791.

George, D., & Mallery, M. (2010). *SPSS for Windows Step by.* Boston, MA: Pearson.

Heerkens, H., & Van Winden, A. (2017). *Solving Managerial Problems Systematically.* Groningen/Houten: Noordhoff Uitgevers.

Hewson, C., Vogel, C., & Laurent, D. (2018). *Ethics in Internet-Mediated Research.* 55 City Road: SAGE Publications Ltd.

Holt, C. C. (2004). Forecasting seasonals and trends by exponentially weighted moving averages. *International Journal of Forecasting 20*, 5-10.

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and Practice (2nd edition).* Melbourne, Australia: OTexts. Retrieved from OTexts.com/fpp2

Hyndmann, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy (Volume 2, Issue 4). *International Journal of Forecasting*, 679-688.

Jain, D. (2018, 8 23). *Skew and Kurtosis: 2 Important Statistics terms you need to know in Data Science*. Retrieved from Codeburst.io: https://codeburst.io/2-important-statistics-terms-you-need-to-know-in-data-science-skewness-and-kurtosis-388fef94eeaa

Jaynes, E. (2003). *Probability Theory.* Cambridge: Cambridge University Press.

Johannsen, F., & Leist, S. (2014). Wand and Weber's good decomposition conditions for BPMN: An interpretation and differences to Event-Driven Process Chains. *Business Process Management Journal 20(5)*. doi:10.1108/BPMJ-03-2013-0031

Kadipasaoglu, S. N., & Sridharan, V. (1995). Alternative approaches for reducing schedule instability in multistage manufacturing under demand uncertainty. *Journal of Operations Management Volume 13, Issue 3*, 193-211.

Karagiannis, D., Mayr, H. C., & Mylopoulos, J. (2016). *Domain-specific Conceptual Modeling.* Springer.

Kheldoun, A., Barkaoui, K., & Ioualalen, M. (2017). Formal verification of complex business processes based on high-level Petri nets. *Information Sciences: an International Journal, Vol. 385, No. C*. doi:https://doi.org/10.1016/j.ins.2016.12.044

King, B. E., & Benton, W. (1987). Alternative master production scheduling techniques in an assemble-to-order environment. *Journal of Operations Management, Volume 7, Issues 1-2*, 179-201. Retrieved from https://www.sciencedirect.com/science/article/pii/0272696387900167

Law, A. M. (2013). A tutorial on how to select simulation input probability distributions. *2013 Winter Simulations Conference (WSC)*, (pp. 306-320). Washington, DC,. doi:10.1109/WSC.2013.6721429.

Law, A. M. (2015). *Simulation Modeling and Analysis, 5th edition.* Tucson, Arizona, USA: McGraw Hill.

List, B., & Korherr, B. (2006). An evaluation of conceptual business process modelling languages. *ACM symposium on Applied computing* (pp. 1532-1539). SAC. doi:https://doi.org/10.1145/1141277.1141633

Maiseli, B. J. (2019). Optimum design of chamfer masks using symmetric mean absolute percentage error. *EURASIP Journal on Image and Video Processing*, 74. doi:https://doi.org/10.1186/s13640-019-0475-y

Maity, R. (2018). *Statistical Methods in Hydrology and Hydroclimatology.* Singapore: Springer.

Milicer Gruzewska, H. (1933). The Precision of the Weighted Average Vol. 4, No. 3. *The Annals of Mathematical Statistics*, 196-215.

Natschläger, C., & Geist, V. (2013). A layered approach for actor modelling in business processes. *Business Process Management Journal*, Vol. 19 No. 6, pp. 917-932.

Nau, R. (2020, 30 6). *Moving average and exponential smoothing models*. Retrieved from Statistical forecasting:: http://people.duke.edu/~rnau/411avg.htm#BrownLES

Nawaz, M., Enscore, E., & Ham, I. (1983). A heuristic algorithm for the m-machine, n-job flow-shop sequencing problem. *Omege volume 11, issue 1*, 91-95.

Rodríguez, A. (2010). Semi-formal transformation of secure business processes into analysis class and use case models: An MDA approach. *Information and Software Technology*, 945-971.

Sahin, F., Narayanan, A., & Powell Robinson, E. (2013). Rolling horizon planning in supply chains: review, implications and directions for future research. *International Journal of Production Research, 51:18*, 5413-5436. doi:10.1080/00207543.2013.775523

Sahin, H., & Robinson Jr., E. P. (2005). Information sharing and coordination in make-to-order supply chains. *Journal of Operations Management 23*, 579-598.

Sedgwick, P. (2012). The normal distribution. *k reader in medical statistics and medical education*. doi:BMJ 2012;345:e6533 doi: 10.1136/bmj.e6533

Shapiro, J. F. (1993). Chapter 8: Mathematical programming models and methods for production planning and scheduling. In A. R. S.C Graves, *Handbooks in Operations Research and*

Management Science, Volume 4 (pp. 371-443). Cambridge, MA, U.S.A.: Sloan School of Management, Massachusetts Institute of Technology.

Shapiro, S., & Wilk, M. (1965). An Analysis of Variance Test for Normality (Complete Samples). *Biometrika Vol. 52, No. 3/4*, 591-611.

Simpson, N. (2001). Questioning the relative virtues of dynamic lot sizing rules. *Computers & Operations Research, Volume 28, Issue 9*, 899-914.

Slack, N., Brandon-Jones, A., & Johnston, R. (2016). *Operations Management.* Harlow: Pearson Education Limited.

Sridharan, V., Berry, W. L., & Udayabhanu, V. (1987). Freezing the Master Production Schedule under Rolling Planning Horizons. *Management Science, Vol. 33, No. 9*, 1137-1149.

Subramaniam, A. (2019, 8 15). *Lot Sizing Techniques.* Retrieved from Slideshare: https://www.slideshare.net/anandsubramaniam/lot-sizing-techniques

Suchenia, A., Lopata, P., Wisniewski, P., & Stachura-Terlecka, B. (2019). Towards UML representation for BPMN and DMN models. *CMES'18* (p. 02007). Krakow: EDP Sciences. doi:https://doi.org/10.1051/matecconf/201925202007

Thesen, A. (n.d.). *The Kolmogorov-Smirnov Test*. Retrieved 10 8, 2020, from IE 642 Simulation of Manufacturing Systems: http://homepages.cae.wisc.edu/~ie642/index.html

Tsay, A. (1999). The Quantity Flexibility Contract and Supplier-Customer Incentives. *Management Science 45 (10)*, 1339-1358.

UvA Wiki Methodologiewinkel. (2014, 7 14). *Normaliteit*. Retrieved from UvA Wiki Methodologiewinkel: https://wiki.uva.nl/methodologiewinkel/index.php/Normaliteit

Van de Poel, I., & Royakkers, ,. L. (2011). *Ethics, Technology, and Engineering : An Introduction.* Wiley-Blackwell.

Wagner-Within Algorithm. (2000). In P. Swamidass, *Encyclopedia of Production and Manufacturing Management.* Bosten, MA: Springer. Retrieved from Encyclopedia of Production and Manufacturing Management.

Weske, M. (2007). *Business Process Management: Concepts, Languages, Architectures.* Berlin: Springer.

Wonders, A. N. (2020). *Increasing the material availability to deliver on time.* Enschede.

Xie, J. (2010). Assessing the value of early order commitment for supply chains with (s, S) policies and lost sales. *International Journal of Applied Management Science 2(3)*, 205-223. doi:10.1504/IJAMS.2010.033565

Yeung, J. H., Wong, W. C., & Ma, L. (1998). Parameters affecting the effectiveness of MRP systems: A review. *International Journal of Production Research, Volume 36*, 313-332. doi:https://doi.org/10.1080/002075498193750

Zaiontz, C. (n.d.). *Statistical Tests for Normality and Symmetry*. Retrieved 07 06, 2020, from Real Statistics Using Excel: http://www.real-statistics.com/tests-normality-and-symmetry/statistical-tests-normality-symmetry/

Zammori, F., Braglia, M., & Frosolini, M. (2009). A standard agreement for vendor managed inventory. *Strategic Outsourcing: An International Journal, Vol. 2, No. 2*, 165 - 186.

Zhao, X., & Lee, T. (1993). Freezing the master production schedule for material requirements planning systems under demand uncertainty. *Journal of Operations Management Volume 11, Issue 2*, 185-205.

Zhao, X., Goodale, J. C., & Lee, T. S. (1995). Lot-sizing rules and freezing the master production schedule in material requirements planning systems under demand uncertainty. *International Journal of Production Research vol. 33*, 2241-2276.

Appendices

Appendix A: Manufacturing Resources Planning

As the name suggests, the Manufacturing Resources Planning (MRP II) is an overview of all resources required to manufacture products. All materials, men and machines that are used for production are included in the MRP II.

Related concepts

To understand what a Manufacturing Resource Planning (MRP II) is, it is important to understand some other concepts, such as MPS and MRP, and how they relate to each other. In this chapter, these concepts will be explained in depth.

Master Production Schedule

The Master Production Schedule, in short MPS, is a tool that helps to determine what a company needs to produce, how much you need to produce and when you need to produce it in order to meet customer demand. This tool only involves completed products, disregarding the several materials and parts that the product consists of.

Inputs for the MPS are planned orders, future orders (forecasted) and both current and future availability of products. The latter include the number of products that are in stock and the number of products that are currently in production. The lead times of products and their standard deviations are therefore very relevant.

Based on the lead-times, the MPS gives an overview that says what products have to start production on what days. The date and the number of to-produce products are the main output of the MPS. These start-dates are the due-dates for the Material Requirements Planning.

Material Requirements Planning

The Material Requirements Planning, also known as MRP or MRP I, is a computer-based tool that uses the output of the MPS to indicate when materials or product-parts have to be ordered and in what quantities. Looking at the full process, the MRP I is a step further in the process than the MPS.

Next to the output of the MPS, this planning needs other inputs: the Bill of Materials (BOM)[1], inventory status of the materials/parts and their lead times.

History of MRP II

Due to the introduction of computers, the Material Requirements Planning (MRP) became very popular in the 1970s. The logic behind MRP had been known for a while already, but the ability to use this new computing power for the calculations behind the planning made the MRP very easy to use.

The accessibility and computing power of computers increased a lot over the years. In the 1980s, MRP II expanded out of MRP, as a result of these rapid technological advancements. MRP II allowed communication between different departments within a business. The big advantage of both MRP I and MRP II is the ability to test situations without the risk of real (financial) consequences. For example, the impact of a change in demand could now easily be calculated. (Slack, Brandon-Jones, & Johnston, 2016)

[1] Bill of Materials (BOM) is a list of required materials to produce a certain product

Definition of MRP II

Manufacturing Resource Planning is a mechanism that combines all resources within an enterprise (Bywater, 1994). This mechanism combines all resources required to enable the manufacturing of products, e.g. material, man and machine. The MRP II starts with creating an overview of when production for certain products has to start, in order to be finished in time. This is done by the MPS. Subsequently, the availability of the required materials and parts has to be checked. The MRP I is used for this. If not all products are available nor cannot be available in time to keep up with the production schedule created by the MPS, the MPS has to be adjusted. When the MPS is adjusted and the MRP is able to provide the required parts in time, the availability of other resources has to be checked. Are there enough machines and employees (with the right competences) to create the products according to the production schedule? If this is not the case, the production schedule has to be adjusted (again). In Figure 29, a schematic overview of an MRP II is given.

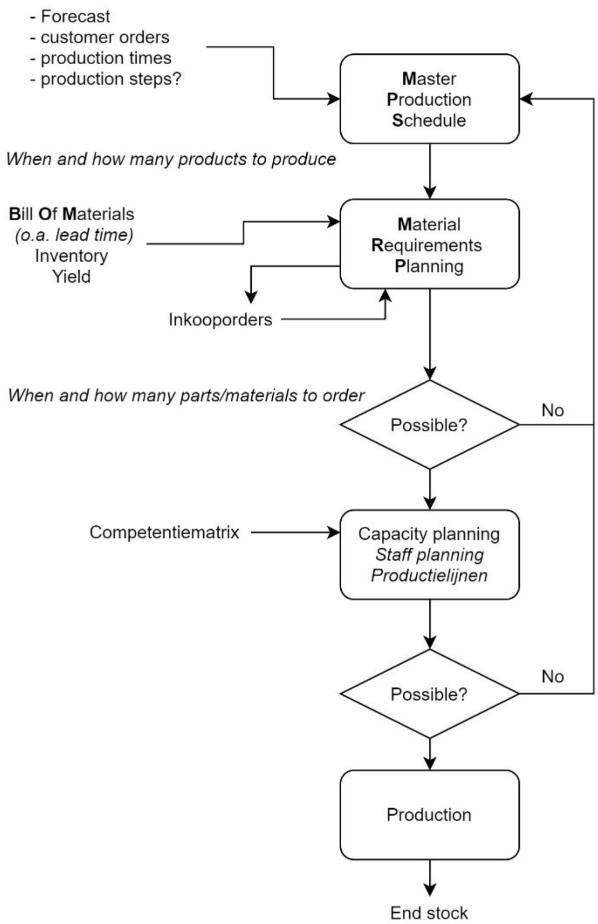


Figure 29 - Manufacturing Resources Planning (MRP II)

Enterprise Resource Planning

In terms of integrating information systems, Enterprise Resource Planning (ERP) is the next step of MRP II. Where an MRP system stops at the purchasing part of a business, focusing on the availability of materials, an MRP II system adds the man and machine power behind the production. An ERP system takes it a step further by involving finances, sales and HR as well. Such a system ultimately integrates all departments within a company. (Slack, Brandon-Jones, & Johnston, 2016)

Appendix B: Goodness-of-Fit hypothesis tests

Chi-square test

The Chi-square test is the oldest goodness-of-fit hypothesis test, dating back to 1900. The test can be seen as a formal comparison of a histogram with a fitted density function. Therefore, the first step of the test is dividing the data into an integer *k* adjacent intervals. These so-called bins enable the test to be applied to both continuous and discrete data sets. The observed data is divided over the mentioned intervals, using the following formula:

$$N_j = \text{number of } X_i's \text{ in the } j\text{th interval } [a_{j-1}, a_j)$$

for *j* = 1, 2, …, *k* and X_i being the observed data points.

Next, the expected data is computed. This is done by finding the probabilities that the tested probability distribution falls in the intervals $[a_{j-1}, a_j)$.

Subsequently, the test statistic can be calculated:

$$X^2 = \sum_{j=1}^{k} \frac{(N_j - np_j)^2}{np_j}$$

In words, the formula for the test statistic can be formulated as $\frac{(observed-expected)^2}{expected}$. Thus, if the tested distribution is a good fit, X^2 is expected to be small. How small the test statistic should be is determined by using the critical points table for the Chi-square test. The table requires an α (or rather 1- α) and a *v* representing the number of degrees of freedom, which is *k* - 1.

The null hypothesis is rejected if the test statistics is larger than the critical value ($X^2 > X^2_{k-1,1-\alpha}$).

(Law A. M., 2015)

Shapiro-Wilk test

In 1965, Shapiro and Wilk designed an approach that tests a certain dataset for its normality. This approach is designed for samples of 3 to 50 elements. There is a revised approach available that can handle more data, but a limit of 50 elements already accounts for over four years of data (when looking at monthly demand), so will not be relevant for DP yet.

For every test in statistics, a null hypothesis has to be formulated. The null hypothesis when using the Shapiro-Wilk test is: H_0 = the data set is normally distributed. If the p-value obtained by performing the test is smaller than α, which is generally 0.05, the null hypothesis is rejected as there is a less than 5% chance that the null hypothesis is correct.

The first step is to rearrange the data in ascending order, thus $x_1 \leq \cdots \leq x_n$. Secondly, the Sum of Squares (SS) is calculated: $SS = \sum_{i=1}^{n} (x_i - \bar{x})^2$.

Next, we find the median (x_m), where *m* = *n*/2 if *n* is even and *m* = (*n*-1)/2 if *n* is an odd number. *m* is used in calculating *b*, the estimate of the slope of Q – Q plot. The formula for *b* is

$b = \sum_{i=1}^{m} a_i (x_{n+1-i} - x_i)$, with a_i being the normalized best linear coefficients.

W, the test statistic for normality, can subsequently be obtained by dividing the squared value of b by the sum of squares: $W = b^2/SS$. If W = 1, it is found that the null hypothesis is true. If W < 1, the dataset might be significantly different from normal.

Now that the test statistic is found, we search for the p-value. This is done by using the tables created by Shapiro and Wilk. By using interpolation, we find a certain p-value.

If the p-value < 0.05, the null hypothesis is rejected. With 95% certainty, it can be concluded that the dataset is not normally distributed.

If the p-value > 0.05, we fail to reject the null hypothesis. Statistically, the dataset is not significantly different from a normal distribution. This, however, does not mean that the dataset is normally distributed, only that it is not significantly different from a normal distribution.

A p-value close to 1 shows little to no difference from normality.

(Shapiro & Wilk, 1965) (Zaiontz, sd)

Kolmogorov-Smirnov test

To illustrate the steps necessary for performing the Kolmogorov-Smirnov test, we use the hypothesis that the dataset is exponentially distributed.

The test statistic for the K-S test is the overall maximum deviation between the fitted distribution and the dataset. The first step is to put the data on the order of greatness, starting from the smallest data point. See row 1 in Table 4, where $n = 4$.

Subsequently, the data is divided into n equal parts. The lower bounds are put in row 2 and higher bounds in row 3.

The next step requires the formula for the exponential distribution: $F(x) = 1 - e^{-\lambda x}$. In the example table, λ equals 0.2.

The F(x) values are compared to their low and high estimates and the largest difference between F(x) and the two estimates is taken (see row 5).

Lastly, the largest overall deviation is taken, which is D_n.

Table 4 - Example K-S test (Thesen, sd)

Row 1	Datapoint xi	1.2	3.1	5.1	6.7
Row 2	Low estimate	0	0.25	0.50	0.75
Row 3	High estimate	0.25	0.50	0.75	1
Row 4	F(xi)	0.21	0.46	0.64	0.74
Row 5	Largest deviation	0.21	0.21	0.14	0.26
Row 6	Overall largest deviation	0.26			

Law (2015) gives an adjusted test statistic that differs per distribution the dataset is tested against. The adjusted test statistic for exponential distributions is $\left(D_n - \frac{0.2}{n}\right)\left(\sqrt{n} + 0.26 + \frac{0.11}{\sqrt{n}}\right)$. This test statistic is used for determining whether or not the null hypothesis should be accepted or rejected. The value against which the test statistic should be tested is $c_{1-\alpha}$. These critical values can be found in Table 5.

Table 5 - K-S test critical values for exponential distributions

$1-\alpha$	0.850	0.900	0.950	0.975	0.990
$c_{1-\alpha}$	0.926	0.990	1.094	1.190	1.308

The null hypothesis is rejected if the test statistic is higher than the critical value.

(Law A. M., 2015)

Appendix C: Forecast accuracy tool results

This appendix includes more elaborate results from the forecast accuracy tool.

Company X

Product A

The overview in Figure 27 is based on the data available for product A. Based on the MAE and SMAPE values, it can be concluded that the forecasts that company X delivers are more accurate than the forecast techniques. The optimal input variables for the forecasting techniques were found, but these could not make better estimates than the company did. Noticeable is that the forecast given two months in advance is more accurate (MAE: 12.13; SMAPE: 16.3%) than the forecast given a month in advance (MAE: 14.29; SMAPE: 29.2%).

Additionally, product A confirms one of the disadvantages of the MAPE technique: the risk of becoming extremely skewed when Y_t nears zero. In May 2020, only one product was ordered. This results in a MAPE-value of over 200% for the whole year, whereas disregarding this month from the equation results in a value of 70%.

Product B

The X=1 and X=2 forecasts delivered by company X result in an MAE of 22.9 and 30.5 respectively. All MAE values of the forecasting techniques exceed 30.50. Therefore, it can be concluded that the forecasts delivered by the client are more accurate than the forecasting calculations based on historic data.

For this product, the MAE is smaller for the estimations made one month in advance (X=1) compared to two months in advance (X=2). This is different than for Product A and can be lead back to the COVID-19 pandemic. A significant drop in orders can be seen when we compare the forecast for May made in February (101 products) to the forecast for May made in April (22). If the months April and May are disregarded, giving company X the possibility of adjusting their forecasts as a consequence of the pandemic, the forecasts two months before the month of ordering become more accurate than the forecasts made one month in advance. The MAE for X=2 becomes 21.43, compared to the MAE for X=1 at 24.17.

Product C

For product C, the forecasts created by company X are significantly worse than the calculated forecasts. The calculated forecasts all have an MAE value between 34 and 43, where the MAE values for the delivered forecasts are all 60+. The lowest MAE value can be found by using the weighted average technique with 0.8 weight for the previous month and 0.2 for three months ago.

However, the badly delivered forecasts can again be traced back to the COVID-19 pandemic. If we disregard the results from April, May and June, we find that the lowest MAE comes from the X=2 delivered forecast, with an MAE of 19.50.

Appendix D: Frozen period

More information about the parameters of the frozen period is described in this section.

Planning horizon and replanning periodicity

The planning horizon (N) is the number of periods beyond the lead time for which production schedules are produced in each replanning cycle. Zhao & Lee (1993) find that the demand uncertainty influences the performance of different lengths of N. When demand is known, longer planning horizons perform better than smaller Ns. In their paper, a planning horizon of 8 natural ordering cycles results in lower costs and lower schedule instability compared to a planning horizon of 4 natural ordering cycles. However, when demand is uncertain and forecasting errors occur, a planning horizon of 4 ordering cycles outperforms the planning horizon of 8 ordering cycles in terms of cost and stability. (Zhao & Lee, 1993)

Another freezing parameter is the replanning periodicity (R). Zhao & Lee (1993) express R as a fraction of the frozen period and find that a higher R results in lower total costs, lower schedule nervousness and higher service levels. Thus, decreasing the number of replannings in the MPS improves MRP performance. The best performance is found for R = 1, meaning that replanning happens when the frozen period is over. (Zhao & Lee, 1993)

Order-based freezing

The information described in the previous sections is focused on period-based freezing, which is the main method used in firms nowadays. An alternative to this is freezing the MPS based on orders. Instead of freezing the schedule for a number of periods, the schedule is frozen on a number of orders. This means that replanning is done after the chosen number of orders.

Table 6 and Table 7 are examples of an MPS using, respectively, period-based and order-based freezing. The order quantities and timings are determined by the lot-sizing algorithm designed by Wagner and Within.

In the period-based example, at the beginning of period 1, 3 and 5, the planning for the upcoming four periods is determined. From these four periods, the first two are frozen. At the start of period 3, the master schedule for period 3 through 6 are determined. Period 5 and 6 can still be changed until the start of period 5.

Table 6 – Example MPS: Freezing two periods

Four-period schedule: freezing the first two periods						
Period	1	2	3	4	5	6
Required	177	261	207	309	64	182
Required	177	261	207	309		
Inventory	261	0	309	0		
MPS	438	0	516	0		
Required		0	207	309	64	
Inventory		0	373	64	0	
MPS		0	580	0	0	
Required			207	309	64	182
Inventory			0	246	182	0
MPS			207	555	0	0
Required				0	0	182
Inventory				0	0	0
MPS				0	0	182

In the order-based example, at the beginning of period 1, the orders for the first four periods are determined. These orders fulfil the demand, the required amount of products, of the first four periods. After these four periods, at the beginning of period 5, the schedule for the next four periods (period 5 to 8) is determined.

Table 7 – Example MPS: freezing two orders

Four-period schedule: freezing the first two orders						
Period	1	2	3	4	5	6
Required	177	261	207	309	64	182
Required	177	261	207	309		
Inventory	261	0	309	0		
MPS	438	0	516	0		
Required					64	182
Inventory					182	0
MPS					246	0

(Sridharan, Berry, & Udayabhanu, 1987)

Zhao & Lee (1993) find that in terms of costs, order-based freezing performs better than period-based freezing. This holds for both stochastics as deterministic demand. In terms of schedule instability, the period-based method can outperform the order-based method, but this negatively affects the service level. (Zhao & Lee, 1993)

Free-interval flexibility

The free interval in Figure 4 leads us to the second MPS design criterion for dealing with instability: non-frozen period flexibility. The planning horizon extends beyond the frozen period. Generally, the assumption is made that both the quantity and the timing can be adjusted freely. This maximizes flexibility for the manufacturer but fails in providing the vendor with stable orders. The orders in this strategy are often referred to as liquid orders.

An alternative is the so-called slushy-order strategy. Slushy orders have a fixed timing, but the quantity of the orders can be changed. Only when the order enters the frozen period, the order quantity freezes. As part of the EOC policy, the order timings and estimated order quantities can be communicated to the vendor. Using this strategy, the vendor is able to prepare for production and even to some extent produce some products as the order quantities might change, but will not be cancelled. (E. Powell Robinson Jr, Funda Sahin & Li-Lian Gao, 2008)

Lot size

Especially in the frozen period and the slushy zone, it is important to determine when and what quantities a company should order or produce. There are several policies available for determining these so-called lot-sizes. In literature, these are often used for determining when and how many materials have to be ordered. However, these different policies can also be used for production schedules. An extensive list of common lot-sizing policies can be found below.

In her paper, Simpson (2001) compares nine lot-sizing rules by subjecting these rules to 3060 rolling horizon simulations. In her concluding remarks, she mentions that the choice of policy seems unimportant when dealing with low-variable demand. However, for sparser demand patterns, two of the nine rules stand out in their cost and nervousness performance: the Wagner-Within algorithm and the lesser-known Maximum Part Period Gain (MPG) algorithm. The paper suggests that the latter algorithm performs as well as the Wagner-Within in most instances, but requires fewer calculations. (Simpson, 2001)

The conclusion drawn by Simpson (2001) is again found by Baciarello *et al.* in their paper on Lot sizing heuristics performance. Baciarello *et al.* found that MPG results to be the most effective heuristics considering all scenarios tested while being an intuitive rule. (Baciarello, D'Avino, Onori, & Schiraldi, 2013)

In literature, several lot-sizing policies have been created and evaluated. Below, a list of frequently-used lot-sizing rules can be found.

- **Lot-for-lot (LFL)** might be the most used lot-sizing policy. Following this policy, the manufacturer has no restrictions in order timing or order quantity.
- The **Fixed Order Quantity (FOQ)** policy restricts the manufacturer to order a certain quantity each time an order is placed. This often relates to the way of transport of the ordered goods, e.g. per pallet or tanks with a certain size.
- The **Economic Order Quantity (EOQ)** is using a formula that seeks the optimum in balancing order costs and storage costs. It minimizes the total costs per item but is based on simplistic assumptions that might fail to represent the real world. (Slack, Brandon-Jones, & Johnston, 2016)
- **Periodic order quantity (POQ)** or Fixed Period Quantity uses the EOQ to determine the number of periods an order should fulfil. The number of periods is calculated as POQ = EOQ / (average usage per period). As this could give a decimal number, it should be rounded to the nearest integer.
- **Periods of Supply (POS)** uses a fixed number of periods (e.g. three weeks) for which the order quantity should fulfil the demand.
- **Minimal Order Quantity** implies that the customer (or manufacturer) is obligated to buy a certain quantity of products when an order is placed.
- **Maximum Order Quantity** implies that the customer cannot order more than a certain quantity of products.
- **Least Unit Cost (LUC)** is a dynamic lot size technique that calculates the total ordering and inventory costs for each possible combination of upcoming periods and then chooses the one with the least costs per unit.
- **Least Total Cost (TLC)** is a dynamic lot size technique that calculates both the order costs and the inventory costs for each possible combination of upcoming periods and then chooses the one where the order costs are nearest to the cumulative inventory costs.
- The **Part Period Balancing (PPB)** algorithm is a variation of the LTC. It first calculates the Economic Part Period (EPP) by dividing the ordering costs by the inventory costs (per unit per period). It then adds demand requirements period by period until the part periods approximate the EPP. For example, let EPP = €50,-/€0,20 = €250,-. For an order combining the requirements for periods 1 and 2, a total cost of €160,- is calculated. For a combined order for periods 1, 2 and 3, a total cost of €270,- is calculated. The part period algorithm chooses to order for the three periods at the same time.
- The **Wagner-Within** policy is based on an algorithm that aims to minimize the costs of ordering by optimally combining net requirements over multiple periods. (Wagner-Within Algorithm, 2000)

- The **Maximum Part Period Gain** was designed by R. Karni in 1981 and uses the Part Period principle to shift orders in time to reduce set up costs. This heuristic is one of the few techniques using *left shifting* rather than shifting orders forward in time. (Simpson, 2001)

(Yeung, Wong, & Ma, 1998) (Subramaniam, 2019)

Appendix E: Scheduling/sequencing techniques

Definitions of relevant concepts

First, some concepts need to be explained before addressing the techniques found in literature.

Heuristics & algorithms

Heuristics are problem-solving approaches that do not guarantee optimal solutions but are nevertheless sufficient for approximating the optimal solution.

Algorithms are well-defined instructions that often aim to solve a problem. The formal language ensures that the algorithm in unambiguous. Algorithms are often designed to find the optimal solution but can be used for approaching the optimum, similar to heuristics. The difference between the two is that heuristics can be any procedure that uses trial-and-error to produce a result, whereas algorithms are a formal set of rules to solve a problem. (eNotes Editorial, 2011)

Branch & Bound

The branch and bound paradigm can best be illustrated by the roots of a tree (see Figure 30). A B&B algorithm branches of the tree, creating multiple candidate solutions. Before computing complete solutions, the algorithm evaluates the candidate solutions (branches) and bounds certain branches if these already differ from the optimal (sub-)solution found.

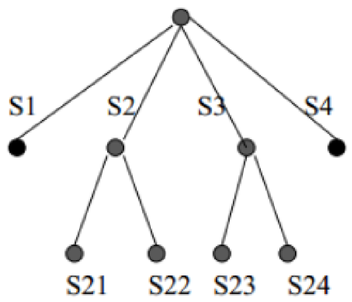


Figure 30 - Branch and bound tree (Clausen, 1999)

Integer programming

If all variables within an optimisation function are discrete, the model is an integer program. Integer programs can be solved by computers that will compute all possible compositions of variables in order to find the optimal solution. Having only discrete variables in combination with some restrictions creates a finite amount of possible compositions. Therefore, formulating a problem as an integer program enables computers to solve the optimisation function. One way of formulating a sequencing problem is by using the Traveling Salesman Problem. More information about this formulation can be found in Appendix E: Scheduling/sequencing techniques.

Often, some of the variables within an optimisation function is not an integer. In this case, such a model is referred to as a mixed-integer program. When the objective function and all constraints are linear, e.g. can be graphically represented by a straight line, the problem is a (mixed-)integer linear program. Nonlinear programs are very difficult to solve. (Chacuat, 2020)

Detailed descriptions of the scheduling techniques

Total enumeration heuristic

1. Calculate production sequences $J_h!$ per product *h*
2. Calculate *makespan_h* for each possible sequence and determine sequence with minimal *makespan_h*
3. Repeat step 1 and 2 for remaining products. Sequences stay fixed afterwards.
4. Determine all possible sequences of products (*H!*)
5. Calculate (total) *makespan* for every sequence obtained and determine sequence with minimal *makespan*

(Bhongade & Khodke, 2012)

NEH

1. For each job *i*, the total timespan (T_i) needs to be calculated: $T_i = \sum_{j=i}^{m} t_{i,j}$ where $t_{i,j}$ is the processing time of job *i* on machine *j*.
2. Arrange the jobs in descending order of T_i.
3. Pick the two jobs that have the longest T_i and find the best sequence for these two jobs by calculating the makespan of both sequence options. For example, start with job 1 then do job 2, or first job 2 then start job 1. When the optimal sequence of both is found, the order between these two jobs is fixed. Set *i* = 3.
4. Pick the job on the *i*th position from the list obtained in step 2 and find the best sequence by placing this job in the sequence of the optimal sequence found in step 3. Note that there are *i* (three) options as the order of job 1 and 2 has been determined already. For example, step 3 indicates order 1-2. Possible sequences that now remain are: 3-1-2, 1-3-2, and 1-2-3.
5. Repeat step 4 with *i* = *i* + 1 until all jobs have been added to the sequence.

(Nawaz, Enscore, & Ham, 1983)

NEH_BB heuristic

1. Calculate the total processing time of each part of product *h* for all operations till assembly.
2. Create a set of parts and arrange it in descending order or processing time.
3. Create subsequent sets of parts by interchanging the part at the first position of the initial set with the other positions in the sequence. J_h sets are formed.
4. Calculate the *makespan_h* for all subsequent sets and determine the sequence with the minimal *makespan_h*. The part on the first position of this sequence is now fixed.
5. Repeat step 3 for by interchanging the part on the second position (J_h – 1 sets are created). Afterwards, determine the minimum *makespan_h* and make the second position fixed.
6. Repeat step 5 until all positions have been fixed.
7. Repeat step 2 through 6 for all remaining products. The sequences found, with the minimal *makespan_h*, are considered fixed.

8. The order of products from step 1 through 7 is kept.
9. Repeat steps 2 through 7 with interchanging the i^{th} products on every position in the sequence. Consequently, minimal *makespan* is found.

Disjunctive heuristic

1. For every product *h*, the set of operations on each machine is identified and the bottleneck machine *BN(h)*, is found.

2. Every set of operations before the *BN(h)* is arranged in ascending order of processing time. The sets of operations after the *BN(h)* are arranged in descending order.
3. Thus the sequence of the parts for product *h* is decided on the first machine.
4. The order of parts in the subsequent machine is decided based on the availability of parts and machine. Preference is given to the order obtained for that machine in step 2. It gives a sequence of parts, *SMh*, to be processed one very machine.
5. Repeat step 1 through 4 for the remaining products and determine their *SMh*.
6. *SMh* for every product is fixed for the rest of the heuristic.

7. The sequence of the products is decided by using the Branch and Bound method from the NEH_BB heuristic, calculating minimum makespan.

(Bhongade & Khodke, 2012)

Johnson's algorithm

1. Divide the set of jobs into two groups, S_1 and S_2, for which hold that S_1: $p_{i,1} \leq p_{i,2}$ and S_2: $p_{i,1} > p_{i,2}$, where $p_{i,1}$ is the processing time of job *i* on machine 1.
2. Order S_1 in ascending order of $p_{i,1}$ and S_2 in descending order of $p_{i,2}$. If a tie occurs, either order is optimal.
3. First sequence the jobs in S_1, followed by S_2.

(Allaoui & Artiba, 2009)

Travelling salesman problem

The travelling salesman problem (TSP) is a famous concept in the fields of process optimization. The goal of the problem is to find the route that minimizes the travel distance for a salesman that has to visit a set of cities. An abstract description of the TSP enables it to be applicable to many other scenarios. The cities can be depicted as nodes, where node 0 is the starting city. Shapiro (1993) considers a network with nodes 0, 1, 2, …, N, directed arcs (*i*, *j*) for all *i* and $j \neq i$, and associated arc lengths c_{ij}.

Applying the TSP to a single machine where the optimal route is the sequence of jobs that minimizes costs. Instead of the distance between cities, this scenario involves changeover and tardiness costs (costs for delivering late). The tardiness costs can be negative when finishing jobs earlier than the due date is rewarded. The TSP formulation is changed to:

- Node *i* corresponds to job *i*;
- T denotes the upper bound on the time to complete all jobs;
- p_i represents the processing time of job *i*;
- d_i represents the due date for job *i*;
- $c_i(t)$ represents the tardiness costs for finishing job *i* at time *t*;
    - $c_i(t) = \begin{cases} 0 & if\ t \leq d_i \\ a_i & if\ t > d_i \end{cases}$
    - or $c_i(t) = \alpha_i \max\{0, t - d_i\} + \beta_i \max\{0, d_i - t\}$

      , where

      α_i denotes the costs for job *i* finishing later than the due date,

      β_i denotes the reward for job *i* finishing before the due date;
- f_{ij} denotes the changeover costs between job *i* and job *j*;
- h_{ij} denotes the changeover time between job *i* and job *j*;
- Node *i* is connected to node *j* for all $j \neq i$ at time $p_i + h_{ij}$.

Assume a system where four jobs need to be performed (N = 4). There are 4! = 24 ways of ordering these four jobs. To find the optimal sequence, the system must be defined as a function. This can be done through integer programming. Assume job 0 to be fixed with a p_i of 2. When *t* = 2, either job 1, 2 and 3 can follow, each having a changeover time of 0, 1, 0, respectively. We define this choice as X_{ijt}, where X_{ijt} can either equal to 0 or 1. In the scenario of a fixed job 0, *i* is equal to 0. The following options remain X_{012}, X_{023}, X_{032}, where j is the next job to be performed and t is the time the next job can start (start time job *i* + processing time of job *i* + changeover time *ij*).

Now that the first (job 0) and the second (job 1, 2 or 3) jobs have been formulated, the third job will be added. From X_{012}, assuming that the processing time for job 1 equals 3 and changeover times are negligible, only X_{125} and X_{135} are possible. From X_{023}, options X_{215} and X_{235}, where $p_2 = 2$ and changeover times are negligible. This is done until all N jobs are included.

Subsequently, the optimisation function must be formulated. As the goal is to minimize costs, the nodes X_{ijt} are multiplied by the costs they incur. These costs can either be the changeover costs or tardiness costs. Let the due date for job 1: $d_1 = 6$. Following sequence $X_{023} – X_{215}$, job 1 (with $p_1 = 3$) would be finished at t = 8. With a tardiness costs of 1 per day, X_{215} will include a cost of (8-6)*1 = 2. Following sequence X_{012}, job 1 is finished at t = 5 and thus one day early. Delivering early can be rewarded by the client, in this example 0.5 per day. For illustration purposes, due dates for other jobs are not relevant and changeover costs are only made for changing to and from job 3, which equal 1.5. Continuing this for all nodes X, we obtain the following optimisation function:

minimize $Z = -0.5\, X_{012} + 0\, X_{023} + 1.5\, X_{032} + 0\, X_{125} + 1.5\, X_{135} + 2\, X_{215} + 1.5\, X_{235} + 2.5\, X_{314} + 1.5\, X_{324} + 3\, X_{217}$ *+ etc...*

In such a function, the optimal solution would be performing X_{012} and stopping there, resulting in Z = -0.5. However, all four jobs need to be performed. Therefore, a set of constraints needs to be set up.

1) $X_{012} + X_{023} + X_{032} = 1$,
2) $- X_{012} + X_{122} + X_{132} = 0$,
3) $- X_{023} + X_{215} + X_{235} = 0$,
4) $- X_{032} + X_{314} + X_{324} = 0$,
5) …

Using computing power, the optimal solution for Z and thus the optimal sequence can be found. (Shapiro J. F., 1993)

Appendix F: Decomposition of time series

Continuation of Section 2.2.2. Trend and seasonality.

Often a combination of the mentioned non-stationary patterns can be identified in time series. Decomposing the data is often done to better understanding the data patterns and to improve forecast accuracy. For simplicity, the trend and the cyclic patterns are often combined into one: the trend-cyclic pattern.

Hyndman & Athanasopoulos (2018) identify two ways of decomposition: additive and multiplicative. Let the data be denoted as y_t, the seasonal component as S_t, the trend-cycle component as T_t and the remaining components as R_t, all for period t. The additive approach gives the formula

$$y_t = S_t + T_t + R_t$$

and the multiplicative approach can be written as

$$y_t = S_t * T_t * R_t.$$

Moving average

The first method of decomposition, originating from the 1920s, is the moving average. Although this method is no longer widely used for decomposing time series, it forms the basis of many other decomposition methods. In this classical method, the moving average was mainly used to estimate the trend-cycle. The moving average can be denoted as a formula:

$$T_t = \frac{1}{m} \sum_{j=-k}^{k} y_t + j$$

where m = 2*k + 1. This method is often referred to as m-MA. If one uses the 5-MA method, the moving average is the average of month $t-2$, month $t-1$, month t, month $t+1$ and month $t+2$. This smoothens the time series data. The greater m, the smoother the data set becomes.

Moving averages of moving averages

As an even number of m gives an asymmetrical result (e.g. more months on one side of month t than on the other), one could use moving averages of the moving average. If 4-MA is used on the data set and 2-MA on the obtained moving average, this is noted as 2*4-MA. An example of the 2*4-MA notation can be found in Table 8.

Table 8 - Moving average of moving average

Month	1	2	3	4	5	6	7	8	9
Observation	10	11	9	13	12	15	8	12	11
4-MA		10.75	11.25	12.25	12	11.75	11.5		
*2*4-MA*			11	11.75	12.13	11.88	11.63		

Weighted moving average

Using the 2*4-MA, the months t-2 to t+2 have the following weights respectively: 1/8, ¼, ¼, ¼, 1/8. These weights can also be adjusted as long as they sum up to one.

Classical decomposition

The classical decomposition method for additive decomposition can be divided into four steps.

1. Obtain the trend-cycle component by using one of the moving average methods.
2. Calculate the detrended series: $y_t - T_t$.

3. The seasonal component is found by taking the average of the detrended values for that season. For example, to find the seasonal component of the month March, one should take the average of all detrended values for March. Afterwards, the obtained seasonal averages should be subtracted by its average to ensure that all seasonal components add up to 0.
4. Finally, the remainder component is found by $R_t = y_t - T_t + S_t$.

For multiplicative decomposition, the steps are quite similar.

1. Obtain the trend-cycle component by using one of the moving average methods.
2. Calculate the detrended series: y_t / T_t.
3. Instead of an absolute number as the seasonal component, a seasonal index is used. These are found by taking the average of all detrended values for a certain month. Subsequently, these averages should be adjusted such that these indexes add to m.
4. Finally, the remainder component is found by $R_t = y_t/(T_t * S_t)$.

(Hyndman & Athanasopoulos, 2018)

X11 decomposition

The X11 decomposition builds upon the classical decomposition method.

1 – 3. Steps are the same as described above.

4. A better estimate of the trend is calculated by taking a moving average over the seasonally adjusted time series (from step 3).
5. Subsequently, the final estimate of the seasonal component is found by using the detrended data from step 4.
6. The data is again adjusted by dividing or subtracting the adjusted seasonal component, found in step 5, from the original series.
7. Using the seasonally adjusted series from step 6, a final estimate of the trend is made.
8. The final trend estimate is subtracted from or divided into the seasonally adjusted series from step 6. (Australian Bureau of Statistics, 2005)

Concluding remarks on decomposition methods

Several other decomposition methods have been developed over the years. Explaining these goes beyond the scope of this thesis as these are very complex. Comparing the classical and the X11 method of decomposition, it becomes clear that the classical method requires relatively little data. Choosing this model for decomposing a time series is, therefore, a trade-off between simplicity and strength of the method.