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Redesigning upstream supply chain operations planning
a case study within the high-tech manufacturing industry

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Redesigning upstream supply chain operations planning

A case study within the high-tech manufacturing industry

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Abstract

Time has become an important factor in competitiveness. Reliable and timely supplies build upon the alignment of different operations that compose the supply network. In order to improve on-time delivery performance of a multi-level supply network in the high-tech industry, this research focuses on supply chain operations planning. A model is developed to study the effects of order releases on utilization, costs, tardiness and therewith delivery performance. Therewith, this study proposes a new delivery performance metric that represents the fraction of demand that is met within a specified lead time. Results demonstrate that order releases can be improved by taking into consideration information from the whole supply network. Therewith, this research shows the potential of centralized planning, coordination, and decision making in a multi-level supply network.

Management Summary

This report presents the results of a study conducted on supply chain operations planning and control. In this context, the multi-level supply network of Prodrive Technologies is used as a case study.

Problem context

Prodrive Technologies strongly believes in the vertical integration of their key manufacturing processes. By the vertical integration of operations, a transparent supply network exists that offers optimal control and flexibility. Currently, upstream operations are executed within a subsidiary manufacturing plant i.e., Prodrive Mechanics. Hence, the internal supply network can be considered as a multi-level network, wherein upstream operations are distinguished from downstream operations. Considering that products are becoming increasingly complex, the company is challenged by an increasing variety of operations and products in the near future. Additionally, the company experiences rapid growth in sales volume. This leads to a strong urge for improved supply chain planning and control.

After the current supply chain and operations planning was compared with formal control structures, it was found that differences exist in information available throughout the supply network. This leads to a decoupled planning and control structure which withholds the current planning from central coordination of order releases. According to academic literature, this negatively affects customer service and operational costs. This is confirmed by a performance analysis of the current upstream operations' on-time delivery performance.

Analysis

Prodrive Technologies defines internal delivery performance as the fraction of demand that is met within a specified lead time. However, analysis of the current situation demonstrated that current measurements consider order-lines and do not represent the fraction of demand. To determine if demands are met within a specified lead time, jobs' finish dates are compared with due dates. However, analysis revealed that job's finish dates are unreliable. On 35% of the late jobs produced upstream in 2017, finish dates were registered before items were actually received. When items are received, corresponding dates are registered as delivery dates. Therefore, measuring on-time delivery performance by delivery dates instead of finish dates yields a more reliable performance indicator. When measuring delivery performance based on delivery dates instead of finish dates, average delivery performance decreased by 17.1 percent points.

To improve the reliability of current measurements, a metric is defined that represents the fraction of demand that is met within a specified lead time. More specifically, a method of measurement is developed that represents the fraction of demand that is met on-time, and the fraction that is delivered with certain tardiness. With this metric, referred to as V-CLIP, deliveries' contribution towards performance is proportional. Firstly, contribution is determined by the volume that is delivered ($\boldsymbol{pq_{partial}}$) compared to the planned production quantity ($\widehat{\boldsymbol{pq}}$). Secondly, a deliveries' contribution reduces in proportion to the complementary cumulative distribution function of deliveries' tardiness $\left(\boldsymbol{F}\left(\boldsymbol{T_{partial}}\right)\right)$. Quantities that are not delivered at all, do not make any contribution to the delivery performance. Mathematically this entails:

$$V - CLIP_j := \sum\nolimits_{q_{partial,j} \in\, j} \frac{pq_{partial,j}}{\widehat{pq}_j} * \left(1 - \left(F\left(T_{partial,j}\right)\right)\right)$$

When measuring according to V-CLIP, upstream operations in 2017 were found to have average a delivery performance of 60.8%.

Design
By a model, the effects of aspects that influence upstream supply chain operations within a multi-level supply network are studied. First, the conceptualization described the design of one upstream supply chain operation that is generalizable to other (upstream) operations in high-tech environments. Based on a formal planning structure's anticipation function, responsible for realizing an order schedule that is lead-time feasible, the model was developed. The model builds upon three design parameters that generate order proposals, determines delivery dates, and allows for manufacturing flexibility considerations.

Numerical analysis of the model output demonstrated that order releases, either multi-echelon or local based, have a large impact on upstream operations' utilization, costs, tardiness and therewith performance. Operational costs were modeled by setup-costs, inventory carrying costs, and machine availability costs. Performance was modeled by the fraction of demand that is delivered and the deliveries' tardiness, leading to V-CLIP.

To find how the release of materials and resources can be best coordinated, three lot-sizing scenarios have been compared wherein different order sizes were generated based on items' average demand. Items' average demands were used to develop three volume categories that were used for lot-sizing decisions. Typically high volume items contained small demand aggregations, securing balanced capacity requirements, and low volume items contained large demand aggregations to justify setup costs.

Results show that current order releases can be improved by taking into consideration information from the whole supply network. Additionally, applying smaller demand aggregations for all volume-categories resulted in balanced capacity requirements and reduced supply chain investments in inventories.

Recommendations
It is demonstrated by academic literature that the decoupling of production units is common in vertically integrated supply networks. However, a supply network's planning and control can only be optimized if information from upstream and downstream operations is shared and taken into consideration with order releases. In addition to the vertical integration of operations, vertically integrated information is required.

Based on this insight, the following recommendations are given to Prodrive Technologies:

It is recommended to measure internal on-time delivery performance by V-CLIP. This research has demonstrated that current measurements are not conforming to what Prodrive Technologies defines as delivery performance. Additionally, it is shown that current measurements depend on unreliable data. By measuring according to V-CLIP, validity and reliability are improved. Also, V-CLIP gives a more accurate representation of the detailed information from the execution function, collected by the company's Manufacturing Execution System.

Secondly, it is recommended to conduct further research with a multi-echelon perspective on demands, buffers, and order sizes. This research shows Prodrive Technologies the potential value of centralized coordination and decision making in the multi-level supply network that consists of Prodrive Technologies and Prodrive Mechanics. It is shown that with order releases based on information from upstream and downstream the supply network, supply and demand can be better aligned resulting in improved on-time delivery performance without increasing operational costs compared to current practices.

Next, it is recommended to reduce differences in commonality from upstream and downstream operations. Numerical analysis of current order releases demonstrates that reducing current order sizes increases on-time delivery performance and reduces supply chain investments in intermediate inventories. Because smaller order quantities directly affect the number of setups, a small increase in capacity may be required to cover for uncertainties. However, analysis demonstrates that the savings in inventory investment outweigh costs of the capacity increase, resulting in reduced overall costs and improved delivery performance. Note that this implication especially concerns Prodrive Technologies' Injection Molding department because this study is built upon historical data and the operational configuration of only this department. However, the model is developed such that the behavior of other operations can also be simulated. Therefore, it is recommended to extend this analysis to other (upstream) operations to find if delivery performance and operational costs can be improved compared to current practices. Additionally, it is recommended to study the potential of starting a program for reducing setup and changeover times. High investments are made in the automation and efficiency of operations. With robots, automated guided vehicles, and automated warehouses, a 'lights out factory' is realized. However, the Injection Molding department still relies on conventional setups that are labor intensive. Therefore, it is recommended to invest in reducing setups and changeovers bringing Prodrive Technologies closer to the realization of a 'lights out factory' in the high-tech industry.

Finally, it is recommended to make upstream material requirements dependent on downstream production orders instead of inter-subsidiary stock-transport orders. By this simple adjustment in the ERP, rescheduling proposals can be automatically communicated if downstream demand changes. This research shows the potential of reducing differences in information available throughout Prodrive Technologies' supply network and therefore the implementation of this recommendation is an important step forward. When empirical data will be at disposal in the near future, order acceptance and replanning decisions will require further attention. Additionally, future research should extend this research to more operations of the supply network. At last, future research should receive an integral approach of planning decisions under the availability of buffers, e.g. safety times and safety stocks that are used to cover for uncertainties in supply and demand.

Preface

This report concludes my graduation project in completion of the MSc program in Operations Management & logistics at the Eindhoven University of Technology. This research was conducted at Prodrive Technologies, the company were I have worked with great pleasure for the past 8 months.

I would like to thank several people who were of great help during this project.

First of all, I would like to express my gratitude to Zümbül Atan, my first supervisor from the Eindhoven University of Technology. In particular, I appreciate your feedback and I am thankful for the pleasant meetings we had wherein you supported me with my project but also personally. You stimulated me to continuously develop myself professionally and personally. I appreciate your way of supporting me during this project and how you helped me to determine the direction of this project. Each time when I left our meetings, I felt determined about how to proceed.

Also I would like to thank my second supervisor from the Eindhoven University of Technology, Ivo Adan. From previous projects you were already familiar with Prodrive Technologies and together with your feedback on my reporting structure and you brought this project to a higher level.

Next, I would like to thank Teun op 't Hoog as my supervisor at Prodrive Technologies. You gave me the freedom to dive-in to the planning and operations departments which gave me the opportunity to learn a lot over the past months. We had regular meetings and constructive discussions during the project, which really helped me keep going forward in the right direction. Also I would like to thank Joost Dillen for supporting me with all kinds of relevant information and insights about Prodrive Technologies and my field of research which gave me a flying start.

Last but not least, I thank my family and friends for showing their interest and support. In particular I thank my parents and my girlfriend for supporting me, believing in me and always being there for me.

Stan de Waal

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1. Introduction

Time, quality, and cost have always been important elements in competitiveness. Prodrive Technologies (PT[1]) strongly believes that the vertical integration of their key manufacturing processes brings the time, quality, and cost elements at their disposal. By vertical integration of operations, the company features a supply network wherein lead times are transparent and can be altered quickly based on planning and control decisions. Knowing that future products are becoming increasingly complex and the company experiences rapid growth in sales volume, a strong urge exists for improved supply chain planning and control.

This project represents a study wherein is sought how on-time delivery performance of PT's most upstream supply chain operations can be improved by improving supply chain planning and control. The upstream supply chain operations that will be considered are characterized as a separate entity within PT that is distinguished from other, more downstream operations.

By considering PT's supply network, supply chain operations planning, manufacturing flexibility, and different performance metrics, the supply chain planning and control matter is reviewed in its full scope. Consequently, this is exactly where lays the academic contribution as well as the added value for PT.

This section will sequentially treat the problem context (1.1), the research problem (1.2), and the research method (1.3). The research method consists of the deliverables, research questions, and methodology. This section will conclude with the thesis outline.

1.1. Problem context

PT is founded in 1993 as an electronics design firm specialized in digital signal processing and motion control. Nowadays the core competence of the company is the design, development, and production of electronic solutions among which Printed Circuit Boards (PCBs). Vertical expansion started in 1999 when PT expanded production of electronics with an automated production line, followed by module assembly. Later, operations were expanded by the integration of cable manufacturing. In 2012, PT decided to vertically integrate its supply chain with an internal supplier (i.e., Prodrive Mechanics) that mainly supplied PT with plastics and metal components that are used in the assembly of PT's end-products. The production of plastics typically includes housings and enclosures for electronic solutions. Manufacturing of machined parts consists of cold plates or heat sinks that can be used for cooling purposes of power conversion modules for example. Later Prodrive Mechanics (PM[2]) also expanded operations with production of inductors, transformers, motors, and actuators by the establishment of the Magnetics operation.

Over the years, the vertical integration of PT's key manufacturing processes has resulted in a wide range of operations, i.e. (I) Surface Mounted Device (SMD) Printed Circuit Board Assembly (PCBA) manufacturing, (II) Conventional PCBA manufacturing, (III) System Assembly, (IV) Cable Harness manufacturing, (V) Magnetics, (VI) Machining, and (VII) Injection Molding. Whereas the integration of

[1] In the remainder of this document, Prodrive Technologies B.V. will be abbreviated as PT.
[2] In the remainder of this document, Prodrive Mechanics B.V. will be abbreviated as PM.

the full front-to-end supply chain offers more in-house control and flexibility, it also urges PT to have a well-organized Supply Chain Operations Planning (SCOP) in place.

In the organizational structure of PT, the Organization Support department is responsible for the SCOP function. The process requires input from Sales, Operations, Planning, and Procurement and is visualized in the control structure below (Figure 1).

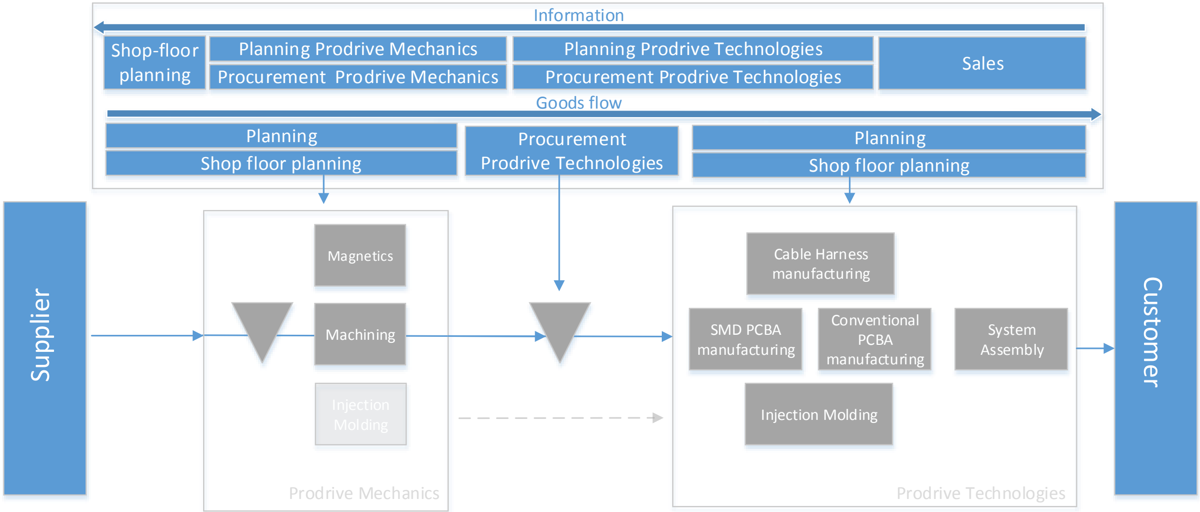


Figure 1: Supply Chain Operations Planning control model

Before products are delivered to the end-customer, products are assembled at the System Assembly department. Assembly includes ‘high volume products’, ‘low volume products’, and ‘in-line low volume products’. This characterizes PT’s demand that consists of high and low volume products. When considering the operations carried out prior to System Assembly, we can distinguish between operations carried out within PT and PM. Operations carried out at PM are executed prior or parallel to the operations carried out at PT and generally have less information available about downstream and future demand. Due to the organizational relation of PT and PM, the organization is considered as a multi-level supply network. PT´s upstream operations carried out at PM produce mostly in larger batch-sizes than PT´s downstream operations which indicates a so-called difference in commonality (Bertrand et al., 2016). In the remainder of this research, Machining, Injection Molding, and Magnetics will therefore, be referred to as PT’s upstream supply chain operations.

Considering that products are becoming increasingly complex, PT is challenged with an increasing variety of operations and products in the near future. In this development, it is of key importance to deliver products on-time with superior quality in order to create a sustainable value towards customers. Closely related to this matter are on-time deliveries from internal operations since delivery reliability towards end-customers is greatly dependent on PT’s internal operations delivery performance. PT’s SCOP is directly responsible for arranging these on-time deliveries. Preliminary research in the orientation phase of this study, i.e. research proposal, revealed that current delivery performance of PT’s upstream operations was insufficient (de Waal, 2018b).

By focusing on the planning of PT’s upstream supply chain operations, a focus on the effects of planning decisions throughout the supply chain and the on-time delivery performance of PT’s internal supplier is secured.

1.2. Research problem

To get an overview of the problem situation as described in the previous section, a cause and effect diagram is developed as is recommended by van Aken et al. (2007). Whereas the complete cause and effect diagram can be found in Appendix A, a concise representation is illustrated in Figure 2. The diagram can be summarized by various causes that negatively affect PT's (I) on-time delivery performance, (II) Operational Equipment Effectiveness (OEE), and (III) planning workload.

The causes originate from different disciplines and a selection had to be made to secure a feasible project scope. To facilitate the selection, causes were categorized by (I) design & engineering related, (II) supply chain & operations related, and (III) practical issues such as human errors. From these three categories, only the effects of supply chain & operations related causes towards on-time delivery performance are taken into consideration within this study.

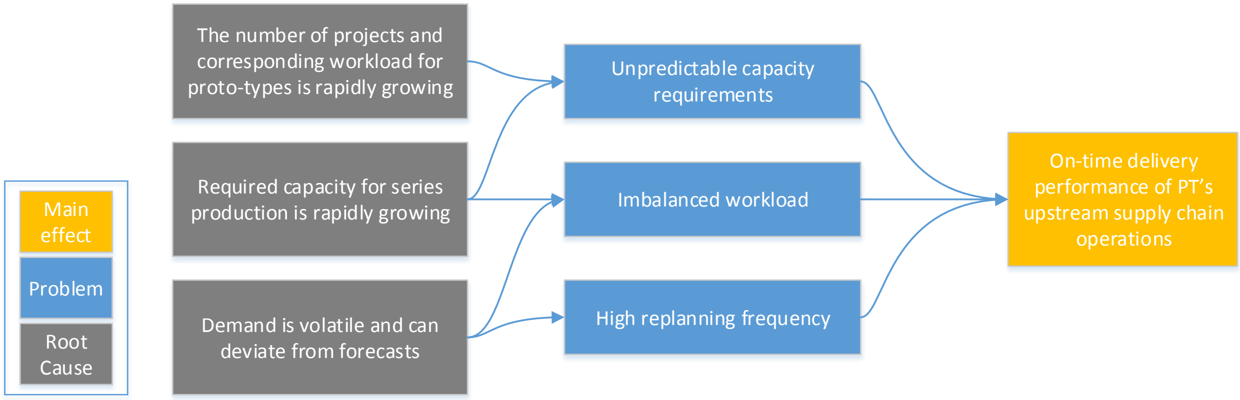


Figure 2: Concise Cause & Effect diagram

PT's demand is characterized by a mix of both high and low volume products. In addition, the product portfolio includes both high and low complexity products. Whether products are assembled or produced to order depends on the particular product market combination as is also pointed out by de Kok & Fransoo (2003). Items that require short customer perceived lead times are generally assembled to order and kept in stock at the Customer Order Decoupling Point (CODP). Considering the case company's supply network, the CODP lays after the upstream supply chain operations. This implies that Machining, Injection Molding, and Magnetics mainly produce based on forecasts and demand prognoses. However, forecasts and demand prognoses are made in conjunction with the customer. Since most high-tech products are customer specific and have a high obsolesce risk, demand prognoses are mostly binding commitments due to contractual agreements.

Besides regular production, a high-tech environment is typically also accompanied with prototypes. Due to the short product life-cycles of high-tech products, many new products are developed, tested, and produced in combination with regular production. This requires a certain flexibility from the supply chains' SCOP. Other typical demand-related attributes of high-tech products are complex product configurations, unreliable and long lead times for procurement items, and volatile demand.

Due to these high-tech characteristics, PT's supply network is subject to frequent replanning, buffers, and unpredictable capacity requirements. Different studies among which Yang & Jacobs (1999), concluded that increased replanning frequency leads to increased production schedule instability and inventory costs. With the establishment of its internal supplier, PT is enabled with more in-house control and flexibility. However, consequently PT’s upstream supply chain operations are challenged with limited time to supply. This is where prioritizing and workload balancing by PT’s SCOP become important since outsourcing at this point is usually no option due to even longer lead times or due to strategical considerations such as intellectual property.

The problem statement that follows from this problem context is formulated by:

‘PT's upstream supply chain operations have insufficient on-time delivery performance.’

1.3. Research method

Based on the problem statement and selected causes, the project aims to gain an understanding of aspects that influence the on-time delivery performance of PT´s upstream supply chain operations. Additionally, it will be researched what planning and control improvements can be made such that the on-time delivery performance of PT´s upstream operations can be improved. In this section will be described what the project’s deliverables are, what research questions the project aims to answer, and what methodology will be used to structure the research.

1.3.1. Deliverables

Besides the relevance of this study and the potential solution designs for PT, this project aims to make a scientific contribution as well. This requires a balanced focus between practical and scientific perspective, also referred to as a balance between rigor and relevance. To assure all stakeholders agree on the focus of the project, deliverables are set as is recommended by van Aken et al. (2007). They describe a business problem-solving project typically has at least the following deliverables:

– A characterization and validation of the selected business problem.
- Analyze how on-time delivery performance should be measured by comparing best practices, research, and PT’s current situation.

– An analysis and diagnosis of causes and consequences of the problem from various perspectives.
- Analyze how SCOP design and control in a high-tech environment can improve on-time deliveries by using PT’s upstream supply chain operations as a case study.

– An exploration of potential solutions.
- Develop solution designs by applying different scenarios. The solution designs and scenarios will be based on a practical perspective and scientific literature base.

– An elaboration of one of the potential solutions into a solution design.
- Summarize and interpret the results. Draw conclusions and present recommendations.

1.3.2. Research questions

In order to structure the research and analyze the problem context such that it can be improved. The following main research question is formulated:

'What are the aspects that influence upstream supply chain operations within a multi-level supply network under constrained operational costs and a targeted on-time delivery performance?'

To adequately answer all aspects of the main research question and fulfill the deliverables, the research is divided into the following sub-questions:

1. How should the **on-time delivery performance** of PT's upstream supply chain operations be measured and how do PT's upstream supply chain operations; Injection Molding and Machining perform accordingly?
2. How should the **planning system** of PT's upstream supply chain operations be designed such that efficient planning results wherein production plans can be optimized, thereby achieving a given on-time delivery performance target?
3. How can PT's upstream supply chain operations design be modeled and how do **model parameters** influence the on-time delivery performance and operational costs of PT's upstream supply chain operations?

1.3.3. Research methodology

This project is a typical example of a business problem-solving project. Van Aken et al. (2007) developed a methodological handbook for solving business problems. In this handbook is referred to the regulative cycle developed by van Strien (1997). In this research, the regulative cycle will therefore be used as a methodological framework. The cycle, shown in Figure 3, comes with five steps; (I) problem definition, (II) analysis and diagnosis, (III) plan of action, (IV) intervention, and (V) evaluation. In addition to the regulative cycle developed by van Aken et al. (2007), this project will also make use of the framework from Mitroff, Betz, Pondy, & Sagasti (1974). In this framework, the total operations research approach is reflected. The model relates to four aspects with cross-functional transitions; (I) Conceptual model, (II) Scientific model, (III) Problem context, and (IV) Solution.

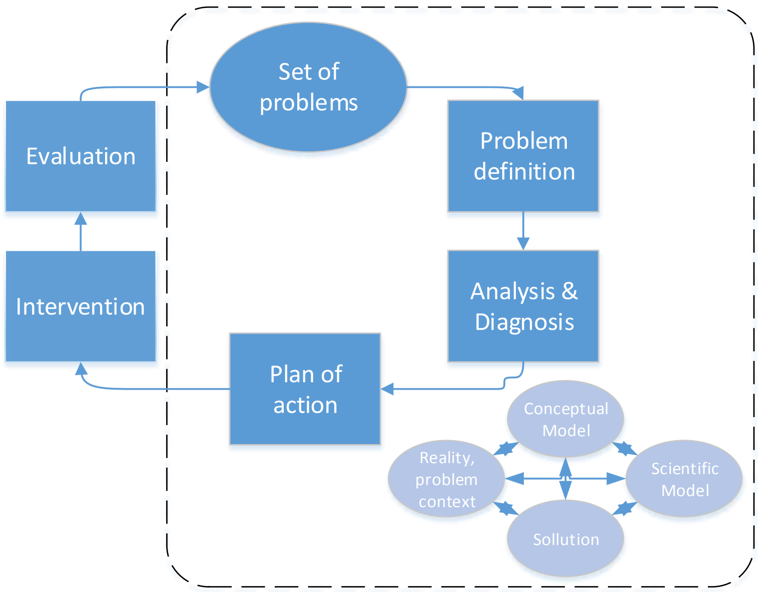


Figure 3: Regulative cycle (van Strien, 1997) *& Framework by Mitroff et al. (1974)*

When identifying the problem, it is crucial to distinguish between the real problem and perceptual problems. Based on the analysis and diagnosis phase described in the regulative cycle, a conceptual and scientific model will be developed based on the framework from Mitroff et al. (1974). When the scientific model is validated, model solving starts which leads to potential solutions and one final solution design. The last two steps of the cycle, intervention and evaluation will be out of this project's scope. An outline of the methodology with the reference sections are described below.

Orientation phase
The orientation phase is conducted mostly in the preliminary stage of this research and was therefore described in the research proposal that preceded this report. The orientation phase contains the problem context and therefore the set of problems, the problem statement, the assignment, the approach, and theoretical background. However, since these elements provide important fundament for the research, the orientation phase is also described in Sections 1.1, 1.2, and 1.3. The theoretical background of the problem context is presented in a literature study (de Waal, 2018a), performed parallel to the research proposal. This information is applied in Sections 2.1 and 3 of this report.

Analysis & Diagnosis
Just as the orientation phase, the analysis and diagnosis were conducted to a large extent in the preliminary stage of this research. In the main phase of the research, the problem context, delivery performance, are further analyzed and diagnosed in Section 2 that led to a more specific selection of causes, such that the project reaches sufficient depth into all relevant aspects of the problem context.

Conceptualization
In the conceptualization, a conceptual model is developed based on the problem context that was studied in the analysis and diagnosis. In this phase, the scope is defined and different input variables are reviewed and selected. It is important that accepted standards, published throughout the years in scientific literature, are used as a reference. Therefore, the literature review performed parallel to this research is used as a scientific reference and is described in Section 2. Based on the literature base and more specific analysis and diagnosis of the problem context, the conceptual model is developed. The conceptual model in this research is based on the operations planning control structure developed by Jansen, De Kok, & Fransoo (2013). The conceptual model is presented and explained in Section 3.

Modeling
The quantification of the conceptual model towards a scientific model is an important step towards potential solution designs. The scientific model needs to be expressed in formal, mathematical terms or algorithms, such that numerical analysis or computer simulation are possible (Bertrand & Fransoo, 2002). The numerical insights should represent the relationships between input variables. In this research, the model will represent causal relations between planning horizon, lot-size, delivery performance, and operating costs. The model is described in Section 4.

Model solving
To solve the scientific model, mathematical algorithms or simulations can be applied. In case of high complexity, computer software simulation can be used instead of mathematical models (Bertrand & Fransoo, 2002). However, when using simulation, verification and validation of the model are very important to ascertain the reliability and validity of the results. By applying different scenario's and combinations of input-variables, near-optimal results can be found in order to solve the model. By combining these input variables, causal relations between input variables can be drawn whereby new insights can be obtained. The model solving and numerical study of this research are presented in Sections 4 and 5.

Implementation

The final phase of the research framework is the implementation and elaboration of one solution design. In this research, the implementation phase will consist of a summarization of the results. Additionally, conclusions are drawn and presented. Conclusions and recommendations from this research are presented in Section 6.

1.3.4. Scope

When conducting scientific research and defining a feasible scope, it is important that insights are generalizable, in this case to other production environments in the high-tech industry. However, to secure a feasible research scope and reach sufficient in depth, not all operations of the case company's supply chain can be considered.

In preliminary research, delivery performance of PT’s upstream supply chain operations was found to be insufficient. Therefore this research focusses on PT’s upstream supply chain operations. In the development of the scientific model, generalizability to other (upstream) operations in high-tech environments is taken into account. However, due to time-limitations the numerical analysis that is done by computer simulation only considers one of PT’s upstream operations, Injection Molding. Due to characteristics such as high product mix, both high and low volume products, and dependent workcenters, Injection Molding is a good representation of other operations in a high-tech environment.

1.4. Thesis outline

The following section of this report will continue with a more in-depth study of the current situation. The study of the current situation is supplemented with theoretical background on SCOP designs, methods of manufacturing flexibility, and performance measurements from the on-time delivery performance. The conceptual model will be described in Section 3. Then, Section 4 includes the detailed description of the mathematical model and Section 5 consists of the numerical study. Finally, Section 6 presents this research’s conclusions and recommendations.

2. Supply Chain Operations Planning

The research questions presented in the previous section require a study of the current planning and control that are executed at PT. First, the current planning design, which is already briefly described in the problem context, will be further described in Section 2.1. Secondly, this section presents different delivery performance measurements. Once these are explained, the case company's current performance will be analyzed and the most representative method of performance measurement will be selected for further analysis throughout the research. At last, this section will conclude with a brief summarization of the findings and a more detailed analysis and diagnosis of the problem context.

2.1. Supply Chain Operations Planning design

To explain the problem context and the current planning design of the case company, PT's current supply chain operations control structure is graphically depicted in Figure 1. The framework includes demand aspects, supply aspects, and execution or production aspects. The control structure is based on a formal framework, originally developed by Bertrand, Wortmann, & Wijngaard (1990). The formal framework is added below in Figure 4.

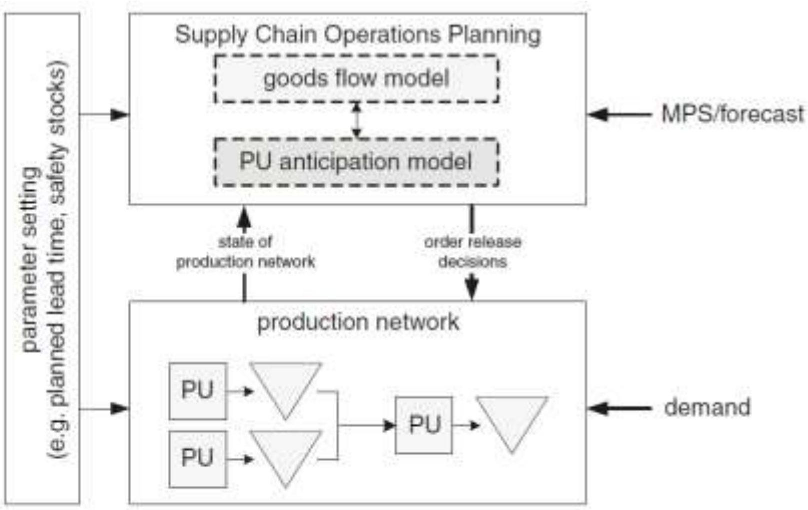


Figure 4: Planning Framework (Jansen et al. 2013)

The original control structure from Figure 4 consists of two levels; (I) Supply Chain Operations Planning (SCOP) and the (II) Production network. It is the responsibility of the SCOP to coordinate the release of materials and resources in the supply network under consideration such that customer service constraints are met at minimal costs (A. G. de Kok & Fransoo, 2003).

As shown in Figure 4, the SCOP function can be decomposed into Goods Flow Control and the Anticipation model. The Goods Flow control model considers the specification of material consumption and the Anticipation model focuses on the capacity of resources. As a representation of the Anticipation model, Jansen et al. (2013) developed the Lead Time Anticipation (LTA) procedure. The procedure iterates between optimization of the SCOP plan and local smoothing at production units. The iteration continues until all production units have been visited once. The LTA procedure is presented below in Figure 5. The procedure targets to obtain a schedule of planned order releases wherein Work In Progress (WIP) can be cleared within the planned lead time. The procedure starts by importing demands ($\widehat{D}_I$). Then, it iteratively adjusts the order release quantity ($\hat{R}_I$) and determines the released workload ($\hat{B}_I$).

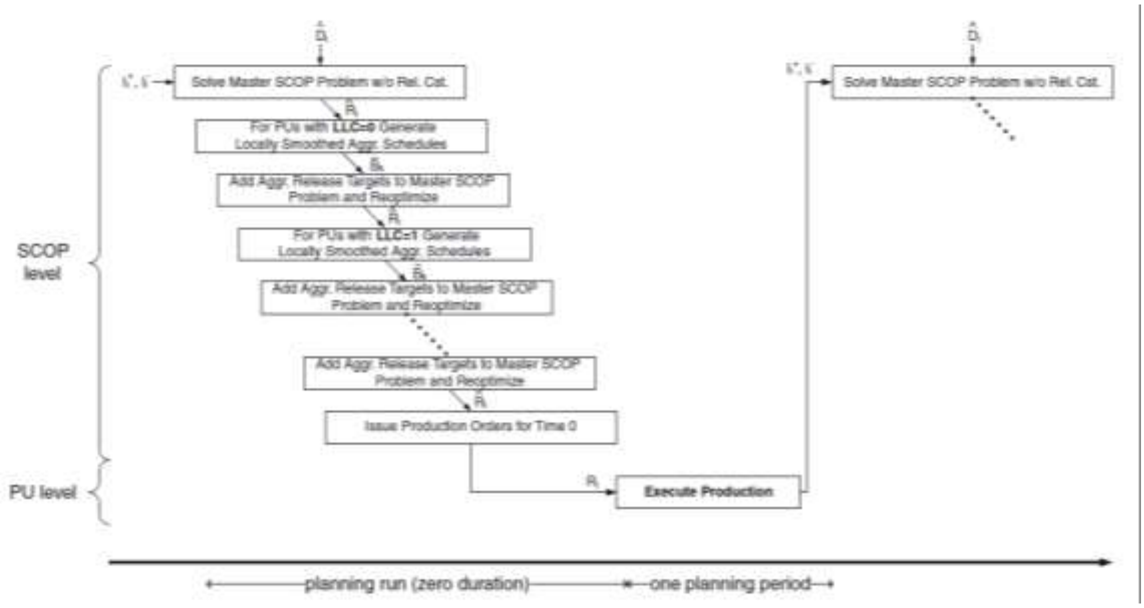


Figure 5: Lead Time Anticipation procedure (Jansen et al. 2013)

When comparing the formal control structure with the case company's control structure, a difference exists due to the fact that the case company's supply structure makes use of an internal supplier (i.e., PM). As briefly described in the introduction, a number of reasons exist that cause the case company's supply network to be considered a multi-level supply network wherein processes, i.e. operations, of PT and PM are decoupled. The operations that are executed within PM are referred to as the case company's upstream supply chain operations. This implicitly leads to downstream operations that are executed by PT.

To return to the number of reasons why the case company's supply network is decoupled, four decoupling criteria specified by Bertrand et al. (2016) are used. Bertrand et al. (2016) specify four criteria for decoupling processes in a production system that are executed sequentially or in parallel. These criteria are; (I) two successive processes are not synchronized in speed, setup, or uncertainty, (II) there is a difference in the opportunity to vary resources, (III) difference in commonality (e.g. different batch sizing), and (IV) difference in information available.

2.1.1. Reasons for decoupling

By a brief description of how the case company currently executes' production planning, the reasons for decoupling will be further explained. The case company's planning is described according to demand planning, order release, and execution. Note that in the context of the control structure and LTA procedure from Jansen et al. (2013), demand planning and order release are part of supply chain operations planning and execution belongs to the production network (see Figure 4).

Demand planning

Most of the case company's sales are initiated by projects. A project phase typically consists of communication from account managers with (potential) customers, research & development, prototyping, and testing. Once a product is ready for series production, account managers provide a demand forecast and actual demand is confirmed. Typically these demand patterns contain a demand ramp-up. Once forecasts and customer demands are known, demand and operations planning follows.

Demand and operations planning is organized based on product portfolios. These product portfolios are controlled by demand planners. One product portfolio consists of the full range of items to be produced internally for a selection of end-customers. This is referred to as the demand planning function. Since the demand planning function is based on product portfolios, the function transcends planning of operations. In other words, generally different demand planners plan production on the same workcenters and operations. However, when it comes to the case company's upstream operations, these are not planned by the case company's demand planners. Production that is executed within PM, is planned by operations planners that focus only on the operations carried out within PM. Material requirements are communicated from PT to PM by internal purchase orders. One crucial difference between communicating material requirements through purchase and production orders is that purchase orders do not communicate changes in demand. Once purchase orders are fixed by inter-subsidiary transport orders, plant to plant demand changes are no longer forwarded through automatic rescheduling proposals. Alternatively, production orders do allow automatic rescheduling proposals when demand changes. The current way of working leads towards a difference in information available throughout operations executed upstream and downstream the supply network. This is, therefore, the first reasons for decoupling and is based on the fourth decoupling criteria from Bertrand et al. (2016) listed earlier.

Production planning and order release

Given that material requirements are defined by demand planners for the case company's downstream operations, load balancing and order release still have to be executed before actual production can start. According to Hopp & Spearman (2000), the order release mechanism builds upon three pieces of information: the item, the required production quantity, and the order due date. These pieces of information are made available for all items through the Enterprise Resource Planning (ERP) system. Production plans are generated based on item-specific routers, setup and cycle times, and material requirement schemes. It is the planners' responsibility to use accurate ERP parameters such that reliable production plans are created. Also, it is the planners' responsibility to balance future capacity requirements by prioritizing orders and to release orders for production once they can be started. Balancing future loads or adjusting future available capacity are examples of manufacturing flexibility (Reichhart & Holweg, 2007). Research from Land et al. (2015) has demonstrated the effectiveness of manufacturing flexibility in reducing tardiness. Reichhart & Holweg describe at least four potential sources of manufacturing flexibility; (I) Machine flexibility, (II) Labor flexibility, (III) Routing flexibility, (IV) Source flexibility. Whereas the first three measures contribute to workload balancing, the last contributes to work load control.

Where the operations planners apply workload balancing measures for upstream operations, demand planners do this for the case company's downstream operations. Source flexibility depends on the particular item. Some items are not outsourced due to intellectual property or quality concerns. Others can be produced externally but only if this is known well in advance. Therefore determining future capacity requirements is of key importance. Usually, make-buy decisions are made by representatives from both sourcing and planning.

In the introduction, where all available operations were listed, it was explained that the case company's upstream operations typically produce in larger batch sizes than PT's downstream operations. This is due to the fact that operations carried out at PM, require larger setups and changeovers that are more labor-intensive than those of PT. This indicates a so-called difference in commonality that corresponds to the third decoupling criteria listed by Bertrand et al. (2016).

Execution

Once orders are released, production can start. However, it may be that workcenters on the shop-floor are still occupied by other jobs. According to Jansen et al. (2013), this is not necessarily problematic. They explain that higher level production plans and order release are made such that it still leaves space for optimizations on the production level, “the PU has a degree of freedom to optimize its own objectives, independently of the SCOP function” (Jansen et al., 2013, p. 253). They motivate this by stating not all events that occur at production are known a priori or can be captured in mathematical formulations. Additionally, they explain that it would become computationally intractable to include all dynamics because each production unit, i.e. operation, has its own objectives.

When comparing the execution of production at operations carried out at PT and at PM, a difference is found in the optimization of production plans. Whereas production at PT is accurately controlled and optimized with shop-floor plans, the optimization of production plans receives less attention at upstream operations. Due to the fact that a number of years ago, PT’s operations (e.g., downstream operations) were the business’ core competence and these were the most capital intensive, a planning function evolved wherein production plans were better optimized at PT’s operations. However, over the years also large investments have been made in PM’s operations while planning and shop-floor planning did not evolve.

2.1.2. Current design

When the case company’s current planning design is placed in the context of formal supply chain operations designs and control models, two important findings result:

1. It is the SCOP’s responsibility to coordinate the flow of materials throughout the supply network. Formal control structures stress the importance of central coordination from the SCOP function. However, currently the control model is decoupled into two structures wherein differences exist in information that is available upstream and downstream the supply network. This negatively affects what the SCOP function intends to do; coordinating the release of materials and resources such that customer service constraints are met at minimal costs.
2. Over the years, vertical integration and large investments in the case company’s upstream operations gave these operations larger impact on the overall customer service level. However, the current planning structure and optimization of shop-floor plans upstream the supply chain did not evolve.

2.2. Supply Chain Operations Planning performance

The case company measures delivery performance according to different metrics. First of all, delivery performance is measured from suppliers and towards customers. Secondly, delivery performance towards customers can be distinguished by internal customers and external customers. Although the case company did not define an exact metric for internal delivery reliability so far, a preliminary study revealed that the upstream supply chain operations; Machining and Injection Molding, had an alarming on-time delivery performance of 69.2%. This figure was obtained based on the case company's current method of measurement; Confirmed Line Item Performance (CLIP). By this method, confirmed due dates are compared with actual finish dates. In other words, the preliminary study revealed that 30.8% of the jobs produced by PM in 2017 is produced later than it's confirmed due date. A more detailed explanation of the current method of measurement according to CLIP will follow later in this section.

The case company defines delivery performance as the fraction of customer demand that is met within a specified lead time without backordering. This study considers backordered demand as the fraction of demand which is not fulfilled within the specified lead time but delivered later instead. When measuring delivery performance, lead times can be compared from a customer's perspective or the manufacturer's perspective. One may refer to corresponding metrics as the Requested Line Item Performance (RLIP) and the Confirmed Line Item Performance (CLIP) respectively. Additionally, delivery performance can be measured according to standardized lead times i.e., Standard Line Item Performance (SLIP).

The RLIP represents the fulfillment of the requested delivery lead times as perceived by the customer. However, these requested lead times may be unrealistic from a supply chain perspective and cannot be easily retrieved from ERP. When a customer demand occurs, lead times are currently confirmed according to standard lead times, material availability, and capacity utilization of resources. This method leads to a delivery performance scenario mostly conforming to CLIP. One other metric with which delivery performance can be measured is by considering the volume that is delivered. This can be referred to as Confirmed Volume Performance (CVP) and can be measured by comparing the planned quantity to be delivered with the actual delivered quantity.

2.3. Current on-time delivery performance

In order to measure the case company's current on-time delivery performance, the above-mentioned methods of measurements will be compared, taking into consideration the available data. Therefore, the available data is described first in Section 2.3.1. Then different methods of measurement are presented in Section 2.3.2. The goal is to determine and define one robust performance indicator for assessing on-time delivery performance. The final method of measurement will be presented and discussed in Section 2.3.3.

2.3.1. Data

In this analysis, historical data is used from all three upstream operations. The data includes; items, planned quantities, produced quantities, due dates, delivery dates and more. The data is logged during 2017[3]. To analyze on-time delivery performance, operations' performance needs to be measured

[3] 01 January 2017 until 31 December 2017

individually. Considering the data of all upstream operations, it appears that 80% of the jobs produced at PM is processed by Machining. This provides an indication of how large Machining is compared to the other upstream operations; Injection Molding and Magnetics (see Figure 6).

The analysis also reveals that just half of the jobs produced by Magnetics and Injection Molding are useful for further analysis (see Table 1). Only jobs that are finished correctly, i.e. correctly received and registered by representatives from the warehouse, contain reliable end dates that are usable for the analysis of on-time delivery performance. A more detailed explanation on reliability of the job history that was used for this analysis can be found in Appendix B. Appendix B will also contain a more detailed explanation on the deletion of outliers, e.g. jobs that are registered correctly but were received exceptionally late, i.e. > 30 days, and therefore deleted from the data-set.

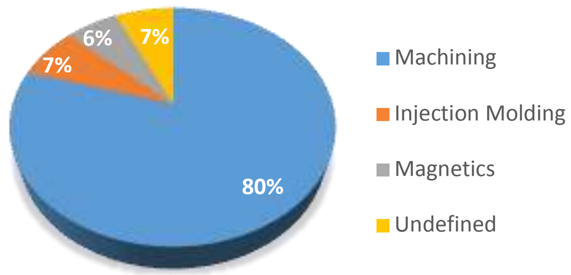


Figure 6: Number of confirmed orders by operation

Operation	Correctly finished orders #	Total orders #	% Correctly finished
Machining	3958	5853	68%
Injection Molding	263	529	50%
Magnetics	225	459	49%
Undefined	134	511	26%

Table 1: Production orders produced by PM, 2017

2.3.2. Measurements

In the current situation, performance is measured by comparing due dates that are job-specific ($\boldsymbol{d_j}$) with dates whereon the job's items are actually received ($\boldsymbol{r_j}$). In this representation, 'j' denotes the job, i.e. a production order. Please note that an overview of all notation is provided in Appendix I.

As explained earlier, the determination of order due dates in the current situation is conforming to CLIP which can be represented by $CLIP_j := \begin{cases} 1 & if\ [r_j - d_j] \leq 0, \quad else \\ & 0 \end{cases}$

As explained earlier, due dates are determined in the current situation based on standard lead times, material availability, and capacity utilization of resources. It is therefore important to stress that lead times and therewith due dates are defined differently for jobs processed at PT or at PM. When jobs are processed at PM, they are subject to standard inter-subsidiary transport time of 1 day (see Figure 7). This shortens warehouse's lead time for order confirmations with 1 day, causing the delivery performance measurements to be made before items are transported to PT. Once they are received at PT, subsequent jobs can be started downstream. Alternatively, on-time delivery performance for items produced by PT is measured just before jobs start at the subsequent operation as shown in Figure 8. This is caused by the fact that items produced at PT don't require inter-subsidiary transport time. However, despite the delivery performances from PT and PM are measured at a different phase in the case company's supply network, due dates and therewith delivery performance measurements are comparable under the assumption that inter-subsidiary transport time never exceeds one day. This assumption is reviewed with representatives from the case company's logistics department. Since inter-subsidiary transport is arranged multiple times per day the assumption is considered reasonable. An elaborate explanation of lead times can be found in Appendix C.

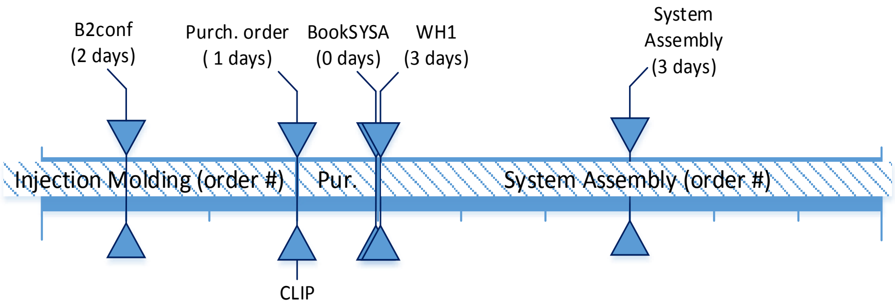


Figure 7: Lead times of operations executed at PM

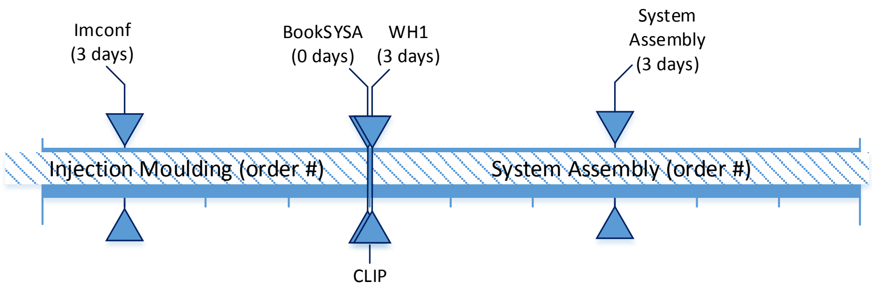


Figure 8: Lead times of operations executed at PT

CLIP by operation

To determine delivery performance on operations level based on a certain time interval, delivery performance of all jobs produced by the particular operation ($\boldsymbol{o}$) and due within the specified time interval is measured as in equation (1).

$$CLIP_o(t_{start}, t_{end}) := \frac{\sum_{j \in o_j} CLIP_j}{|o_j|} \quad where \;\; t_{start} \leq d_j \leq t_{end} \tag{1}$$

By applying this metric, it appeared that $CLIP_o(01-01-2017,\ 31-12-2017)$ from Injection Molding (88%) is much higher than from Machining (69%). This may partly be caused by the higher utilization of Machining compared to Injection Molding. Utilization in relation to on-time delivery performance will therefore be discussed later in more detail. However, when interpreting these results, it should be taken into consideration that just 50% of the orders produced by Injection Molding were used in the analysis. All other jobs were incorrectly finished or were considered as outliers. When all job history would have been logged correctly, different results might have been found. This stresses the importance of correctly monitoring and reporting e.g. finishing, jobs during the process. Results are presented below in Table 2.

Tardiness

By applying CLIP, delivery performance is based on line-item performance, making CLIP a boolean metric. This implies that CLIP does not represent a relative difference between 1 or 10 days late for example. Alternatively, order lateness can also be represented by Tardiness ($\boldsymbol{T_j}$) (van Ooijen, 1996). Tardiness is measured by $T_j := max[\,0\,,\ r_j - \ d_j\,]$.

In the current situation[4], Machining produces all late orders with an average tardiness of 11 days and Injection Molding produces with average tardiness of 5 days (see Table 2).

Tardiness and Utilization

Different studies among which Land, Stevenson, Thürer, & Gaalman (2015) demonstrated that periods of high utilization, generally worsen on-time delivery performance. To study and verify the effects of high utilization on-time delivery performance, average utilization per operation over 2017 is determined by considering all jobs produced in 2017 at the relevant workcenters. This implies that also incorrectly logged orders were considered in this analysis in order to obtain historical capacity requirements. In the analysis, norm processing times ($\widehat{\boldsymbol{cc}}$) are multiplied with planned order quantities ($\widehat{\boldsymbol{pq}}$). The resulting component is supplemented with norm setup times ($\hat{\boldsymbol{f}}$). Together this composes the required capacity which is then divided by the available capacity ($\boldsymbol{C}$). The workcenter utilizations ($\boldsymbol{\rho_k}$) are determined by $\rho_k := \frac{\sum_{j \in k_j}(\hat{f}_j + \widehat{cc}_j * \widehat{pq}_j)}{C_k}$.

Utilizations from all workcenters that compose an operation can then be averaged to determine the average operation's utilization ($\boldsymbol{\rho_o}$). The average utilization of Injection Molding over 2017 was 45% and is shown in Table 2. In Figure 9 and Figure 10, the utilization is depicted together with the number of tardy orders per week. Between these two variables, a weak positive correlation (21%) is found which aligns with the conclusions from Land et al. (2015). A possible explanation for the considerable weak correlation is the low number of jobs from Injection Molding that were usable in the analysis of job tardiness (50%). At Machining, where the number of correctly finished orders is about 68% and utilization was 86%, a moderate positive correlation (49%) is found between the utilization and number of tardy orders (see Figure 10).

Department	Count of confirmed orders	Count of Tardy orders	Average CLIP $CLIP_O$	Average Tardiness (days)	Average Utilization $\bar{\rho}$	Average Volume performance
Machining	3958	1839	69%	11	86%	96%
Injection Molding	263	49	88%	5	45%	95%
Magnetics	225	171	54%	10	-	97%

Table 2: Tardiness analysis PM, 2017

[4] From 01-01-2017 until 31-12-2017

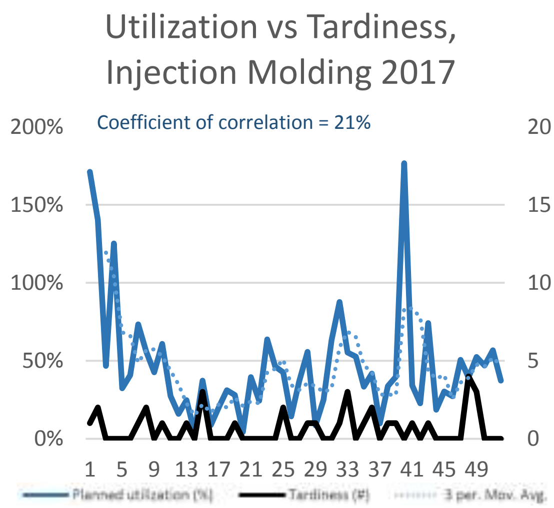


Figure 9: Injection Molding 2017

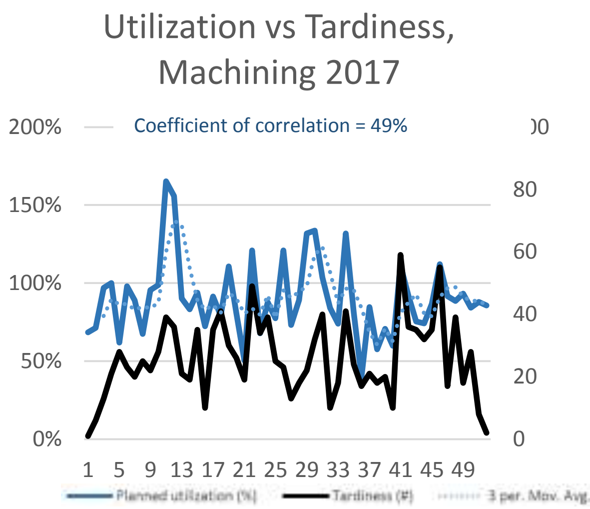


Figure 10: Machining 2017

Volume performance

Now that relative lateness can be expressed by means of tardiness, a representation of the number of produced items is still missing. Hence, the case company aims to measure on-time delivery performance by the fraction of demand that is met within a specified lead time. In order to represent the fraction of fulfilled demand, volume performance is analyzed. Volume performance is measured by comparing the planned order quantity $(\widehat{\boldsymbol{pq}}_{\boldsymbol{j}})$ with the produced quantity $(\boldsymbol{pq_j})$. Due to yield loss or material shortages for example, volume performance can be negatively affected. Current operations' volume performance $(\boldsymbol{V_o})$ is calculated by $V_o := \frac{\sum_{j \epsilon o_j} \frac{pq_j}{\widehat{pq}_j}}{|o_j|}$ $where\ pq_j = \mathrm{MIN}[pq_j, \widehat{pq}_j]$.

From all jobs that had a volume performance greater than 100%, a volume performance of 100% was used to prevent a biased average. The outcomes show that average volume performance is currently greater than or equal to 95% (see Table 2). However, in this volume performance, on-time is not considered yet. This implies that also late deliveries are considered and could positively influence volume performance.

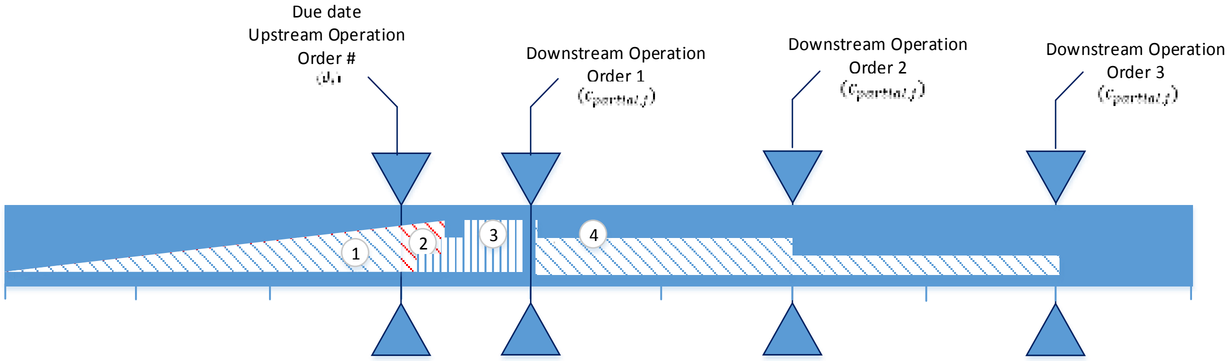
Volume performance considering on-time

In order to assess which fraction of customer demand is met on-time, it is reviewed for each delivery whether it was received before the corresponding job was due and if not, how tardy it was received. This implies that partially delivered quantities $(\boldsymbol{pq_{partial}})$ and corresponding dates whereon items were received $(\boldsymbol{r_{partial}})$ had to be taken into consideration. Within the case-company's production environment, partial deliveries result from serial batch production and transfer batches that are sent to the warehouse, sometimes even parallel to production (see Figure 11).

To express the deliveries' fraction of demand, volume performance is measured for each partial delivery. Thus, the fraction is obtained by the volume that is delivered $(\boldsymbol{pq_{partial}})$, divided by the planned production quantity $(\widehat{\boldsymbol{pq}})$. If the delivery is on-time, the corresponding fraction of demand contributes fully to the delivery performance. If the delivery is received late, the fraction that is delivered is discounted by the extent to which it was tardy. In this analysis, lateness of partial deliveries is expressed by $T_{partial,j} := max\ [\ 0\ ,\ r_{partial,j} - \ d_j\ ]$.

Hence, the fraction that is delivered late, is multiplied by the complementary cumulative distribution function of the deliveries' tardiness $\left(\boldsymbol{F}(\boldsymbol{T}_{\boldsymbol{partial}})\right)$. By means of this multiplication, a deliveries' contribution to the on-time performance reduces in proportion to its tardiness. This logic is mathematically expressed in equation (2). Quantities that are not delivered at all, do not make any contribution to the delivery performance. From this point onwards this method of measurement will be referred to as Volume-Confirmed Line Item Performance ($V - CLIP$).

$$V - CLIP_j := \sum\nolimits_{q_{partial,j} \in j} \frac{pq_{partial,j}}{\widehat{pq}_j} * \left(1 - \left(F(T_{partial,j})\right)\right) \tag{2}$$



1.	Serial production batch	3.	Transfer batches (Warehouse)
2.	Late production	4.	Partial consumption downstream

Figure 11: Material flow

Appendix H.1 is provided with a numerical example of V-CLIP and two possible extensions. The extensions provide a more critical look on which delayed items are actually causing delays downstream and which not. This insight is obtained by comparing partial deliveries of upstream operations with consumption downstream. Due to the process characteristics such as long setup times, PT's upstream operations generally produce in larger batch sizes than PT's downstream operations. This implies that the produced quantity from upstream supply chain operations $(\boldsymbol{pq_j})$ is consumed partially $(\boldsymbol{c_{partial,j}})$ over time by downstream operations. By considering the real time inventory position, it can be analyzed whether late deliveries actually cause delays in downstream production. If so, performance can either be penalized by the delay of the whole production batch downstream or just for those items which were delayed.

A more detailed explanation of this extension can be found in Appendix H.1. However, due to the limited focus on inventory management in this project's scope, extensions of V-CLIP will not be taken into further consideration and are marked as a direction for future research.

V-CLIP

In order to assess delivery performance by V-CLIP, a cumulative distribution function on the partial deliveries first needs to be determined. Based on historical data, a Negative Binomial distribution was fitted to the partial deliveries. A more elaborate explanation on distribution fitting to the tardy deliveries can be found in Appendix D. When comparing outcomes of V-CLIP with CLIP, performance is slightly higher (8.2 percent points) due to consideration of volume performance and tardy deliveries (see Table 3). One interesting finding is that many partial deliveries are made after jobs were registered as finished. This can be derived from the large differences in delivery performance between CLIP and CLIP–actual– in Table 3. In Table 3, CLIP is calculated as in equation (1) and based on the dates whereon jobs are registered as finished $(\boldsymbol{r_j})$. Instead, CLIP–actual– is based on partial deliveries $(\boldsymbol{r_{partial,j}})$ which leads to a decreased performance of 17.1 percent points. This indicates that on a large number of jobs (35%[5]), items are received while jobs are already registered as finished. This implies that the registered finish dates are unreliable. Since delayed partial deliveries are significantly later than order due dates and material comes only available once deliveries are made, measuring delivery performance by deliveries is much more representative than measuring it by registered finish dates.

Current performance: V-CLIP

When measuring according to partial deliveries instead of finish dates and taking tardiness into consideration, the current performance of PT's upstream supply chain operations is on average 60.8% (See Table 3).

Department	CLIP	CLIP –actual–	V-CLIP
Machining	69%	52%	60%
Injection Molding	88%	81%	86%
Magnetics	54%	24%	42%
Total:	69,7%	52.6%	60.8%

Table 3: Current V-CLIP

2.3.3. Final method of measurement

As explained before comparing all performance metrics, the case company defines delivery performance as the fraction of demand that is met within a specified lead time.

Now that all potential performance metrics have been compared, it can be concluded that only V-CLIP allows the assessor to measure both the fraction and the extent to which deliveries are made on time. The extent to which a delivery is made on-time is represented by tardiness. From this point onwards, this study will assess on-time delivery performance by V-CLIP.

Targeted performance: V-CLIP

One of the main objectives of this research is to provide insights and recommendations on how on-time delivery performance of upstream supply chain operations can be improved. This aim is linked indirectly to improving the case company's overall customer service. From a multi-echelon perspective, it is known that (downstream) customer service levels say 95%, do not necessarily require upstream service levels of 95% (Rosenbaum, 1981). Literature has demonstrated this especially for serial production systems. The analysis of batch production systems, like the operations carried out by PM, has received less attention in these studies and therefore offers potential for this research.

For the determination of the targeted customer service level, a target is applied that the case company has set itself in 2016. PT pursues to achieve a 99.8% customer service level by 2020 (Prodrive Technologies, 2016). By means of safety stocks and safety time throughout downstream supply chain

[5] 35% of all jobs of which' deliveries were due, produced by Machining, Magnetics, and Injection Molding in 2017

operations, delivery performance perceived by the end-customer can be increased. This may automatically justify low upstream performance. However, safety stocks are costly and safety times can enlarge customer waiting times and therefore an optimum should be sought in terms of costs and service levels. Due to limitations, this research will not follow a multi-echelon approach for determining desired upstream service levels. Instead, it is assumed that items can be externally outsourced and delivered with similar costs as in the current situation and a delivery performance (V-CLIP) of 90%. Therefore, this study applies a target delivery performance of 90% for the case company's upstream operations.

2.4 Insights and Conclusions

In the previous sections, the current supply chain design and the current methods of performance measurement were analyzed and described. According to the regulative cycle by van Strien (1997), this analysis should now enable the researcher to draw more specific diagnosis of the problem context which can form a foundation for the conceptual design, described in the following section.

Insights

After that the current design is placed in the context of a formal supply chain operation's control structure, two findings result that are also presented in Section 2.1.2. The first concerns the decoupled supply and control structure which withholds the current SCOP function from central coordination of order releases. According to formal SCOP designs, this negatively affects customer service and operational costs. This is confirmed by the performance analysis on the current situation, presented in Section 2.3. The analysis revealed that when looking at how PT desires to measure its delivery performance, performance can be best measured by V-CLIP. Applying V-CLIP, the case company's upstream operations currently have an average on-time delivery performance of 60.8%. Additionally, the performance analysis and assessment of available data demonstrate that on-time delivery performance is best represented by considering delivery dates instead of dates whereon jobs are confirmed as finished.

The second finding on the current planning design in the context of a formal supply chain operation's control structure concerns the execution. Investments in vertical integration and the case company's upstream operations increased the impact of those operations on the overall customer service level. Jansen et al. (2013) explain that operations need some space to optimize execution towards its own objectives because not all events can be known a priori. These optimizations by means of shop-floorplans are not made at upstream operations. The diagnosed problem situation is also graphically summarized in Figure 12.

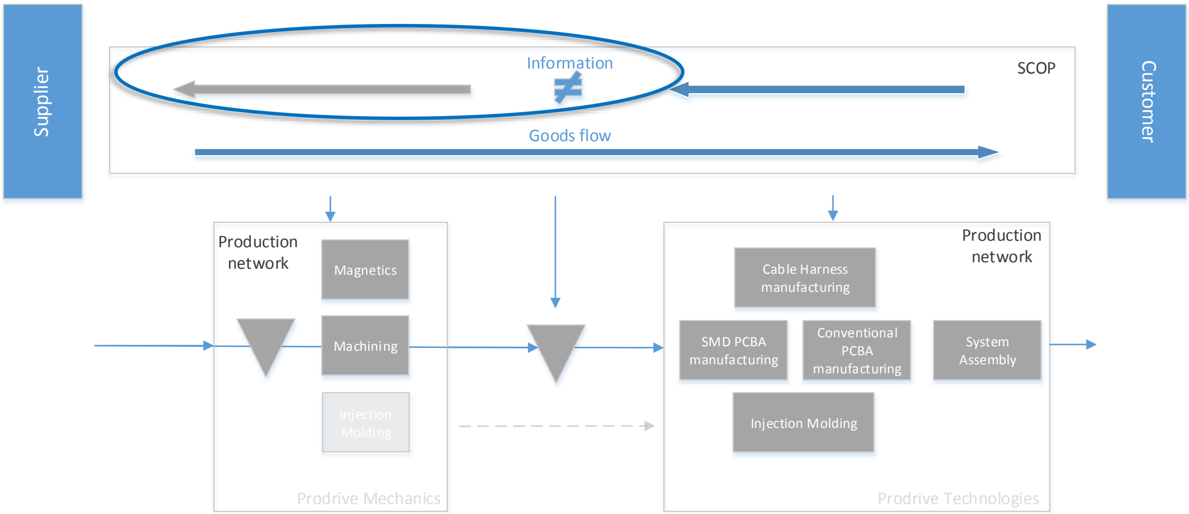


Figure 12: Multi-level control structure & Multi-level supply network

Conclusions

Based on the control structure developed by Jansen et al. (2013), and a literature base on supply chain operations planning and desings (Bertrand et al., 2016; A. G. de Kok & Fransoo, 2003; Jansen et al., 2013), improvements can be made that are conceptualized in the following section.

To develop a redesigned SCOP function that features a central order release mechanism, fundamental elements from the lead time anticipation model can be applied. These fundamental elements consist of demand planning, order release, and execution. Based on these three elements, the SCOP's performance can be assessed based on the customer service level by V-CLIP and on projected operational costs as compared to the current situation. The SCOP requires many input variables such as items, quantities, and due dates that can be adjusted and numerically compared to find causal relations and effects on performance outcomes. Additionally, manufacturing flexibility measures can be applied to improve performance. A more detailed conceptualization of redesigned SCOP function follows in the next section.

3. Conceptual Model

Even in the most principal reports and guides on designing SCOP's function, it is stated that the largest pitfall in designing operations planning and control systems is to start making calculations right away. Probably this applies to most complex business problems. To have a structured plan, and develop a solution design that potentially meets all requirements, the conceptualization phase is used. According to the framework of Mitroff et al. (1974), the conceptualization phase starts by defining the model's scope. The scope then helps to form the right and complete set of Functional Requirements (FRs). To satisfy FRs, Design Parameters (DPs) are defined. Additionally, the required input and output variables are defined and explained.

3.1. Scope: upstream supply chain operations

In this research, the supply chain structure of the case company led to a focus, especially on the company's SCOP structure and the company's upstream operations (see Figure 12). According to supply chain operations literature, processes executed sequentially or in parallel can be decoupled based on four criteria presented in Section 2.1. Based on those criteria and the current SCOP structure, it is motivated that the case company's production network and SCOP function are currently decoupled. This decoupled structure contradicts with SCOP designs proposed by supply chain and operations literature. Therefore the model's scope is set on central order coordination from the SCOP function and its effect on upstream supply chain operations. The conceptual model of this research's scope is graphically depicted in Figure 13.

The case company's upstream operations are generally carried out sequentially. Due to different process characteristics, e.g. differences in commonality, differences in speed, and differences in opportunity to vary resources, also upstream operations are decoupled. Since the model design will be generic such that is generalizable and applicable to other (upstream) operations in high-tech environments, it is decided to consider only one operation i.e., production unit. This also allows for more detailed focus on the operation that is in scope. The unit which is selected is based on the Injection Molding department and considers demand and process behavior based on empirical data that is made available by the case company. The production unit consists of four interdependent workcenters.

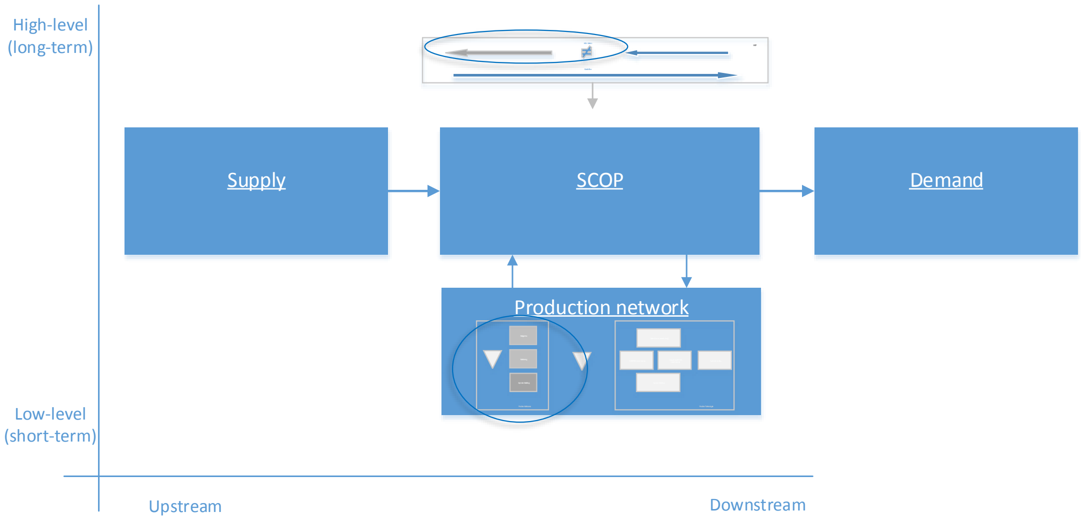


Figure 13: Conceptual model

3.2. Functional Requirements

To define FRs, one first needs to define FR for the entire system (Bertrand et al., 2016). As described in Section 2, the case-company has set itself the goal to deliver with an average customer service level of 99.8% by 2020. Therefore it is considered that the overall system requirement is a customer service level (V-CLIP) of at least 99.8%. To develop a scenario wherein acceptable operational costs result, the second system FR is that the service level has to be met under smaller or equal operational costs as in the current situation.

Based on the FRs for the entire system, FRs are determined for the system that is in scope. Because the production system that is considered consists of different echelons, buffers can be applied to compensate for disruptions in the system. By applying buffers in the form of safety times or safety stocks, downstream performance can be improved. Consequently, operational costs will increase and that safety times can enlarge customer waiting times. Therefore an optimum should be sought in terms of costs and service levels. As explained in Section 2.3, this research will not follow a multi-echelon approach for determining desired upstream service levels. Alternatively, it is assumed, based on interviews with the case companies' representatives from procurement and planning, that items can be externally outsourced and delivered with similar costs and a delivery performance (V-CLIP) of 90%.

3.3. Design parameters

Now that a targeted delivery performance is defined for the case company's upstream operations, this functional requirement needs to be translated into design parameters. Design parameters are used to adjust the model that represents the case company's planning function. By making adjustments, new insights can be obtained from causal relations between planning parameters and its interdependencies. Based on the three fundamental elements of the LTA procedure developed by Jansen et al. (2013), the following design parameters are formulated:

DP1: Order release – Order proposal mechanism

DP2: Determining due dates, delivery dates and performance – Load balancing mechanism

DP3: Adjusting available capacity – Manufacturing flexibility considerations

3.4. Input and Output variables

Besides the order proposal mechanism, the load balancing mechanism, and manufacturing flexibility considerations, the model has two important output variables that are directly related to the functional requirements that have been formulated. First of all, the model aims to provide insights into the aspects that influence on-time delivery performance (V-CLIP) in a multi-level supply organization in a high-tech environment. Secondly, operational costs are included such that realistic scenarios are modeled wherein higher delivery performance is offset by higher operational costs. Before output parameters are described in more detail in Sections 3.4.6 and 3.4.7, first input variables are further explained. At last, this section will conclude with a schematic overview of all input and output variables.

3.4.1. Items and item parameters

To mimic a manufacturing environment which is representative for the case company's upstream supply chain operations, historical demand is considered. The historical demand that is available includes sales orders and forecasted demands. In total 221 items are considered that have average demands ranging from 50 pieces to 2000 pieces per month. More about demand data is explained in Section 3.4.2. Before going further into demand characteristics, required input parameters that are pre-determined for all items are described.

Bill Of Materials (BOM)
All items have a BOM wherein raw materials, sub-assemblies, and assemblies are listed. The BOM also includes information about the quantities or the ratio of parts to succeeding parts. Because some raw materials and sub-assemblies may be used in more than one end product, upstream demand may consist of aggregated downstream demands. The upper BOM level is referred to as level 0, the most downstream BOM level is referred to as level 'M' and can be up to 8 levels for complex products.

Routers
Besides that all items have BOMs, all items are linked to operations and workcenters by standard routers. The router specifies which (sequence of) operations an item is subject to. When a router is completed, items are booked to stock, waiting for shipment or a subsequent operation, e.g. assembly. An overview of the routers that are used to model the case company's Injection Molding department is provided in Table 4. Four workcenters compose six unique routers. In Table 4 and Figure 14, the workcenters, routers and its respective occurrence are presented. The occurrence represents the fraction of jobs produced on the particular router. One can derive that especially the first three workcenters are utilized most. From Figure 14 it appears workcenters 1, 2, and 3 can be predecessors of workcenter 4. Additionally, workcenter 4 is dependent on other workcenters and will therefore always be a successor of workcenters 1, 2, or 3.

Cycle- and Setup times
For each processing step that is workcenter specific, item-specific cycle- and setup are pre-determined. With these 'norm' times, predictions on capacity requirements can be made as presented in Section 2.3.2. The cycle times represent the actual processing time, where the total predicted processing time equals the order quantity multiplied by the norm cycle time. Additionally, setup time is defined as the time that a job is prepared, affecting machine availability. This implies that job preparation which can be carried out off-line is not incorporated in the setup time that is considered in the model. Next to the cycle- and setup times, also throughput times are determined which represent the predicted lead times. The lead times are specified for each router and shown in Table 4. Lead times consist of processing time, waiting or queue time, and handling and transportation time.

Router	Workcenter	Occurrence	Lead time
A-1	Wc1	32%	6 days
A-2	Wc1 + Wc4	8%	10 days
B-1	Wc2	32%	6 days
B-2	Wc2 + Wc4	8%	10 days
C-1	Wc3	16%	8 days
C-2	Wc3 + Wc4	4%	12 days

Table 4: Routers & Occurrence

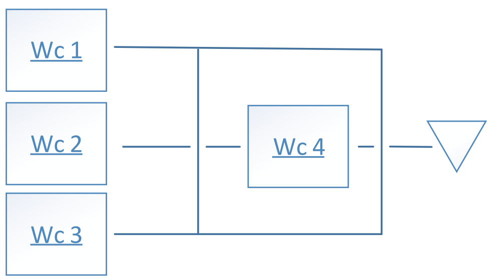


Figure 14: Workcenters & Routers

3.4.2. Demand

To model and simulate a demand pattern, the case company's sales order history is used as empirical data. The data includes a combination of high and low volume items. The demand that is considered contains aggregated sales history from the first three months of 2018. The data consists of forecasts and actual orders. For all end-items, forecasts up to one year are available. Changes in forecasts such as adjusted requirement dates or orders sizes are available. However, currently these are only available for end-items. To prevent the data-set will consist of duplicate order-lines, changes in demand are disregarded. Moreover, it is questionable to what extent these changes are reflected to upstream operations. Alternatively, the model will incorporate only actual demands.

Average demand and order size

Based on average (monthly) demand ($\overline{\boldsymbol{q}}_{\boldsymbol{i}}$) that is item specific, lot-sizing decisions can be made. When determining planned production quantities ($\widehat{\boldsymbol{pq}}_{\boldsymbol{i,j}}$), a lot-size horizon ($\boldsymbol{lh_i}$) is defined. This logic is derived from the case company's ERP system and earlier research carried out by Krajewski, King, Ritzman, & Wong, (1987). A lot-size horizon refers to the time interval wherein an item's future demands can be aggregated into order quantities. Based on items' average monthly demands, different lot-size horizons can be created and compared wherein high volume products have relatively short lot-size horizons and low volume products have relatively large demand aggregations, resulting in larger order quantities to justify setup costs. In Figure 15, average monthly demands are plotted for all 221 items. In Table 5, volume categories are presented based on the items' average monthly demands. Therein, 47% of the items are categorized as low demand items, 32% as moderate demand items, and 21% as high demand items.

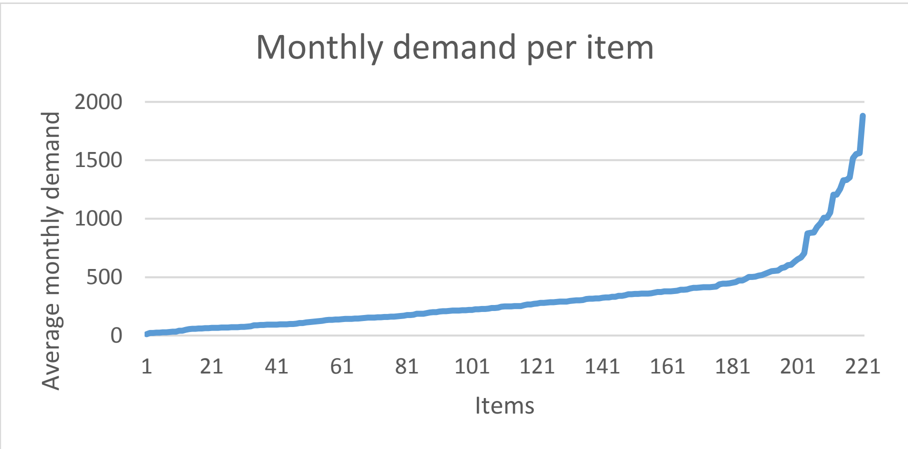


Figure 15: Average monthly demand per item

Volume categories			
Low	0 - 250	103	47%
Mid	251 - 500	70	32%
High	501 >	47	21%

Table 5: Volume categories

Demand uncertainty

Demand uncertainty is mainly caused by incoming information about the future (e.g., changes in forecasts, sales order changes) and by information about the past (e.g., rejected production in the form of yield loss). Information received by upstream operations planning is typically received from downstream operations planning that receives information about forecasts and sales orders directly from the customer. This implies that the case company's SCOP consists of a multi-level supply structure with interdependencies of different operations and has differences in information available along the organization.

Supply chain and operations literature proposes different methods of modeling demand changes over time. De Kok & Inderfurth (1997) proposed to model demand changes from respective time-periods and different levels of the production structure by one overall demand uncertainty parameter. This procedure can be considered as an alternative to taking into account planned order deviations of all periods at all production levels. In their research, de Kok & Inderfurth (1997) constructed demand uncertainty by setup stability and quantity stability. These are directly related to the case company's deviations in requirement dates and order quantities.

Demand distributions

To be able to create multiple realistic future demand scenario's, distributions are fitted to historical demand data. The data is fitted by aggregated demand on customer-level and demand aggregated on item-level. However, neither of those aggregations resulted in an adequate fit. Therefore, empirical data is used as upstream demand as an alternative. A more elaborate description of the demand fitting procedures can be found in Appendix E. Because downstream demand (i.e. sales order history) is used as a direct input for upstream demand, BOM ratios and lead times of intermediate operations are not considered. Below is described how downstream demand is modified such that is still representative as upstream demand.

Downstream versus Upstream demand

One important consequence of considering (downstream) demand data for upstream operations, is that the effects of intermediate planning decisions are not taken into consideration. This is illustrated below in Figure 16. Planning decisions from intermediate operations $(D_2, .., D_{n-1})$ such as lot-sizes and safeties influence original demands (D_1). Because this study aims to provide insight into the effects of lot-sizing decisions from upstream operations onto delivery performance, the best insights can be obtained with demands that are not influenced by planning decisions from intermediate operations. Note that in future research, also planning decisions from intermediate operations can be taken into consideration, ultimately leading to research on full-scope supply chain operations planning decisions. When considering the supply network in its full scope, effects of intermediate operations planning decisions will have to be taken into consideration as well.

Although downstream demand is representative for upstream demand, some small modifications had to be made such that BOM ratios are applied for instance. The demand includes BOM ratios of *1:1, 1:2, 1:3* and *1:4*. This ratio reflects the relation of end products to upstream parts. For most products produced upstream, think of covers, housings, or cold plates, not more than 4 items are assembled into an end product. However, end products may consist of multiple, different components that are produced upstream. A front cover and back cover for instance. This characteristic was incorporated by assigning downstream demand of approximately 700 items, to only 221 upstream items. This represents the fact that multiple upstream parts can be assembled into one end-item. At last, it is important to mention that material requirements are received by upstream operations' start dates. This will be further explained in Section 4.2.

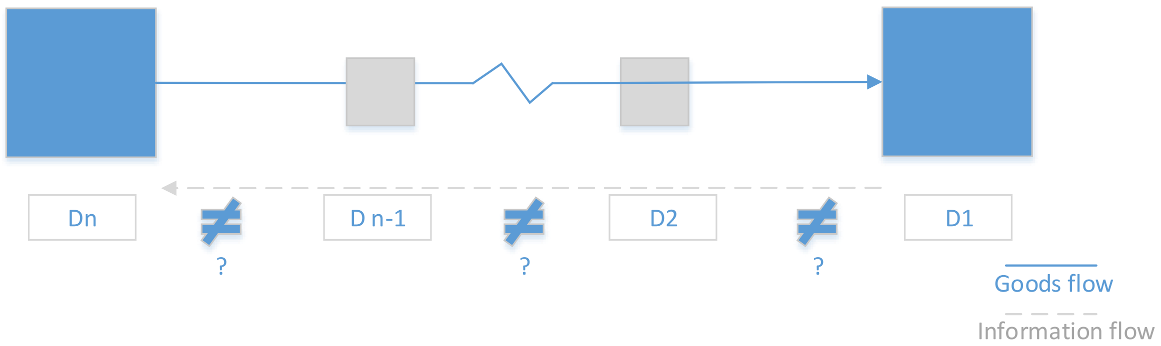


Figure 16: Demand patterns

3.4.3. Capacity and capacity requirements

To create a realistic supply chain and operations planning model, available capacity is limited. To initiate the model, a standard available amount of hours per day is assigned to each workcenter, representing the current available capacity. Based on the manufacturing flexibility measures proposed by Reichhart & Holweg (2007), available capacity can be adjusted. By adding shifts or machines available capacity can be increased, but consequently higher operational costs will result. In contrast to labor and machine flexibility, routing and source flexibility are rare for PT's upstream operations. Some items cannot be outsourced due to intellectual property or quality concerns. Others cannot be outsourced or produced at other workcenters since equipment and tooling are very specific.

Capacity requirements at each workcenter are determined by considering item specific setup- and cycle times, and order quantities. By aggregating all required capacity per day, based on the workcenters' start dates, it can be determined how much available resources are utilized and whether available capacity will be sufficient.

Start dates are determined based on standard lead times. Based on an item's router, a standard lead time can be subtracted from the requirement date to determine an item's start date. Because a job has a standard amount of days wherein it has to be processed at a certain workcenter, the job has a certain lead time wherein it has to be produced. Based on the requested date from downstream which is equal to the upstream due date ($\boldsymbol{d_j}$), lead times can be subtracted resulting in planned start dates ($\hat{\boldsymbol{s}}_j$). The production environment of the case company is represented by producing according to 'Earliest start date'. However, to some extent 'Earliest start date' may be overruled by 'First Come First Served' since it is possible that a job at one workcenter is delayed, causing a delay in the subsequent workcenter. In this case, the delayed job will not disrupt other jobs in queue that can be processed right away. For the Injection Molding department, this would mean a delayed job at workcenters 1, 2, or 3 which would cause a delay to workcenter 4 (see Figure 14).

3.4.4. Supply behavior

Besides that the case company is subject to demand uncertainties, generally high-tech manufacturing environments also experience supply uncertainties such as yield losses due to quality issues and stochastic processing times.

Yield loss
Due to quality issues, either from raw materials, purchased items, or production itself, yield losses occur. Yield loss occurs when products do not pass the embedded quality tests and thereafter operators are not able to resolve it.

Lead time
The setup- and cycle times that are used as an input to determine capacity requirements are averages of actual setup- and processing times, determined by the planners in correspondence with support engineers. Obviously, these times actually also include variances which demonstrate statistical patterns. In addition to setup- and cycle times, throughput time also consists of waiting times, and times for handling and transportation. These are all aggregated and reflected by the lead times that are defined for each workcenter, and also for each router. These lead times are defined with a certain safety, such that it also covers (most) timing variabilities.

In PT's current planning process, variabilities are covered by safety time. However, information regarding timing variances both processing time variability and total lead time variability can potentially be determined based on the machine software and the Manufacturing Execution Software. Because machine software is in place only for the first three workcenters, processing time variability for the first three workcenters could be analyzed. The results are provided in Appendix F. Similarly lead times were analyzed by considering start- and stop confirmations for each order processed via Manufacturing Execution Software system. However, due to the unreliability of order confirmations that is already discussed in Section 2.3, historical lead time variabilities could not be determined and are not included in the model. Instead, total lead time is modeled as if it is only dependent on order size, cycle time, and waiting times due to limited capacity. Consequently, delays occur when waiting times plus processing times exceed a job's standard lead time and therewith the predetermined due date. In this case, a job is modeled as having (partial) tardy deliveries. The exact determination of tardiness and delivery performance is further described in Section 3.4.7.

3.4.5. Starting inventory

To initiate the model and prevent the model from creating repetitive lumps of capacity requirements over time, starting inventories $\left(\boldsymbol{IP_i}(0)\right)$, are required. Since the demand stream which is used as input, is based on sales orders from a certain time interval, nearly all items have to be produced in the first 30 days if no inventory would be assumed. This results in capacity requirements as shown in Figure 17. Besides that all items will have to be produced in the first 30 days, it also leads to repetitive peaks in capacity requirements which is also not representative for actual capacity requirements.

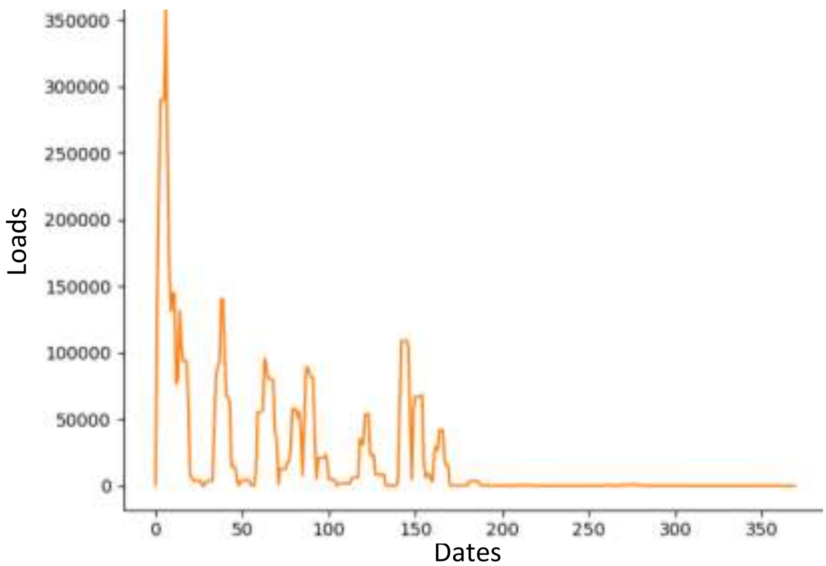


Figure 17: Capacity requirements without inventory (wc1)

To generate a more realistic capacity requirements scenario, starting inventories are considered for a selection of 120 items. This prevents the large peak in capacity requirements from occurring in the first period and spreads capacity requirements more evenly. Sections 4 and 5 will treat the resulting capacity requirements and load balancing in further detail.

3.4.6. Costs

The operational cost parameters that are included in this model consists of startup costs, inventory carrying costs, and machine availability costs. Startup costs will be accounted for each new job setup. Depending on the workcenter, set-up times and therewith set-up costs differ. Generally, producing large order quantities will reduce total startup costs. However, producing large order quantities increases inventory carrying costs. PT uses a standard carrying cost of 12% which consists of interest, holding costs, and opportunity costs of capital. To calculate inventory carrying costs of each job, the item price is multiplied by the order quantity and the carrying cost ratio, which are then multiplied by the time the item will be in stock. Since items are not booked to stock between workcenters 1, 2, 3, and 4, intermediate inventory costs are disregarded.

In addition to carrying- and setup costs, machine availability costs also compose a significant part of operational costs. Although machines operate mostly autonomously, machines require setups, maintenance, and (un-) loading. Based on average up-time, workcenters are available 8 hours per day per machine, including weekends. Workcenters with x machines have x-fold availability. During standard machine availability hours, a standard hourly rate of 60 EUROS is considered. When the available capacity is increased by adding shifts, operational costs will increase. In the model, each extra hour that is added to increase machine availability and therewith available capacity, imposes 150% of the standard hourly costs.

3.4.7. Delivery performance

From Section 2.3 it became apparent that it is most accurate to consider deliveries instead of order confirmations. Because data from the case company shows that orders are often confirmed before all deliveries are made, and items are actually only available once they are delivered, delivery performance is best represented by dates whereon (partial) deliveries are received ($\boldsymbol{r_{partial,j}}$). To model partial deliveries it is assumed that production at the end of each day, is delivered, booked to stock and available for downstream operations. This implies that if 50% of the job's required processing time ($\boldsymbol{z_j}$), is produced at the due date, at least 50% is produced on time. When the remaining 50% of the job is produced at ($\boldsymbol{d_j + 1}$), the remaining 50% is produced with Tardiness ($\boldsymbol{T_j}$) equal to 1 day. To express delivery performance and penalize tardiness of partial deliveries, Volume Confirmed Line Item Performance (V-CLIP) will be applied as presented in equation (2).

All deliveries that are tardy, are multiplied by the complementary cumulative distribution function of the deliveries' tardiness. The cumulative distribution for this research was determined by statistical distribution fitting to historical tardy deliveries made at the case company's upstream operations during 2017. The distribution fitting process and results are explained in more detail in Appendix D. The analysis demonstrated that tardy deliveries considered in this study can be best approximated by a Negative Binomial distribution ($T_{partial,j} \sim NB(1, 0.08755)$).

3.4.8. Item overview

In Figure 18, all input and output variables are graphically depicted. Notice that the scope of the research mainly focuses on the most upstream production unit(s) of the production network. Within this upstream production unit, four different interdependent workcenters are modeled. On the workcenters, items can be processed that have one out of six routers displayed in Table 6. The table also provides insight into the occurrence and lead times of the routers. The simulated occurrence represents the occurrences of routers from the data-set that will be used as model input.

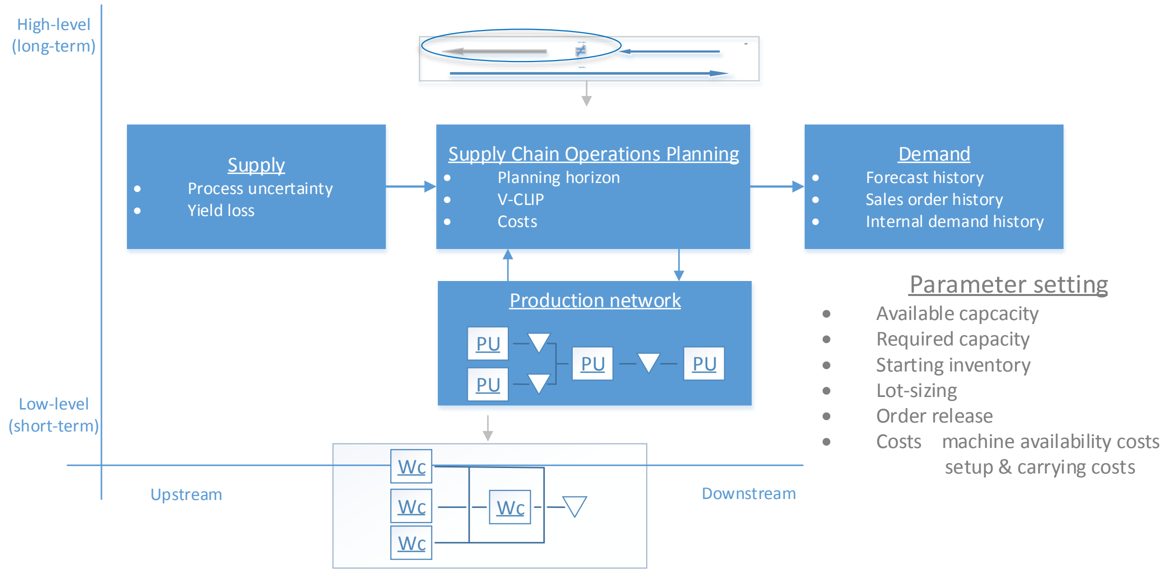


Figure 18: Items for inclusion

Router	Workcenter	Lead time	Occurrence	Cum. Occ.	Simulated occurrence	Delta
A-1	Wc1	6 days	32%	32%	32%	0%
A-2	Wc1 + Wc4	10 days	8%	40%	7%	-1%
B-1	Wc2	6 days	32%	72%	32%	0%
B-2	Wc2 + Wc4	10 days	8%	80%	9%	1%
C-1	Wc3	8 days	16%	96%	17%	1%
C-2	Wc3 + Wc4	12 days	4%	100%	3%	-1%

Table 6: Router description

4. Modeling

The model that is constructed in this research project uses the scope, design parameters, input and output parameters that were presented in Section 3. In this section, the relations between parameters are described and motivated by means of algorithms and mathematical expressions. The algorithms' functions are referred to as 'mechanisms'. Before considering the mathematical model in depth, an overview and motivation for all relevant assumptions is given below. This section will conclude with the verification and validation of the model.

4.1. Assumptions

- **Delivery performance of suppliers is disregarded. Therewith, the capacity of suppliers is assumed to be infinite.**

Although historical data on delivery performance of the case company's suppliers is available, it has been decided to exclude these from the model and focus mainly on internal delivery performance.

- **The supply network belongs to a single organization.**

The case company that is within the scope of this research consists of a multi-level supply network as is also described in Sections 1 and 2. In this organizational structure, information about inventory positions and (internal) demand are shared.

- **Multi-level operations plans are updated independently.**

The case company's multi-level supply network consists of different operations that are executed parallel or sequentially. Additionally, the case company's control structure is decoupled by upstream and downstream planning. This leads to operations plans that are updated independently. Consequently, differences exist in information available downstream and upstream the organization.

- **In case of an available capacity shortage, production is backordered and will be produced the first upcoming period (day).**

When resources are unavailable, items are produced and delivered the first upcoming period when the resource becomes available.

- **Forecast accuracy decreases over time.**

When modeling forecast accuracy, generally forecast accuracy decreases over time (Lin & Krajewski, 1992). The model's demand is based on the case company's sales order history. The data contains aggregated sales history from the first three months of 2018 and future demands that were available at that time. This leads to a demand pattern wherein the first five months accurately represent actual demands and demands decrease further into the future.

- **Human factors are incorporated in process variability.**

Factors such as level of skills, motivators, or stress are incorporated in lead times because capturing these separately would become computationally intractable.

- **Jobs are produced at workcenters serially.**

Jobs can be processed only by one workcenter at a time. Process batch splitting is not considered. Additionally, workcenters are modeled such that only one job at a time can be produced. However, the router's last workcenters' partial deliveries are considered and therefore transfer batch splitting is allowed.

- **Jobs are only started when the preceding workcenter is finished.**

When a job is processed by two workcenters, the job may only start at the second workcenter if it is finished by the first workcenter.

- **No yield loss. Scrap percentages compensate for non-conforming goods.**

The case-company compensates yield losses by applying a scrap percentage to each job. In extreme circumstances, it may be that the scrap percentage is insufficient. However, in the model is assumed that scrap percentages cover all yield losses.

- **Outsourcing is only possible on a structural basis. No ad-hoc outsourcing can be arranged due to intellectual property and quality.**

When available capacity is running short and quick actions are needed it can be decided to add extra shifts. In case extra machinery has to be purchased, a standard lead time of 8 months is considered. In case extra capacity is needed within 8 months and extra shifts provide insufficient increase in capacity, items can be outsourced. In the model, outsourcing costs three-fold of regular in-house production.

- **Although inventory is not dynamically modeled, starting inventory is assumed.**

As described in Section 3.4.2, upstream demand that is considered in this model consists of historic sales data wherein nearly all items show demands during the first 30 days of the simulation. Because this creates large repetitive peaks in capacity requirements it has been decided to consider starting inventory and exclude some of the demands during the first weeks of simulation. A list of the 120 items and corresponding starting inventories is provided in Appendix G.

- **Upstream demand is requested by start date. This means that standard lead time is already subtracted from the requirement date downstream.**

For simplicity, it is assumed that input data consists of requirement dates where lead times are already subtracted. This implies that incoming demands already specify start dates for production.

- **Items are not distinguished by priority or importance.**

By assessing performance with V-CLIP, the importance of items for the case company's most important customers is not included. All items are of equal importance and have equal impact on average delivery performance and operational costs.

4.2. Model design

Based on the model that is conceptualized in Section 3, the detailed model design and modeling choices are presented in this section. The detailed design is elaborated with algorithms and mathematical expressions.

In Section 3.3, three design parameters are presented that are based on elements from the LTA procedure (Jansen et al., 2013). These design parameters are represented by three model mechanisms wherein (I) order proposals are generated, (II) load balancing is applied and end dates are determined, and (III) on-time delivery performance is determined by V-CLIP. Additionally, the model calculates operational costs and allows for manufacturing flexibility in the form of extra shits, machines, or outsourcing. The relations between the three different mechanisms and additional functions are graphically depicted in the model design in Figure 19.

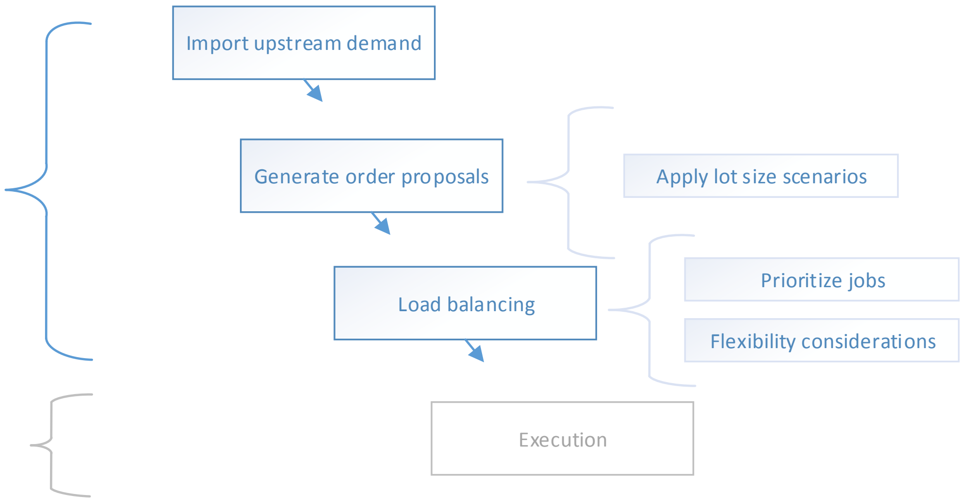


Figure 19: Model design

4.2.1. Objective function

The main objective of the model is to provide this study with insights and understanding of the aspects that influence on-time delivery performance (V-CLIP) in a multi-level supply organization that operates within a high-tech environment. To model realistic scenarios wherein high delivery performance is offset by higher operational costs, the model's objective function includes a cost minimization function. The cost minimization function is formulated by:

$$Min(Ac + Cc) \tag{3}$$

To minimize costs, two cost variables are expressed by equations (4) and (5). The cost variables reflect availability costs ($\boldsymbol{Ac}$) and carrying costs ($\boldsymbol{Cc}$) respectively. The terms and concepts are also explained in Section 3.4.6 that is devoted to operational costs. Note that the standard hourly rate ($\boldsymbol{hr}$) for availability increases with 150% ($\boldsymbol{hr}_{extra}$) for each hour that exceeds the standard 8 hours of availability time ($\boldsymbol{avai}$) per day. Carrying costs consist of a 12% carrying ratio ($\boldsymbol{cr}$). The carrying cost, incurred for each job are added with a standard setup cost ($\boldsymbol{fc}$). In order to determine the total costs, the cost elements rely on a time-frame that consists of the full planning horizon. Availability costs are calculated for each day ($\boldsymbol{t}$) of the planning horizon. Carrying costs and setup costs are determined for each job of the whole planning horizon.

$$Ac = \sum_{t=1}^{T} (avai(t) * hr \; + \; avai_{extra}(t) * hr_{extra}) \tag{4}$$

$$Cc = \sum_{i=1}^{I} \sum_{j=1}^{J} (\widehat{pq}_{i,j} * \frac{lh_i * \; cr}{2} + fc_{i,j}) \tag{5}$$

4.2.2. Import upstream demand

To model incoming material requirements, a demand-set is imported that is based on customer demands (downstream sales order). As explained in Section 3.4.2, the data is modified such that BOM ratios are included and requirement dates are specified as start dates.

4.2.3. Generate order proposals (mechanism 1)

Once material requirements are available, the model continues by calculating order proposals. The procedure for generating order proposals is summarized by a pseudo code that is presented below in Algorithm 1.

The algorithm starts by determining the average monthly demands for each item ($\boldsymbol{\overline{q}_i}$). These monthly averages are used for lot-sizing decisions as described in Section 3.4.2. To obtain monthly average demands, future demands for each item are summed and divided by the length, expressed in months, of future demands that are available ($\boldsymbol{months_i}$).

Once the average monthly demands are determined, the mechanism groups items into volume categories. The volume categories represent items with low monthly demands, moderate monthly demands, and high monthly demands. Once all items are categorized, items are subject to a lot-size function wherein, based on the item's volume category a so-called lot-size horizon ($\boldsymbol{lh_i}$) is coupled. The lot-size horizon reflects a certain amount of weeks wherein future demands will be aggregated to form an order proposal for the particular item. Based on an item's lot-size horizon, a lot-size interval ($\boldsymbol{ls_{i,j}}$) is defined that starts from the item's nearest requirement date and has a length equal to the item's lot-size horizon ($\boldsymbol{lh_i}$). The item's nearest requirement date from downstream is then used as the job's planned start date ($\boldsymbol{\hat{s}_j}$).

The length of an item's lot-size horizon may be shorter than the length of an item's available future demands. In this case, not all future demand can be covered by one production order. Therefore, the mechanism may generate multiple order proposals for one item. If so, each new lot-size interval will start from the first upcoming requirement date. The algorithm repeats this process for each item until all future demands are converted into order proposals.

To provide insights into the effects of different lot-sizing decisions, different scenarios ($\boldsymbol{sc}$) will be compared. Based on the average monthly demands, three scenarios are created wherein high volume products have a relatively short lot-size horizon and low volume products have a relatively long lot-size horizon to justify setup costs. The lot-size scenarios in combination with the volume groups that were already presented in Table 5 are summarized in Table 7. Numerical results and effects of different lot-sizing decisions will be compared and evaluated in Section 5. An elaborate numerical example of algorithm 1 is provided in Appendix H.2.

Algorithm 1: Generate order proposals

Input: q_i, sc $\quad \triangleright\ \forall\, i \in \{I\}$

Output: $\widehat{pq}_{i,j}$

read downstream demand (q_i)

average monthly demand $(\bar{q}_i) = [requested\ downstream\ demand_i].sum(q_i)\ /\ months_i$

lotsize$(sc, \bar{q}_i)$

function: lotsize$(sc, \bar{q}_i)$

sc = 1	*sc = 2*	*sc = 3*
If $\bar{q}_i$ *<= 250:*	*If* $\bar{q}_i$ *<= 250:*	*If* $\bar{q}_i$ *<= 250:*
$lh_i = 26$	$lh_i = 20$	$lh_i = 8$
elif $\bar{q}_i$ *<= 500:*	*elif* $\bar{q}_i$ *<= 500:*	*elif* $\bar{q}_i$ *<= 500:*
$lh_i = 13$	$lh_i = 10$	$lh_i = 4$
else:	*else:*	*else:*
$lh_i = 4$	$lh_i = 4$	$lh_i = 2$

end function

 # Generate production orders

for i **do***:*

determine job's start date $(\hat{s}_{i,j}) = \min[requested\ delivery\ dates\ of\ downstream\ demand_i]$

determine job's lot-size interval $(ls_{i,j}) = \hat{s}_{i,j} + lh_i$

determine planned job quantity $(\widehat{pq}_{i,j}) = [requested\ downstream\ demand_i < ls_{i,j}].sum(q_i)$

 # While not all downstream demand is covered, generate more production orders

while $\widehat{pq}_i < [requested\ downstream\ demand_i].sum(q_i)$:

$j = j+1$

$\hat{s}_{i,j} = \min[requested\ delivery\ dates\ of\ downstream\ demand_i > ls_{i,j-1}]$

$ls_{i,j} = \hat{s}_{i,j} + lh_i$

$\widehat{pq}_{i,j} = [d_{i,j} < requested\ downstream\ demand_i \leq ls_{i,j}].sum(q_i)$

		Lot-size scenarios		
		High (1)	Mid (2)	Low (3)
Low	0 - 250	26 wks	20 wks	8 wks
Mid	251 - 500	13 wks	10 wks	4 wks
High	501 >	4 wks	4 wks	2 wks

Table 7: Lot-size scenarios & Volume categories

4.2.4. Load balancing (mechanism 2)

Once job proposals are generated, Algorithm 2 continues by determining capacity requirements and actual end dates. The model will later use these to compare actual end dates with planned end dates, i.e. due dates, to determine tardiness and therewith delivery performance.

The Load balancing mechanism starts with sorting jobs ascending by start date. Then, it sorts jobs by its corresponding workcenters. Note that based on the pseudo code, care has to be taken when referring to job's indices after sets have been sorted. In the mathematical model, this ambiguity in referencing is overcome by referring to indices of the sorted sets, for example when selecting a preceding job $(j-1)$. This is illustrated below in Table 8 where 'old' refers to the index before jobs were sorted by start date and workcenter. 'New' refers to the changed indices that are used by the mathematical model. Note that the example considers 4 workcenters and just 20 jobs.

k = 1		k = 2		k = 3		k = 4	
old	new	old	new	old	new	old	new
3	1	2	6	4	11	1	16
5	2	6	7	7	12	8	17
11	3	9	8	10	13	12	18
16	4	15	9	14	14	13	19
20	5	19	10	18	15	17	20

Table 8: Indexing

To determine whether the required capacity can be fulfilled within the available lead time, available and required capacity are calculated. To calculate available capacity, the mechanism relies on workcenter availability $(\boldsymbol{C_k})$. The daily availability of workcenters, expressed in hours, depends on the standard availability time $(\boldsymbol{avai_k})$ and extra availability time $\left(\boldsymbol{avai_{k,extra}}\right)$ as shown in equation (6). With flexibility considerations, workcenter availability $(\boldsymbol{C_k})$ can be (temporarily) increased. Obviously, this is offset by higher operational costs. More about improving current performance by flexibility considerations is described in the numerical analysis, presented in Section 5.

$$C_k\ (t) = \ avai_k(t) + \ avai_{k,extra}(t) \qquad (6)$$

Required capacity is calculated by norm setup times $\left(\boldsymbol{\hat{f}_{j,k}}\right)$ and norm cycle times $\left(\boldsymbol{\widehat{cc}_{j,k}}\right)$ for each job at each workcenter. The model features plots, wherein capacity loads per day per workcenter are depicted as shown before in Figure 17.

Once jobs are sorted and required capacity is determined, the mechanism initializes end date calculations by setting end dates ($\boldsymbol{e_j}$) equal to due dates ($\boldsymbol{d_j}$). Since the model intends to improve current load balancing practices, the algorithm will later search if jobs can be produced earlier in case of capacity shortages.

Because the demand data that this model considers contains start dates, equations (7) and (8) are used to determine a job's due dates. Since the model includes dependent workcenters, workcenter specific due dates are defined as in equation (7). Hence, if a job processed at workcenters 3 and 4 incurs a delay at workcenter 3, the job's end date at workcenter 3 will affect the start date at workcenter 4.

$$d_{j,k} = s_{j,k} + l_{j,k} \tag{7}$$

A job's overall due date is determined as in equation (8). The job's overall due date is equal to the largest due date of the job at all relevant workcenters.

$$d_j = \max[d_{j,k}] \tag{8}$$

The load balancing mechanism uses two functions that iteratively update the available capacity and resulting end dates (see Algorithm 2). The mechanism iterates until all jobs are processed sequentially by the corresponding workcenters. The available capacity is determined by taking a job's due date ($\boldsymbol{d_{j,k}}$) and subtracting the planned end date from the preceding job ($\boldsymbol{e_{j-1,k}}$). This may lead to front-loading of capacity requirements. Net available capacity is then determined by subtracting the required capacity from the available capacity.

When the net available capacity is insufficient to finish the job before the planned due date, a negative net available capacity will result. Based on the number of days required for processing the capacity shortage, the job's end date will be postponed. However, for those jobs that contain routers with more than one workcenter, the start date of the job at a particular workcenter is not only dependent on the end date of the preceding job at this workcenter but also on the end date of this job at the preceding workcenter. This logic is presented in equation (9).

$$available\ capacity_{j,k} = min(\ d_{j,k} - e_{j-1,k},\ \ d_{j,k} - e_{j,k-1}\ ) * C_k \tag{9}$$

Note that ambiguity in referencing may emerge when referring to workcenters just as referring to jobs' indices described earlier in this section. The model has overcome this ambiguity in referring to workcenters by referring to a unique job number and a corresponding router as described in Section 3.4.1. Alternatively, one could also decide to reset workcenters´ indices as was described for jobs in Table 8. Also Algorithm 2 is numerically demonstrated by an example in Appendix H.3.

Algorithm 2: Load balancing

Input: $\widehat{s_j}, \widehat{pq}_j, l_k, C_k$ $\rhd \forall j \in \{J\}$
Output: e_j

sort jobs ascending by planned start date $(\widehat{s_j})$
sort jobs by workcenter (J_k)
$required\ capacity_{j,k} = \hat{f}_{j,k} + \widehat{pq}_j * \widehat{cc}_{j,k}$
$gross\ available\ capacity_{j,k} = l_k * C_k$
set end date of job j equal to due date: $e_{j,k} = d_{j,k}$

function: Available capacity during lead time$(d_{j,k}, e_{j,k}, C_k)$
$available\ capacity_{j,k} = (d_{j,k} - e_{j-1,k}) * C_k$
$net\ available\ capacity_{j,k} = available\ capacity_{j,k} - required\ capacity_{j,k}$
end function

function: End date$(net\ available\ capacity_{j,k})$
if $net\ available\ capacity_{j,k} < 0$:
$e_{j,k} = e_{j,k} + (capacity\ shortage_{j,k}\ /\ C_k)$
else
$e_{j,k} = e_{j-1,k} + (required\ capacity_{j,k}\ /\ C_k)$
end function

while $e_{j-1,k} > e_{j,k}$: $\rhd$ *for* $j \in \{2,3,\ldots,J\}$
Available capacity during lead time$(d_{j,k}, e_{j,k}, C_k)$
End date$(net\ available\ capacity_{j,k})$

4.2.5. Delivery performance (mechanism 3)

In order to calculate delivery performance, the Volume-Confirmed Line Item Performance metric is used which is also presented in Section 2.3. Delivery performance calculations are made by the third mechanism and are summarized by the pseudocode in Algorithm 3.

The mechanism calculates performance based on tardiness of (partial) deliveries. As explained earlier in Section 3.4.7, partial deliveries are modeled by transfer batches that follow after daily production. It is assumed that production at the end of each day is delivered, booked to stock, and available for downstream operations. Therefore, the V-CLIP mechanism first determines tardiness $(\boldsymbol{T_j})$. Then, the mechanism assigns delivery performance of 100% if the fraction of demand is fully met on time. When the job's actual end date, determined in Algorithm 2, exceeds the due date, the mechanism starts by calculating the fraction of demand that is delivered late, i.e. tardy. In other words, it checks on which days tardy deliveries are made and what the corresponding quantities are.

There are two types of tardy jobs. One is started on-time and finished tardy. The second is started with a certain tardiness and also finished tardy. Note that jobs are started with a certain tardiness due to delays from preceding jobs (e.g. WIP) or delays incurred at preceding workcenters. To detect at what time period the first partial deliveries are made, the required days of production $(\boldsymbol{z_j})$ is determined and compared with the job's tardiness $(\boldsymbol{T_j})$.

When the required days of production is less than the job's tardiness, the job is actually started later than the due date. The actual start date is then determined as in equation (10). To determine V-CLIP performance in Algorithm 3, the pseudocode loops over all partial deliveries. Therefore, the code loops from the actual start date, referred to by ***diff*** until the actual end date referred to by $(\boldsymbol{T_j})$. This is modeled by Algorithm 3 in lines 11 until 13.

$$\textit{Start date when job is started late} = d_j + (T_j - z_j) \tag{10}$$

When the required processing time exceeds the job's tardiness, it is certain the job is at least started before it is due. In this case, the corresponding volume of on-time production will not have to be multiplied by the cumulative distribution function of the deliveries' tardiness. For all deliveries that are made tardy, Algorithm 3 uses the same logic that was used to calculate delivery performance for jobs that are started later than the due date. The loop is represented in lines 15 until 20 from Algorithm 3. Just as the previous algorithms, Algorithm 3 is provided with a numerical example that can be found in Appendix H.4.

Algorithm 3: V-CLIP

Input: d_j, e_j, z_j $\quad\quad\quad\quad \rhd\ \forall\, j \in \{J\}$
Output: $V - CLIP_j$

1: determine Lateness (L_j) = *Due date* (d_j) – *End date* (e_j)
2: determine Tardiness (T_j) = *abs*$[L_j]$
3: sort jobs by workcenter (J_k)
4: determine required days of production for job $(z_j) = \textit{required capacity}_{j,k} \,/\, C_k$

5: **for** j **do:**
6:   **if** $T_j == 0$:
7: $VCLIP = 1$
8:   **else:**
9: $VCLIP\,(T_j, z_j)$

function: VCLIP(T_j, z_j)
10: **if** $z_j \leq T_j$:
11: $diff = T_j - z_j$
12:   **for** x **in range** $(diff, T_j)$:
13: $VCLIP = VCLIP + (C_k / \textit{required capacity}_{j,k} * (1 - nbinom.cdf(x, 1, 0.08755)))$
14: **else:**
15:   **for** x **in range** $(0\,, T_j)$:
16: $diff = z_j - T_j$
17:   **if** $x == 0$:
18: $VCLIP = \max[diff * C_k, C_k] / \textit{required capacity}_{j,k}$
19:   **else:**
20: $VCLIP = VCLIP + (C_k / \textit{required capacity}_{j,k} * (1 - nbinom.cdf(x, 1, 0.08755)))$
end function

4.3. Simulation characteristics

Because empirical demand data is used as input data, and only one set is available and prepared to run the model it is important to justify certain decisions regarding (I) simulation length, (II) warm-up period, (III) and the number of replications.

Simulation length

The empirical data contains aggregated sales history from the first three months of 2018. Because forecasts were disregarded, future demands from April 2018 onwards gradually decrease over time where the last demands appear by the end of 2018. The complete demand-set contains over 300 time periods, i.e. days. The total number of downstream material requirements that are sent to upstream operations consists of 3580 order-lines. According to Metha (2000), who described methods for modeling and simulation, a random number stream should occur 15 to 20 times. Considering the demand-set, each of the 221 items occurs on average 16 times. However, since there are low and high volume products, some items occur less than 10 times whereas others occur more than 25 times (See Table 9). Despite some items have low occurrences, it is unlikely that these amounts are contradictory to the amounts recommended by Metha (2000). Considering the figures from Metha, the most significant item characteristic that varies throughout the simulation are the routers. Since even the most exceptional router, C-2, has 90 occurrences in the demand-set the simulation length is considered sufficient.

Number of occurrences	Count of items	Number of occurrences	Count of items
7	1	18	23
8	2	19	21
9	7	20	12
10	3	21	10
11	11	22	10
12	18	23	5
13	18	24	3
14	17	25	1
15	22	26	1
16	19	27	0
17	16	28	1

Table 9: Frequency distribution of demand occurrences

Warm-up period

Instead of using a warm-up period, this study applied data preparation and included starting inventories such that a warm-up period was not required. This decision is made because a warm-up period instead of starting inventories does not necessarily yield realistic outcomes. As already motivated in Section 3.4.5 where starting inventories were explained, the demand set without starting inventories leads to a large peak of capacity requirements continued with repetitive cycles of capacity requirements. This is caused by the repetitive process of generating order proposals wherein future demands are aggregated into production orders. Since new jobs are only started when there are material requirements downstream, this may defer some job proposals whereby demands and corresponding capacity requirements are leveled over time. However, there was not enough empirical data available to increase the demand-set by several months in order to include a warm-up period of several months and this would increase computation time considerably. Instead, starting inventories are considered for 120 items, presented in Appendix G. Next to starting inventories, so-called sub-runs are applied whereby only the first five months of simulation are used for performance measurements. Sub-runs were required since the demand-set contains data wherein the first five months accurately represent actual demands and demands decrease further into the future. This can also be derived from a gradual decrease in capacity requirements depicted in Figure 17. Consequently, performance is measured only over the near future such that a more reliable interpretation of results is secured.

Number of replications

Over time, several methods have been developed to determine the required number of simulation replications. According to Chung (2004), the required number of simulations is determined by the replication mean and the standard deviation of the replication mean. With these figures a relative precision can be calculated, leading to a required number of simulation replications.

For a robust statistical analysis, the standard error should be relatively small in comparison to the sample mean ($\bar{\boldsymbol{x}}$). The standard error is calculated by equation (11). Then, to determine the desired amount of replications ($\boldsymbol{n}$) the relative precision determines a ratio by dividing the standard error by the sample mean of the data (see equation (12)). Later, during numerical interpretation of the results performances will be compared that range around 86% that represents the current situation. To have a reliable interpretation of results, it is desired to have a standard error not larger than 1 percent point, say. In equations (11) and (12), $\boldsymbol{t}$ indicates the t-distribution where $\boldsymbol{\alpha}$ represents the confidence level and $n-1$ the degrees of freedom. In the equations, $\boldsymbol{s}$ represents the sample standard deviation.

$$Standard\ Error = t_{1-\alpha/2,n-1} * s/\sqrt{n} \tag{11}$$

$$Relative\ Precision = \frac{t_{1-\alpha/2,n-1} * s/\sqrt{n}}{\bar{x}} \tag{12}$$

When the model is checked with 10 observations, a relative precision of 0,012 is obtained (see Table 10). When the model is checked with 5 replications, a relative precision of 0,017 is obtained. To secure the correct interpretation and comparison of results, numerical results will be obtained by doing ten replications.

n	α	$\bar{x}$	s	$Standard\ Error$	$Relative\ Precision$
10	0.95	0,868	0,014	0,010	0,012
5	0.95	0,866	0,014	0,014	0,017

Table 10: Replications

4.4. Model verification & validation

In this phase of the research, the mathematical model is checked for conceptual and mathematical errors or coding errors that potentially cause incorrect calculations and results.

4.4.1. Verification

The verification of the model consists of the assurance that the model meets the requirements. The mathematical model is built in Python programming language. To verify no coding errors exist, the mathematical model and program have been checked separately for coding errors. Additionally, calculations were checked by comparing the output from the model with manual computations. Manual computations for all three mechanisms of the model are motivated in Appendices H.2, H.3, and H.4. If the model did not behave as expected, the error was traced and the program was corrected until the model generated trustworthy results.

In addition to the manual computations, three important modeling phases are also manually computed and checked to verify the results. These are the (I) job proposal mechanism, (II) capacity requirements calculations, and (III) verification of performance and cost calculations. One important model mechanism, the load balancing mechanism that determines the actual end dates, is not treated in further detail although it has a considerable effect on the model output. Instead, numerical computations provided in Appendix H.3 together with the verification of the model output provide sufficient overall assurance that the model meets the requirements.

Verification job proposal mechanism

The model is initiated by importing downstream demand and transferring all requirements to job proposals. To verify that the model considers the correct lot-size horizons and therewith proposes the correct number of jobs, the number of proposed jobs are manually checked and verified. As the results in Table 11 indicate, the first mechanism of the model can be verified since the number of proposed jobs is correct.

	Scenario 1	Scenario 2	Scenario 3
Model	569	662	1189
Manual	569	662	1189

Table 11: Verification job proposal mechanism

Verification of capacity requirements

Once all job proposals have been initiated, capacity requirements are determined by considering pre-determined setup and cycle times for each job at each workcenter. Note that the capacity requirements as plotted in Figure 20 and Figure 21 are predictions. Due to variabilities in processing times, actual capacity requirements may deviate. In Figure 20, a plot is shown based on the second lot-size scenario for the first workcenter. Since the plot corresponds exactly with the capacity requirements computed by the model shown in Figure 21, the capacity requirements function is verified.

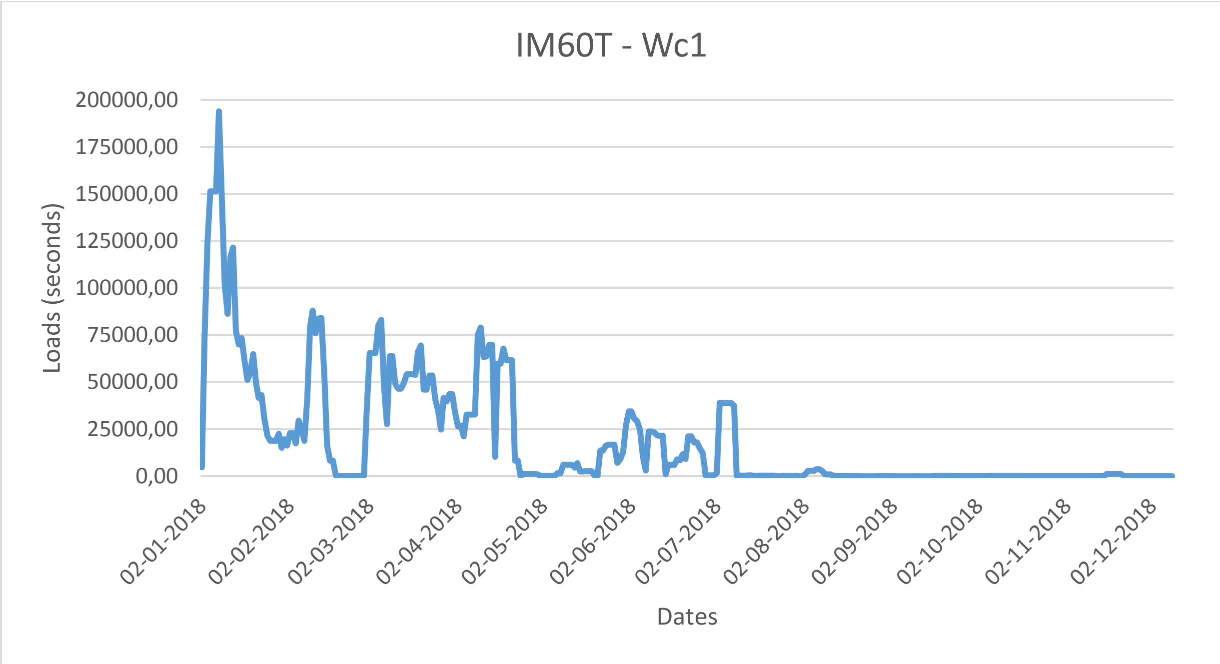


Figure 20: Manual computation of capacity requirements wc1

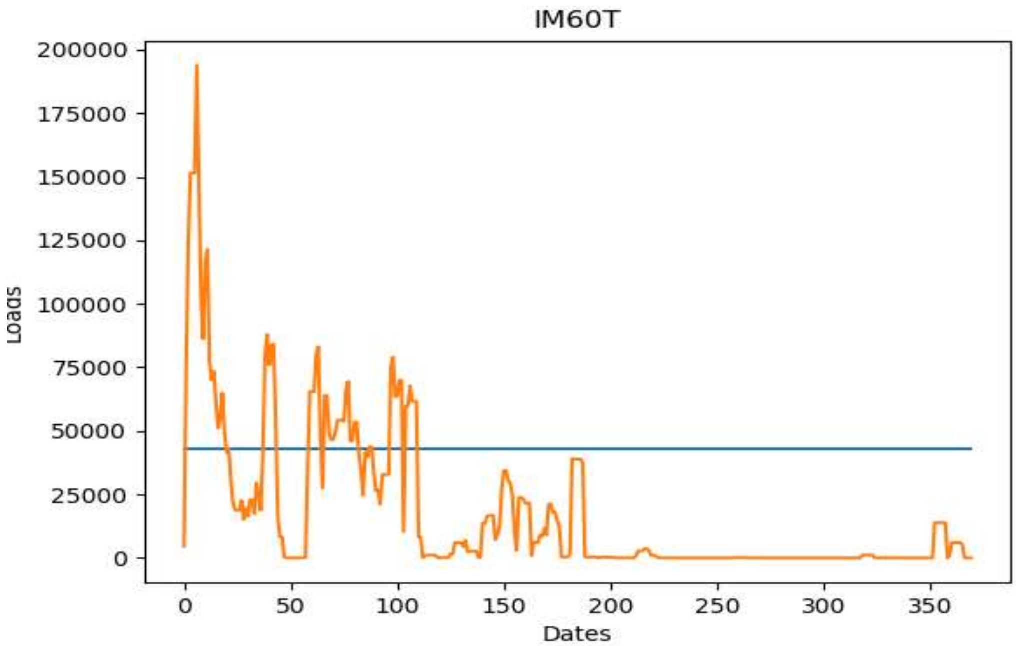


Figure 21: Model computation of capacity requirements wc1

Verification of results: costs & delivery performance

To verify if operational costs are computed correctly and delivery performance is measured as intended, calculations for all three scenarios are also made apart from the model. Because manual computations correspond with the model output, the model is verified.

		Scenario 1	Scenario 2	Scenario 3
Model	V-clip	65.2%	83.3%	91.4%
	Costs	€ 838,476.64	€ 778,917.80	€ 697,247.12
Manual	V-clip	65.2%	83.3%	91.4%
	Costs	€ 838,476	€ 778,917	€ 697,247

Table 12: Verification of results

4.4.2. Validation

The validation step checks whether the model is an accurate representation of the system that is in scope. Sargent (2005) distinguishes face validity and historical data validity. Whereas face validity is used to ask individuals if the model's behavior is reasonable, historical data validity uses empirical data to validate if outcomes match with actual results.

Historical data validity could only be assessed to a limited extent. First of all, historical data is not always reliable enough for comparison with model outcomes. As described in Section 2.3, only 50% of the jobs produced by Injection Molding were finished correctly and considered reliable. Also, it was concluded that mainly partial deliveries can be considered reliable compared to order confirmation dates. However, partial deliveries from the model are not collected separately by the model and therefore only the final partial deliveries, equal to the actual end dates can be compared with historical data. From Figure 22 it can be derived that the simulated tardiness in all three scenarios has a high correlation with the historical tardiness. One remark is that the data from the simulation and the historical data, are not from the same time period. However, the data from the simulation is based on similar parameter settings such as lot-sizing and cycle times whereby similar tardiness is obtained.

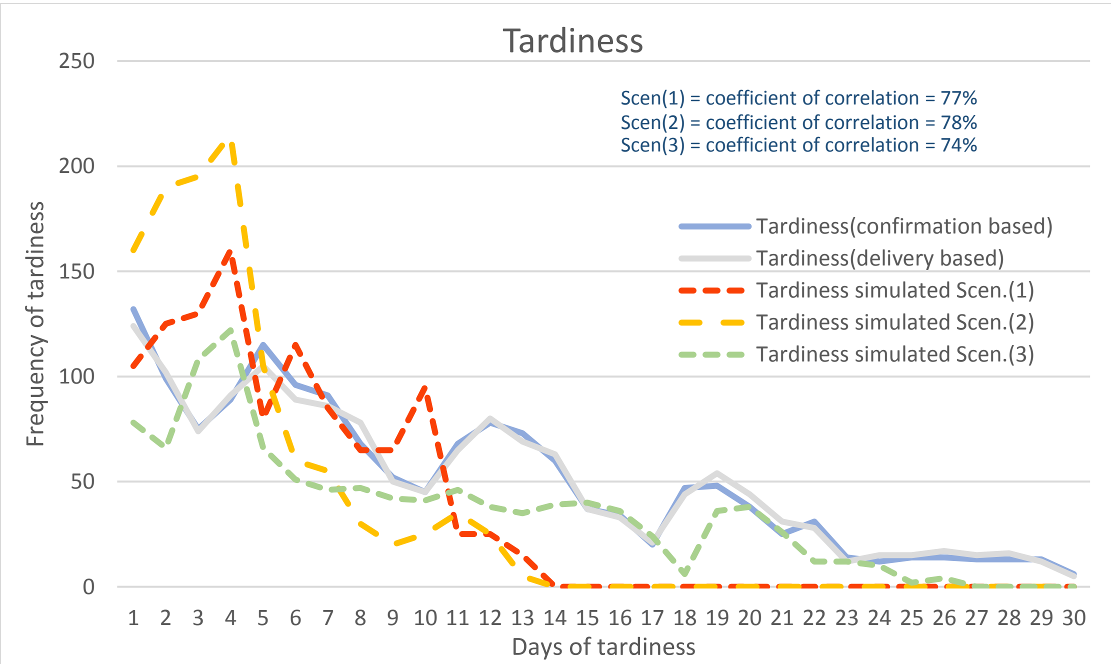


Figure 22: Tardiness: historical data versus simulated data

Face validity is secured by interviews with different employees throughout the case-company. Representatives from the planning department were asked to validate outcomes regarding lot-sizing and other planning decisions. Representatives from the administration office and planning department were asked to review the cost calculations and results. Support Engineers from the Injection Molding department were asked to review cycle times, lead times and setups. At last, the overall model is validated by the project supervisor, working at the organization support department.

After these verification and validation actions, it can be concluded that the developed model generates reliable and valid results.

5. Numerical study (model solving)

Throughout numerical experiments and different combinations of simulation runs and parameter settings, insights into aspects that influence on-time delivery performance and operational costs are obtained and explained in this section.

5.1. Experiments

In order to obtain useful insights from the model, experiments are set-up that provide fundament for answering the research questions that were presented in Section 1.2

The first research question presented in Section 1.2 addresses the case company's current performance. Because this performance was extensively measured and described in Section 2, it follows that a scenario can be simulated wherein the model mimics the current situation. This scenario will, therefore, make use of parameters that correspond with the current situation. The current situation will be described in Section 5.2.

1. What is the model output under parameters that correspond with the current situation?
2. Is the model output, based on the current situation, in line with the actual output?

The second research question presented in Section 1.2 mainly focusses on planning design and is used as a motivation for modeling decisions that built upon the planning design. An interesting extension for numerical experiments on the proposed planning design would be the consideration of different replanning policies wherein consequences different of frozen horizons (**F**) and replanning intervals (**R**) can be compared in terms of delivery performance and operational costs. However, this research only represents a planning wherein one future scenario is calculated without considering changes in demand or forecasts that will emerge in later time periods.

Especially the third research question will receive much attention within this section since the numerical study can be used to compare different planning decisions, i.e. parameter settings. By sensitivity analysis, the impact of different lot-sizing decisions on utilization, operational costs, and delivery performance is analyzed. Additionally, model output under different available capacity will be compared. From these insights and a sensitivity analysis, it can finally be concluded under which capacity and release, the most favorable on-time delivery performance and operational costs will result.

3. What happens with the model output when different lot-sizing decisions are applied?
4. What happens with the model output under different available capacity?
5. What is the best mix given the targeted delivery performance?

5.2. Current situation

To approximate the case company's actual planning function, current ERP parameters and orders sizes were analyzed. With the insights that are derived from this analysis, a simulation can be developed wherein a scenario is created that corresponds to historical planning decisions and outcomes. By using these current ERP parameters as input for the planning model, the model output can be compared with the historical output that is also documented in Section 2.3.

ERP parameters: lot-sizing and throughput parameters

The first model mechanism generates order proposals. These are based on lot-size horizons. The logic of these lot-size horizons is also applied by the case company's ERP. Therefore, it could be analyzed what historical lot-size horizons were, based on current ERP parameters. The current horizons are summarized by a frequency distribution in Figure 23. The lot-sizing horizons are also provided in tabular form in Appendix J. Figure 23 depicts three types of lot-size horizons. One lot-size horizon is based on the case company's current ERP parameters from the Injection Molding department. The second type of lot-size horizon is based on historical order sizes. Planners sometimes use different order sizes than proposed by ERP based on standard parameters. These decisions are usually based on a planners' insights about yield losses or future demands that are not at the disposal of ERP at that time. Due to these deviations in order size, it is relevant to consider 'actual' lot-size horizons in addition to ERP-based lot-size horizons. Whether the 'actual' lot-size horizons are correct, is validated by representatives from the planning department. Finally, insights from the ERP-based and 'actual'-based lot-size horizons were used to generate simulated lot-size horizons.

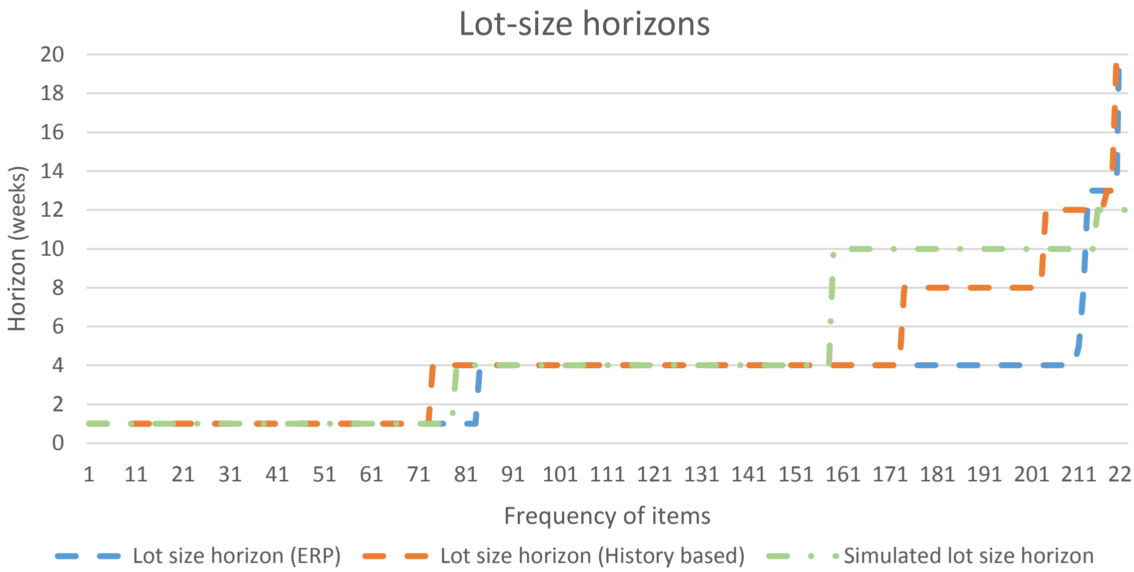


Figure 23: Frequency distribution of lot-size horizons

Scenario: ERP-based

From the analysis of ERP parameters and historical order sizes, it appeared that on 33% of the items, demands are aggregated by only 1 week (see Figure 23). As explained in Section 4.2.3 where the order proposal mechanism is described, the model's three lot-sizing scenarios aggregate the highest demands only by 4, 4, or 2 weeks respectively. Therefore, an extra lot-sizing scenario is developed that resembles the current planning function and its decisions. This extra lot-sizing scenario is developed with four lot-sizing categories wherein the fourth category aggregates demands by just one week. Obviously, this leads to a large number of setups. Taking into consideration the relatively long set-up times of the case company's upstream supply chain operations, this scenario led to an average utilization larger than 100%. Capacity requirements at the first workcenter are shown below in Figure 24. By increasing machine availability with extra capacity, utilization could be decreased. However, this led to high operational costs (see Table 13).

Total cost	Service level	Capacity requirements
772,450.64	59.7%	85.8%

Table 13: Performance ERP-based scenario

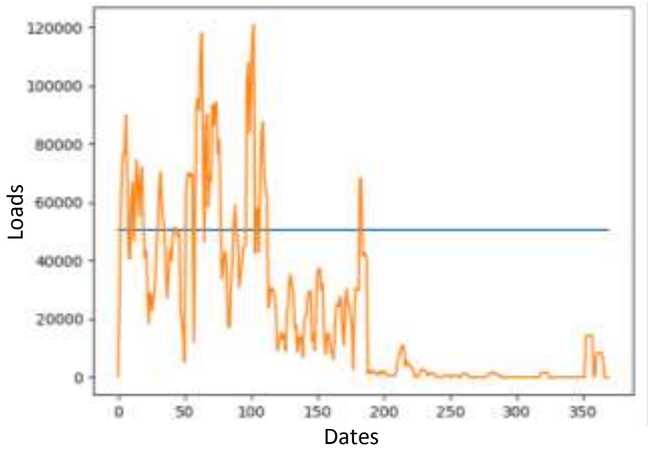


Figure 24: Capacity requirements (wc1)

Although the planning parameters that are used as input for the model correspond with current ERP parameters, still a significant difference is found between simulated and historical performance i.e., utilization, V-CLIP, and costs. This remarkable result can be explained when considering multiple echelons of the case company's supply network.

For many items produced upstream, downstream planning and lot-sizing decisions e.g., demand aggregations, are incorporated into the planning. In other words; when incoming demands at upstream echelons are already aggregated by planning and lot-sizing decisions from downstream operations, further aggregation is not necessarily needed. To explain this by an example, when planning at downstream echelon $\boldsymbol{D_{n-1}}$ would aggregate demands by 4 weeks, incoming demands at the preceding echelon $\boldsymbol{D_n}$ that exists upstream will be received as if they are aggregated by 4 weeks. This is illustrated in Figure 25. In this scenario, aggregating demands by one week at the upstream echelon $\boldsymbol{D_n}$ will effectively be equal to demand aggregation equal to four weeks.

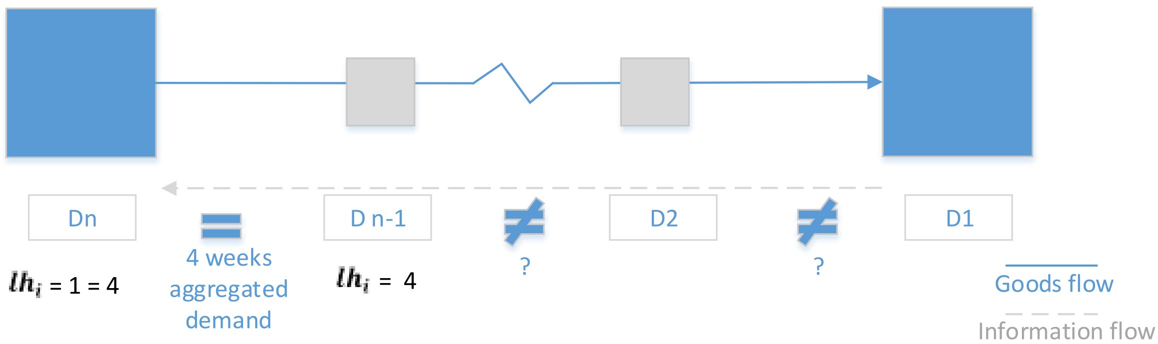


Figure 25: Multi-echelon demand aggregations

It is without the scope of this research to analyze the planning and lot-sizing decisions from downstream echelons. However, a more detailed analysis on planning and lot-sizing decisions from downstream echelons could potentially lead to better insights into actual demand aggregations throughout the case company's supply network. These insights can also be useful for central order coordination of the SCOP function. Analyzing the impact of demand aggregations throughout the supply network is therefore marked as a direction for further research. Instead, this research will generate a more realistic approximation of the case company's current planning function by demand aggregations ranging from 4 to 12 weeks. This corresponds with the three scenarios that were described in Section 4.2.2.

Scenario: Multi-echelon based

Because the ERP-based scenario leads to contradictory results compared to historical performance, a second scenario is made that is based on a so-called multi-echelon approach. Multi-echelon based lot-size horizons are determined and validated just like the 'actual' lot-size horizons were validated in coordination with representatives from the planning department. With this approach, multi-echelon stands for the consideration of planning decisions from downstream operations and its effects on lot-sizing from upstream operations. The multi-echelon approach resulted in lot-size categories shown in Table 14.

Lot-size horizons	Volume categories ERP based	Volume categories Multi-echelon based
12 wk	4%	21%
8 wk	8%	32%
4 wk	50%	47%
1 wk	38%	0%

Table 14: Current scenario

In comparison with the ERP based scenario, the multi-echelon scenario shows a large decrease in setup-costs and required capacity. Additionally, the service level approximates the average delivery performance that resembles current practices and was presented in Section 2. Therefore, studying lot-sizing decisions according to a multi-echelon based scenario is considered to yield a better approximation of current practices.

Total cost	Service level	Capacity requirements
€ 718,494.64	85.5%	79.9%

Table 15: Performance multi-echelon based scenario

5.3. Sensitivity analysis

With the sensitivity analysis is targeted to obtain better insights into the causal relations between; (I) demand aggregations and order quantities, (II) capacity requirements and available capacity, and (III) performance. Additionally, the robustness of the model is demonstrated.

In the development of the model, three different lot-sizing scenarios were incorporated. The different lot-sizes have a direct effect on order quantities that are generated. The model output for each scenario is summarized in Table 16. An overview of the lot-sizing scenarios can be found in Section 4.2.3, Table 7.

Producing large order quantities, with scenario 1, results in large peaks in capacity requirements. The peaks are costly since machine availability needs to be temporarily increased and large inventories result. These extra costs do not outweigh cost reductions due to fewer setups and changeovers in periods of low utilization. Additionally, overall delivery performance is decreased with 20.3 percent points (-20.3 p.p.) compared to current practices which makes it unfavorable to produce large order quantities as with scenario 1.

		Lot-size scenarios		
		Scenario (1)	Scenario (2)	Scenario (3)
Costs		€ 838,475.64	€ 778,916.80	€ 697,247.12
V-CLIP (CLIP)		65.2% (52.7%)	83.3% (68.8%)	91.4% (74.7%)
Utilization		78.5%	80.0%	83.1%
Difference with current situation (multi-echelon based scenario)	Costs	€ 119,981.00	€ 60,442.16	€ -21,247.52
	V-CLIP	-20.3%	-2.2%	5.9%

Table 16: Sensitivity analysis lot-sizing scenarios

The second scenario leads to similar order quantities as with the multi-echelon based scenario presented earlier in this section. However, the second scenario applies larger order quantities to low-volume items, reducing setups and changeovers but increasing inventory. Model output indicates that this leads to reduced utilization but higher operational costs (+8%) and similar delivery performance compared with current practices shown in Table 16.

The third lot-sizing scenario wherein the shortest lot-size horizons are applied, yields the best overall performance. Although capacity requirements are better leveled than with scenarios 1 and 2, the large number of setups cause an increase in required machine availability. At workcenters 1 and 2, where capacity requirements are highest, available capacity is therefore increased by 7% resulting in comparable operational costs as with current practices. Additionally, this configuration leads to improved on-time delivery performance (+5.9 p.p.). For completeness, Table 16 also includes conventional delivery performance, measured by CLIP. One can derive from CLIP compared to V-CLIP that it behaves by a similar trend under the different lot-sizing scenarios.

To find if further optimization is possible, the lot-size horizons from each volume category in the third scenario were separately adjusted (+1 and -1) to find if performance in terms of operational costs and on-time deliveries could be improved. From this iterative search, it appeared that the lot-sizing horizon for the **high volume** category could not be further optimized. Decreasing the high-volume category's lot-size horizon to 1 week led to increased utilization and even a small decrease in performance (see Figure 26). Increasing the high-volume category's lot-size horizon to 3 weeks reduced performance even more (-2.1 p.p.). Adjusting lot-size horizons for the **moderate volume** category also did not yield significant improvements. By increasing the horizon to 5 weeks, delivery performance decreased (-0.4 p.p.). By decreasing the lot-size horizon to 3 weeks, capacity requirements increase (+1.7 p.p.) and resulting improvements of delivery performance are negligible (+0.1 p.p.). At last, adjustments on **low volume** lot-size horizons neither improve performance. Results for the high, moderate, and low volume lot-sizing horizons are graphically depicted in Figure 26, Figure 27, and Figure 28.

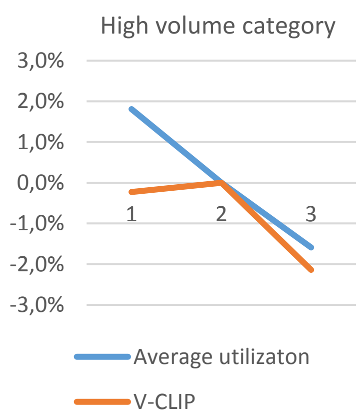


Figure 26: High volume category

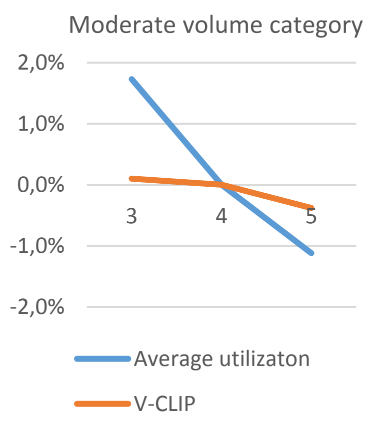


Figure 27: Moderate volume category

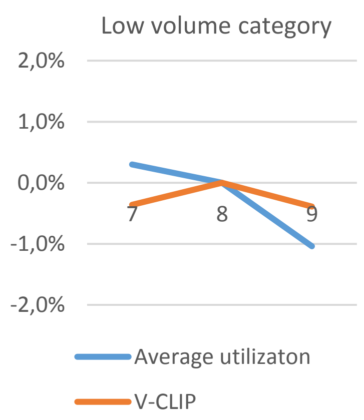


Figure 28: Low volume category

5.4. Best mix

From the approximation of the current planning model in Section 5.2, it became clear that in terms of utilization and V-CLIP, it is infeasible to have weekly changeovers and setups (see Table 13). The numerical analysis of lot-size scenarios in Section 5.3, demonstrated that extraordinary large lot-size horizons led to large repetitive peaks in capacity requirements, dramatically affecting tardiness. From the sensitivity analysis, it became apparent that the best mix of the case company's demand aggregations and order release consists of 2-week, 4-week, and 8-week lot-size horizons for respectively high, moderate, and low volume categories. To justify the increase in setups and changeovers compared to current practices, machine availability on workcenters 1 and 2 is increased by 7%.

5.5. Insights

Now that the model output is numerically compared and sensitivity analysis is executed, the following insights are obtained:

1. What is the model output under parameters that correspond with the current situation?
Upstream planning decisions are affected by downstream planning and lot-size. To provide an accurate representation of the current situation, multi-echelon analysis on ERP parameters and planning decisions is required. Model output under lot-sizing parameters that correspond with the current situation, based on a multi-echelon perspective, is presented in Table 15.

2. Is the model output, based on the current situation, in line with the actual output?
Numerical analysis demonstrated that a multi-echelon analysis on planning decisions from the whole supply network would provide the best representation of actual performance. However, this study received most focus on planning decisions from one upstream echelon and therefore approximated a multi-echelon scenario by using insights from representatives of the planning department. This led to three volume categories and corresponding lot-sizing horizons ranging between 4 to 12 weeks. This approximation of the current situation led to model output that is comparable with actual performance (85.5% versus 86%). Note that the actual performance of the Injection Molding department is extensively reported in Section 2.3. Resulting operational costs from the model output were validated by representatives from the planning department and administration office.

3. What happens with the model output when different lot-sizing decisions are applied?
It is demonstrated that reduced order quantities lead to reduced tardiness. However, reducing order quantities leads to more setups which increases utilization. As is described for the 'best mix', available capacity may need to be (temporarily) increased to justify higher capacity requirements due to an increased number of setups. Clearly, an optimum exists between the number of setups, utilization, operational costs, and overall on-time delivery performance.

4. What happens with the model output under different available capacity?
Sensitivity analysis was carried out on the third lot-sizing scenario. By increasing available capacity on workcenters 1 and 2, tardiness was reduced and V-CLIP improved. In other words, by increasing available capacity the consequence of reducing order quantities can be offset. By increasing available capacity at workcenters 1 and 2 just as in the best mix, the effectiveness on V-CLIP and utilization gradually decreases as shown in Figure 29.

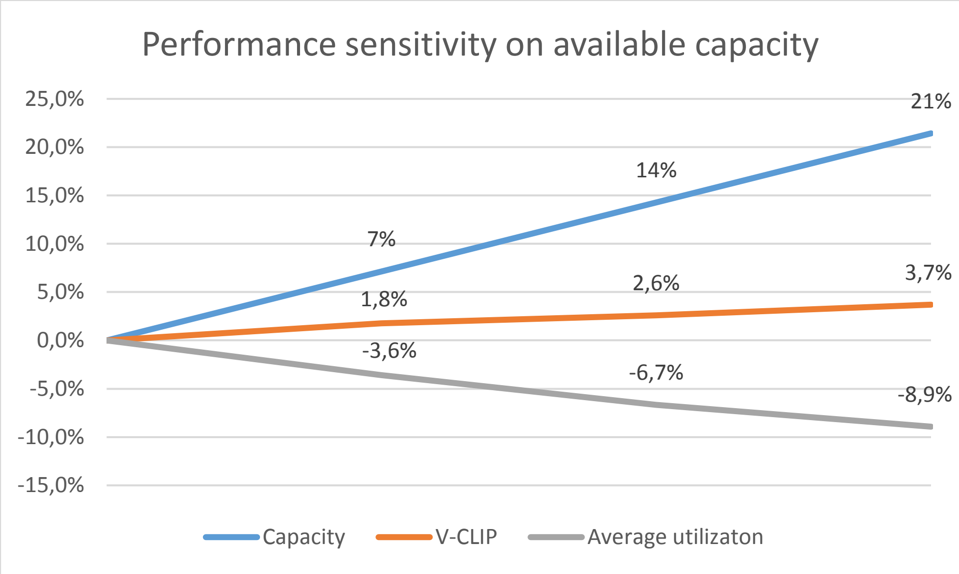


Figure 29: Sensitivity of utilization

5. What is the best mix given the targeted delivery performance?

When the planning was conceptualized in Section 3, functional requirements were listed for the entire system, i.e. the case company's complete supply network. Based on the system requirements, requirements were listed for the operations in the scope of this research, i.e. the case company's upstream supply chain operations. Requirements concerned delivery performance and operational costs. It was determined that at least 90% V-CLIP is required by operational costs that do not exceed current costs. By applying the third scenario and increasing available capacity on workcenters 1 and 2 by 7%, a delivery performance of 91.4% can be realized by a cost reduction of € 21,247.52 (-1.0%) compared to operational costs of current practices.

6. Conclusions & Recommendations

Now that the numerical results have been analyzed and reported, overall conclusions are presented in this section. Conclusions will be given by the structure of the research questions that were formulated and presented in Section 1.3. This section will conclude with a discussion wherein implications and recommendations are given.

6.1. Conclusions

This research is focused on the case company's planning design and therewith the decoupled supply and control structure that is applied for supply chain operations planning. Throughout the research, different findings and conclusions emerged that are presented below.

6.1.1. Conclusions by research questions

- *How should the planning system of upstream supply chain operations be designed?*

Due to the vertical integration of the case company's supply network and product characteristics such as short life-cycles and complex configurations, a strong urge exists for a well-organized SCOP function. It is the SCOP's responsibility to coordinate the release of materials and resources in the supply network such that customer service constraints are met at minimal costs. In the current situation, the case company's supply and control structure is decoupled into two structures wherein differences exist in information available throughout the supply network. This withholds the SCOP function from central coordination, resulting in insufficient on-time delivery performance.

After the current planning design was compared with formal supply chain operation's control structures it was found that the SCOP's anticipation function, responsible for realizing an order schedule that is lead-time feasible, consists of elements that are useful for developing the case company's SCOP function. The fundamental elements consist of demand planning, order release, and execution.

After that the model was conceptualized and translated into mathematical expressions, the outcomes from different releases of materials and resources could be numerically compared by on-time delivery performance and operational costs. From this numerical analysis, the impact of limited information available throughout the supply network became clear. When planning only with the information that is available upstream the supply chain, frequent setups and changeovers led to high operational costs and exceptionally poor on-time delivery performance. When planning based on information available throughout the whole supply network, supply and demand from upstream and downstream operations could be better aligned resulting in reduced operational costs and improved on-time delivery performance. It is therefore important that the planning design of upstream operations relies on a central coordination and release mechanism that is represented by the company's SCOP.

- *How should on-time delivery performance of upstream supply chain operations be measured?*

To assess whether the SCOP function coordinates the release of materials and resources such that on-time delivery performance constraints are met at minimal operational costs, robust performance indicators are required.

The case company defines delivery performance as the fraction of demand that is met within a specified lead time. However, analysis of the current situation demonstrated the case company's metric for internal on-time delivery performance does not reflect the fraction of demand but considers order-lines instead. Additionally, it is found that current performance measurements are based on unreliable data. Currently, the case company measures internal on-time delivery performance by comparison of a job's finish date and due date. Analysis demonstrated that on 35% of the jobs produced late by all upstream operations in 2017, finish dates were registered before all items were received. Measuring on-time delivery performance of upstream operations in 2017 by delivery dates instead of finish dates gives a more reliable performance indicator and decreased average delivery performance by 17.1 percent points.

To improve current measurements, a metric is defined that represents the fraction of demand that is met within a specified lead time. More specifically, a method of measurement is developed that represents the fraction of demand that is met on-time, and the fraction that is delivered with certain tardiness. Tardy deliveries' contribution towards performance reduces in proportion to the deliveries' tardiness by partial deliveries' cumulative distribution function. The fraction of demand that is not delivered at all, does not make any contribution to the performance. When applying the improved performance metric that is referred to as 'V-CLIP', outcomes are slightly higher due to the consideration of the fraction of demand that is delivered and the contribution of tardy deliveries.

- *How should the planning system of upstream supply chain operations be modeled and how do model parameters influence on-time delivery performance and operational costs?*

Based on elements from the anticipation function developed by Jansen et al. (2013), a model is developed that consists of three mechanisms wherein (I) order proposals are generated, (II) load balancing is applied, and (III) on-time delivery performance is determined by V-CLIP. Additionally, operational costs are calculated based on setups, inventory carrying costs, and machine availability. To secure a feasible scope but include all characteristics of upstream supply chain operations, one operation is modeled that is represented by four interdependent workcenters.

Numerical comparison and sensitivity analysis demonstrated that order releases, either multi-echelon or local based, have a large impact on utilization, costs, tardiness and therewith performance. To find how the release of materials and resources can be best coordinated by the case company's SCOP, three lot-sizing scenarios have been compared wherein different order proposals were generated based on items' average demand. Items' average demands were used to develop three volume categories that were used for lot-sizing decisions. Typically high volume items contained small demand aggregations, securing balanced capacity requirements, and low volume items contained large demand aggregations to justify setup costs. Results show that an optimum exists in demand aggregations for each volume-category in terms of on-time delivery performance under consideration of constrained operational costs. Also, it was found that current order releases can be improved by applying smaller demand aggregations, resulting in balanced capacity requirements and reduced supply chain investment in inventories. Therewith, the difference in commonality, i.e. difference in order size upstream and downstream the supply network, can be reduced. With an increase of 7% of the available capacity at workcenters 1 and 2, V-CLIP can be increased towards 92.1% with similar operational costs as in the current situation.

With all sub-questions answered, an answer to the main research question can be formulated. It can be concluded that the current coordination of order releases can be improved with a central release mechanism. With centralized decision making over a multi-level supply network, consisting of internal production and internally subcontracted production, differences in information and differences in commonality upstream and downstream the supply network can be reduced. It is found that better alignment of demand aggregations throughout the supply network, leading to order proposals used by the central release mechanism, can reduce tardiness and improve internal on-time delivery performance without increasing operational costs.

6.2. Discussion

Besides the findings and conclusions that emerged throughout this study, a reflection of the research is provided below. The reflection consists of implications of this study for scientific research and for the case company.

6.2.1. Implications for scientific research

Based on the above-presented findings and conclusions, this study has made three contributions to existing academic literature. First, existing central release mechanisms, which are studied in detail by anticipation and clearing functions, represent a supply network that belongs to a single organization wherein information is shared freely (Hackman & Leachman, 1989; Jansen et al., 2013; Missbauer, 2011). However, this study has demonstrated it is not straightforward that a supply network is designed accordingly in practice. Therefore, this study compared a release mechanism in a multi-level supply network wherein differences exist in information available upstream and downstream the network. By this study it was found and confirmed that a difference in information available leads to sub-optimal delivery performance and operational costs. Secondly, this study adds to existing literature by the development of a delivery performance metric that represents the fraction and the extent to which deliveries are made within a specified lead time. To the best of our knowledge, this combination is not represented by other existing delivery performance metrics that are used for assessing internal delivery performance. Additionally, this measure of on-time delivery performance has been used in the comparison and assessment of order release mechanisms which provides a use-case example of the newly proposed service measure. Thirdly, this research adds to the existing literature by comparing the impact of different demand aggregations from the central release mechanism to utilization and therewith delivery performance and operational costs. By grouping items into different volume categories and linking these to volume dependent demand aggregations, different order quantities are generated. By comparing different order sizes, it is revealed that in the context of this particular study, on-time delivery performance could be improved without increasing supply chain investment compared to current practices. When reviewing multiple production units or even a full supply network by the impact of demand aggregations, this approach could potentially allow the central coordination mechanism to make further improvements.

6.2.2. Implications and recommendations for the case company

This research has shown the case company the potential value of centralized control in the multi-level supply network that consists of Prodrive Technologies and Prodrive Mechanics. Although it is confirmed by academic literature that decoupling of production units is common in vertically integrated supply networks, decision making can only be optimized if information between upstream and downstream operations is shared and taken into consideration with order releases. In addition to the vertical integration of operations, vertically integrated information is required.

Based on this insight, a number of recommendations are given to the case company:

Measure on-time delivery performance by V-CLIP
It is recommended to measure internal on-time delivery performance by one standardized metric such that the performance of different operations is comparable over time. During this research, a metric is developed that is conform to what the case company intends to measure; 'the fraction of demand that is met within a specified lead time'. It is recommended that the newly developed metric, referred to as V-CLIP, will be used for future measurements of internal on-time delivery performance. Compared to the current method of measurement wherein confirmed line item performance is measured, V-CLIP yields a slightly higher output since also tardy deliveries contribute to overall performance. However, this research also revealed that current performance is actually lower than what is measured due to the unreliable registration of jobs' finish dates. It was found that 35% of the jobs produced late by upstream operations in 2017, finish dates were registered before all items were received. Since material comes only available once deliveries are made, it is recommended to start measuring delivery performance by delivery dates instead of finish dates. Also, it is recommended to improve registration of finish dates such that the reliability of data is enhanced. In the near future, the company's existing Manufacturing Execution System allows for accurate registration of partial deliveries and jobs' finish dates on operations-level. This data can then be compared with existing delivery registrations made at the warehouse. Depending on how reliable data will be registered with MES, V-CLIP allows comparing future delivery performance by data from MES and warehouse. Potentially these performance outcomes can then also be compared to assess operations' and warehouse's performance.

Analyze demand, inventories, and order sizes from a multi-echelon perspective
Although a multi-echelon analysis received limited attention in this research, it is demonstrated that planning decisions can be improved when demands, inventories, and orders sizes are considered from a multi-echelon perspective. Therefore, it is recommended to conduct further research with a multi-echelon focus on the impact of order release decisions. In this context, extra insights could be obtained by the inclusion of multi-level demand and buffers in the form of inventories and safety times throughout the supply network.

To facilitate this kind of future research it is strongly advised to collect data on forecasts, (intermediate) demands, ERP parameters, replanning and rescheduling, and data that represents the execution function e.g., setup times, cycle times, yield loss, deliveries, and order confirmations. Currently, only data is available from forecasts, customer demands and the execution function. With this research, it is demonstrated that it would be valuable if also intermediate demand and intermediate demand changes are studied in future research.

Reduce difference in commonality between upstream and downstream operations
Numerical analysis of the impact from current order releases on operational costs and on-time delivery performance has demonstrated the potential of reducing currently applied order sizes. By applying smaller order sizes, on-time delivery performance increases due to leveled capacity requirements. Additionally, supply chain investments in intermediate inventories between upstream and downstream operations can be reduced. Because smaller order quantities directly affect the

number of setups, a small increase in capacity may be required to cover for uncertainties. Analysis demonstrates that to some extent, savings in inventory investment may outweigh costs of a capacity increase, resulting in improved delivery performance and reduced operational costs compared to current practices. Note that this implication especially concerns Prodrive Technologies' Injection Molding department because this study is built upon historical data and the operational configuration of only this department. However, the model is developed such that the behavior of other operations can also be simulated. Therefore, it is recommended to extend this analysis to other (upstream) operations to find if delivery performance or operational costs of the current situation can be improved by order release decisions.

Because numerical analysis revealed the potential of decreased order sizes for the Injection Molding department, it is recommended to start a program for reducing setup and changeover-time. High investments are made in the automation and efficiency of upstream operations. With robots, automated guided vehicles, and automated warehouses, a 'lights out factory' is realized. However, the Injection Molding department still relies on conventional setups that are labor intensive. Therefore, it is recommended to invest in the potential of reduced setups and changeovers bringing Prodrive Technologies closer to the realization of a 'lights out factory' in the high-tech industry.

Reduce difference in information available between upstream and downstream operations

At last, it is recommended to facilitate upstream operations executed by PM with information from downstream. Due to the multi-level supply structure of PT and PM, material requirements are currently communicated through stock-transport orders. Because stock-transport orders don't incorporate changes in demand, downstream demand changes are not automatically communicated through rescheduling proposals to upstream operations. Therefore, it is recommended to make upstream material requirements dependent on downstream production orders instead of inter-subsidiary stock-transport orders. By this simple adjustment in the ERP, rescheduling proposals can be automatically communicated if downstream demand changes. This matter received limited attention in this research since only one upstream production unit was modeled and downstream demands were considered only from one point in time. However, this research has shown the potential of reducing differences in information available throughout the supply network and therefore the implementation of this recommendation is an important step forward. It is likely that under the availability of rescheduling proposals and robust on-time delivery performance metrics, order acceptance and replanning decisions will require more attention in the future.

6.2.3. Limitations & Future Research

Despite the contributions of this research, also a number of limitations were encountered. The largest limitation of this research is that only a single production unit was modeled and downstream demand from intermediate operations was not at disposal. Instead, incoming demands were modeled based on historical customer demands. Through the numerical study and comparison of results, it appeared that downstream planning decisions had indirect effects on upstream planning. Because no intermediate demands were available, these effects were difficult to retrieve from the ERP parameters that were available. However, in correspondence with representatives from the planning department, effects of downstream planning decisions were represented such that numerical analysis of this study could still demonstrate the potential of multi-echelon planning.

If in future research intermediate demands would be incorporated, the impact of planning decisions throughout the whole supply network can be further studied. Additionally, with the availability of intermediate demands, V-CLIP can be extended by the inclusion of downstream consumption, as it was referred to in this research. When considering the full supply network in future research, it is recommended to include interdependencies of workcenters within one production unit. Previous studies have generalized output from one production unit by only modeling the bottleneck workcenter. In the context of the case company's manufacturing network, interdependent workcenters lead to shifting bottlenecks which require a representation of all workcenters as is applied in this research.

Rolling planning horizon

Another limitation of this research concerns the consideration of future demands from only one point in time. Hence, the impact of rescheduling and demand changes received little attention in this research. When intermediate demand data is available and empirical data is available about rescheduling proposals, a planning under a rolling horizon can be studied (Yang & Jacobs, 1999). By considering a rolling planning horizon, the planning functions' decisions regarding replanning can be optimized by defining a frozen internal, wherein no replanning is allowed, and a replanning interval, wherein planned production may still be rescheduled.

Buffers

Earlier in this report, it was remarked that downstream customer service levels say 95%, do not necessarily require upstream service levels of 95%. Therewith, the potential of a comparison from service levels throughout the supply network was addressed. However, this research received limited focus on buffers throughout the supply network, e.g. safety times, safety stocks that can be used to cover for uncertainties in supply or demand. Although this research included the effects of upstream inventories, no integral focus exists on buffers throughout the whole supply network. Jansen et al. (2013) argued that optimization of safety stocks under rolling planning is to-date an unsolvable and intractable problem[6]. However they also mention that earlier experiments showed that eliminating safety stocks "is especially appropriate in situations where value added downstream in supply networks is relatively small" (2013, p. 257). This contradicts with Prodrive Technologies' supply network and therefore it is considered relevant to gain further insights into improvements of planning decisions and buffers within a supply network as from Prodrive Technologies.

[6] to-date concerns 2013

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Appendix

A Introduction

A.1 Organization chart

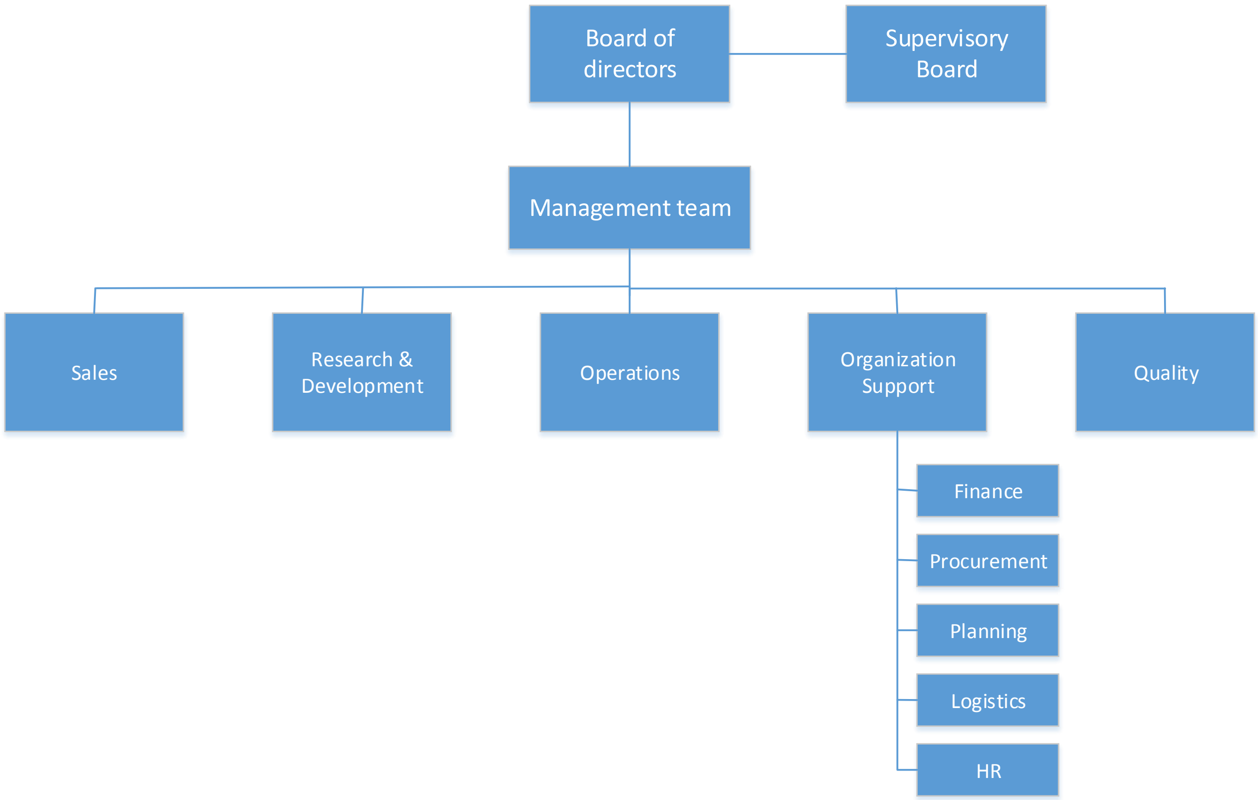


Figure 30: Organizational chart

A.2 Cause and effect diagram

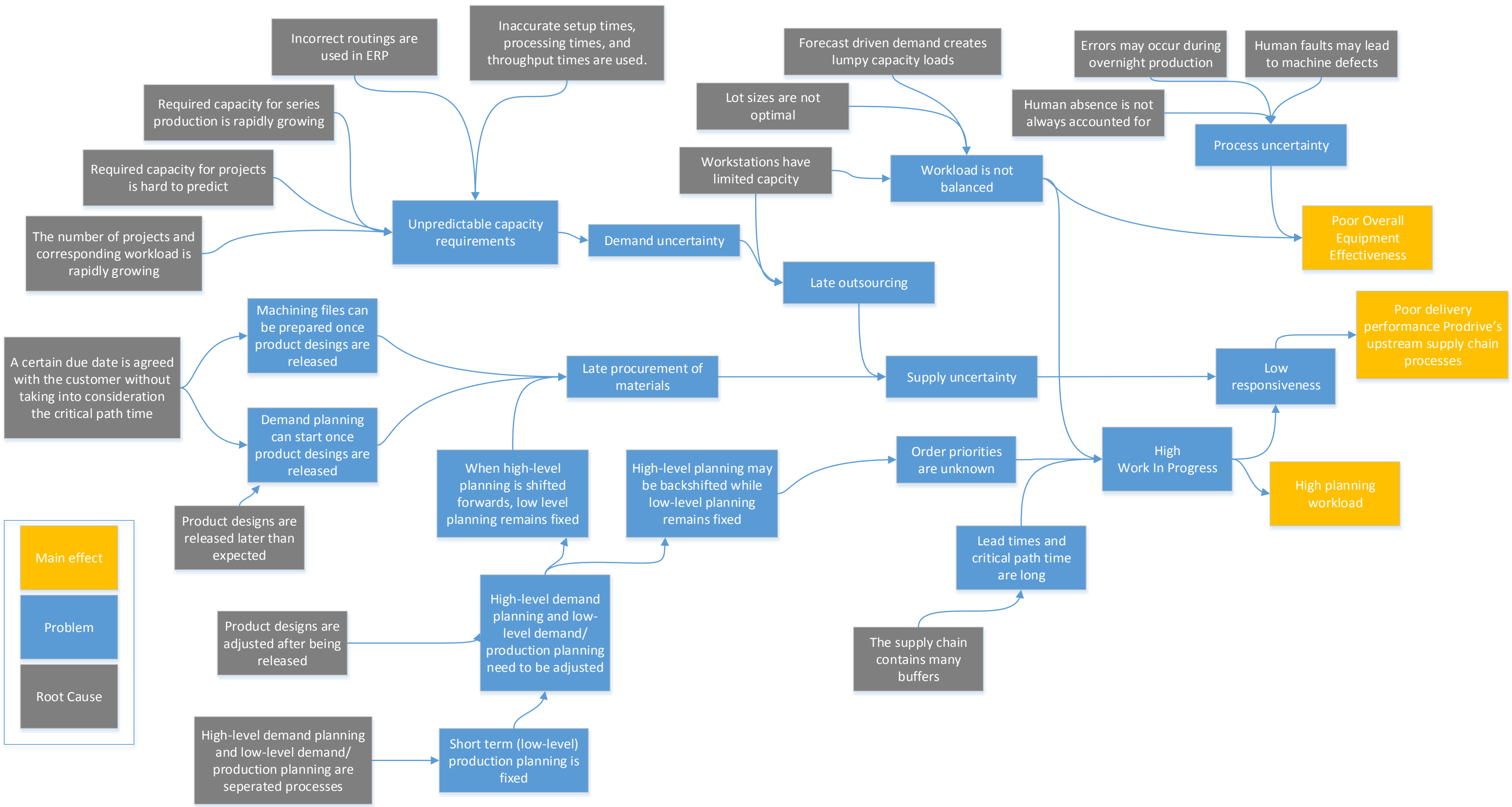


Figure 31: Cause and Effect diagram

B Data reduction

From the order history that is available, a selection was made of all orders processed by Prodrive Mechanics over 2017. From these orders, only the ones that were processed by Machining, Injection Molding, and Magnetics are considered. To determine tardiness, scheduled end dates can be compared with actual end dates (i.e., finish date of order confirmed by warehouse). Because not all orders are logged correctly during the production and warehouse processes, the data contains many incorrect or missing information. Only 68% of the orders in the data set is actually confirmed by warehouse. Because it is questionable whether all confirmations were logged correctly by the formal process, incorrectly logged order confirmations are deleted from the data set. More specifically, orders are assumed to be logged incorrectly when the confirmation date is more than 31 days before or more than 31 days after the scheduled end date. This elimination of outliers reduced the available data by 3% to 65%.

	count	count of confirmed	% confirmed	count of order with tardiness ≤ 31 days	% confirmed correctly	count of order with tardiness ≥ -31 days	% confirmed correctly
Machining	5853	4108	70%	3990	68%	3958	68%
Injection Molding	529	290	55%	288	54%	263	50%
Magnetics	459	237	52%	226	49%	225	49%
totals:	6841	4635	68%	4504	66%	4446	65%

Table 17: Data reduction

C Determining due dates

Items produced by Machining are produced at a subsidiary manufacturing plant named PM. This results in different lead time as compared to operations carried out at PT. Lead times play an important role in the determination of due dates, tardiness, and therewith delivery performance. To prevent ambiguity in performance measurements between PT and PM, it is described below how these differences in lead times are taken into consideration when determining due dates and tardiness.

To compare the definition of lead times within PT and PM the Injection Molding department provides an interesting example because Injection Molding is moved recently from PM to PT. Due to the movement of Injection Molding in February 2018, different lead times are applied since then, but delivery performance based on due dates still has to be comparable with the former scenario wherein Injection Molding was still part of PM. When Injection Molding was still part of PM, items were 'procured' with a standard inter-subsidiary transport time of 1 day (see Figure 32). This transport time applies for all jobs processed at PM. Since the movement, goods are still physically transported from the production site to the central warehouse and to the subsequent operation. However, just as with PT's operations, Injection Molding does no longer require inter-subsidiary transport time. Therefore, also internal lead time between the production site and the central warehouse is set to a standard of 3 days. Note that lead time as in the old scenario equals internal throughput time from the new scenario when we assume inter-subsidiary transport time to be deterministic (i.e., B2conf + Purch. order = Imconf = 3 days). Under this assumption, the definition of due dates and end dates is the same for production at PT and production at PM. Therewith, delivery performance at both plants is comparable.

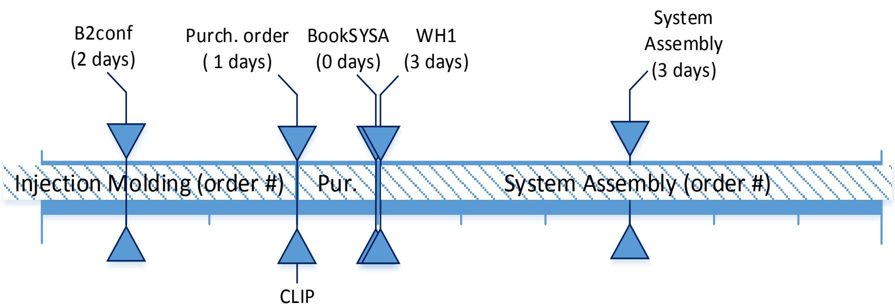


Figure 32: Lead times at PM

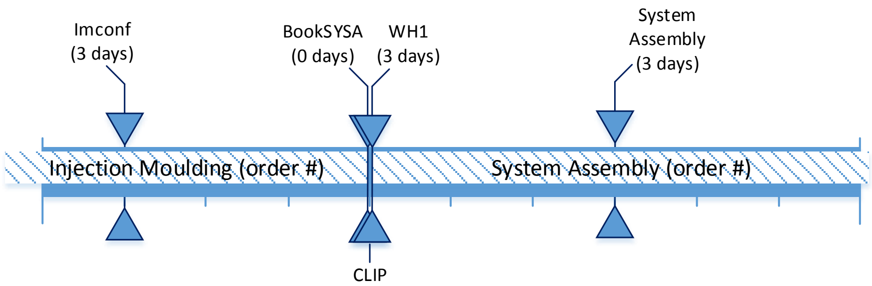


Figure 33: Lead times at PT

For completeness, another example is added of lead times from Machining, executed at PM. These lead times still includes inter-subsidiary transport time similar as in the old scenario of Injection Molding. The example is graphically depicted in Figure 34.

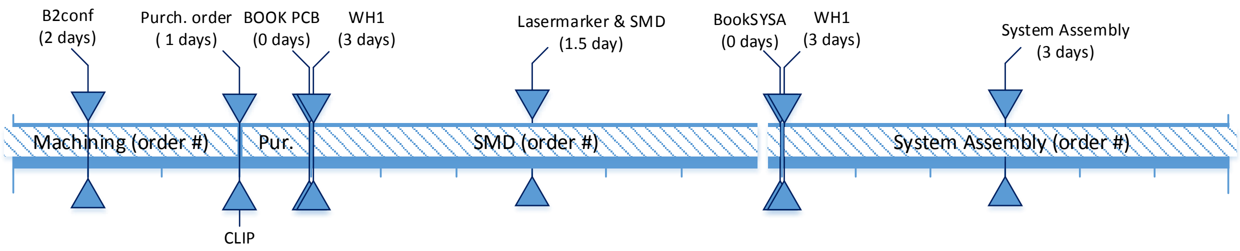


Figure 34: Lead times at PM – Example Machining

D Distribution of partial deliveries

In Section 2.3 it was already pointed out that 35% of the tardy jobs were registered as finished while items produced at these jobs were received later than the due date. Obviously, this gives misleading results. To demonstrate that items are actually received significantly later than the orders were due, tardiness of partial deliveries is plotted in Figure 35.

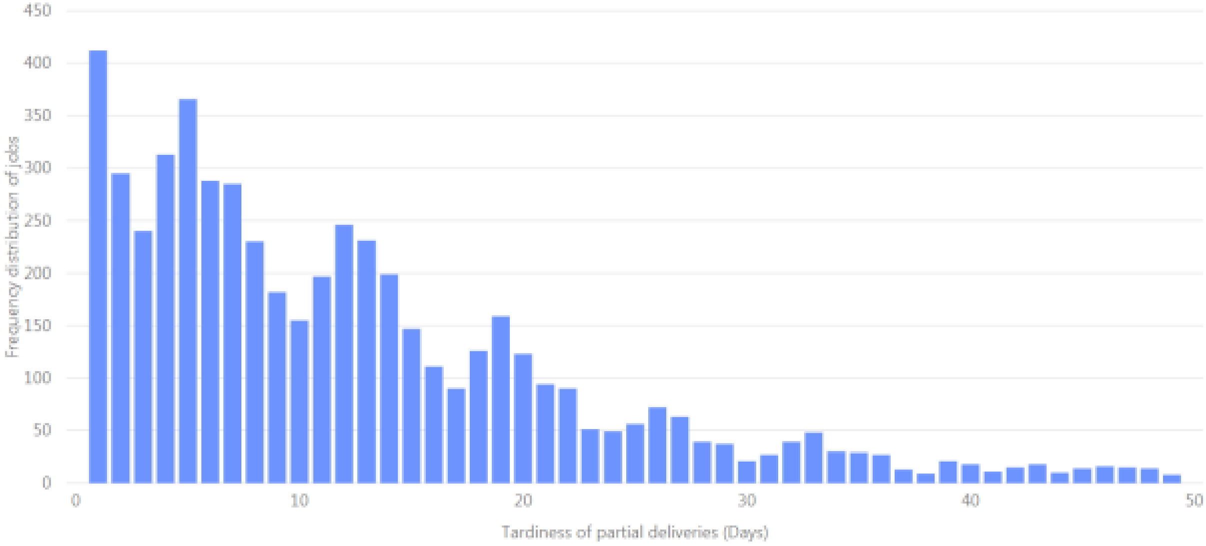


Figure 35: Frequency distribution of partial deliveries' tardiness

Because the cumulative distribution function of all deliveries is needed to determine V-CLIP, a statistical distribution was fitted to the tardy deliveries. Two software programs were used for distribution fitting. First, a rough analysis was made with EasyFit to determine what demand distributions were appropriate. Then, by means of a more detailed statistical analysis with the program R, it was tested what distributions gave the best fit. From the analysis, it appeared that tardy deliveries could be best approximated by a Negative Binomial distribution ($T_{partial,j} \sim NB(1, 0.08755)$). The Negative Binomial plot versus the sample data plot is shown in Figure 36.

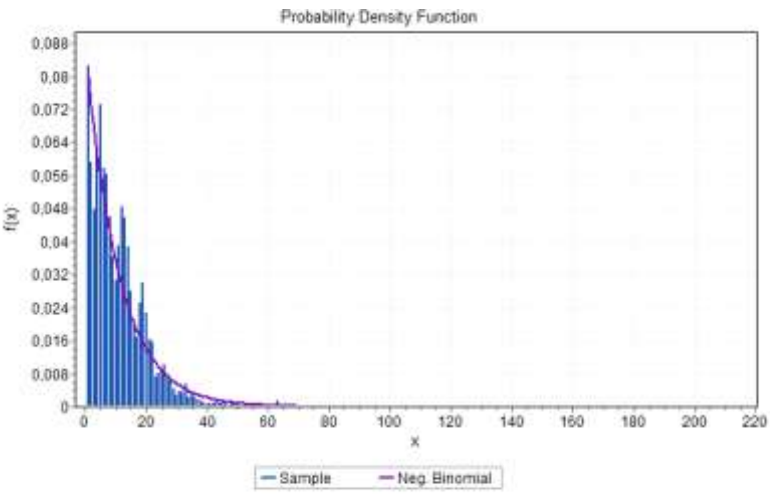


Figure 36: Negative Binomial probability density function versus sample data

E Demand distribution

To determine the demand fluctuations that the case company's supply network is confronted with, sales orders are analyzed. Over a period of several months, data was gathered from sales orders which is shown in Figure 37. To aggregate sales data, demand changes were neglected and only the final sales orders were considered.

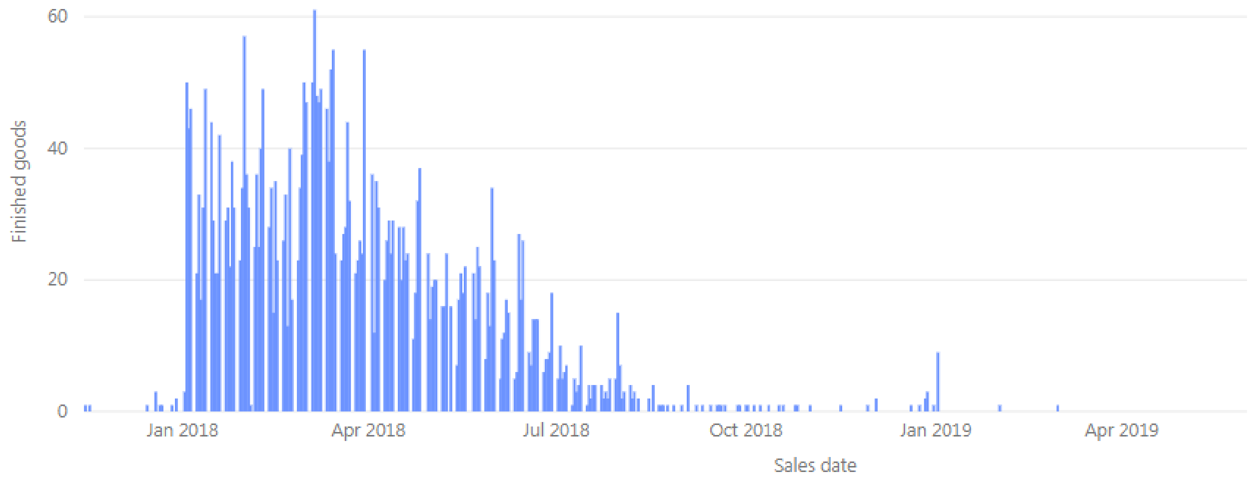


Figure 37: Sales orders Q1 2018

To analyze the demand, and create multiple scenario's later, different distributions were fitted to the empirical data. To obtain an adequate fit, sales were aggregated on customer level and item level. However, neither of those aggregations led to good results. Two software programs were used for distribution fitting. Just as with distribution fitting to Tardiness described in Appendix D, first a rough analysis was made with EasyFit and later a more detailed analysis was made with R.

The first analysis, carried out with Easyfit provided results allong three tests, (I) the Kolmogorov-Smirnov test, (II) the Anderson-Darling test, and the (III) Chi Squared test. Based on the outcomes of those three tests, a weibull distributed demand seemed to have the most promising fit.

Kolmogorov-Smirnov test:
Although the sales order history cotains discrete values, the test assumes a continious distibution. With the test, the hypothesis is tested whether the data follows a particular distribution, in this case a weibull distributed demand. Since the test statistic is greater than the critical value, the hypothesis was rejected.

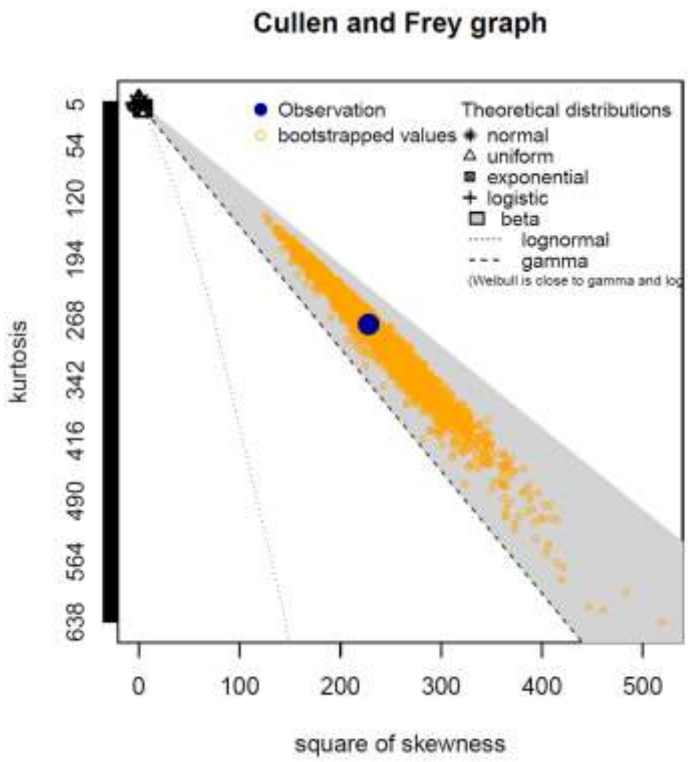
Anderson-Darling test:
Just as with the above described K-S test, it is checked whether the critical value is under the test statistic. Also for this test, the hypotheses were rejected, indicating that no adequate fit is found between the sales history and the weibull distribution.

Chi Squared test:
The chi-square test is an alternative to the Anderson-Darling and K-S tests. In contrast to the previous tests, this test allows for discrete distributions. For all levels of significance, the test statisctic exceeded the critical value meaning that no adequate fit was found between the sales history data and a weibull distribution.

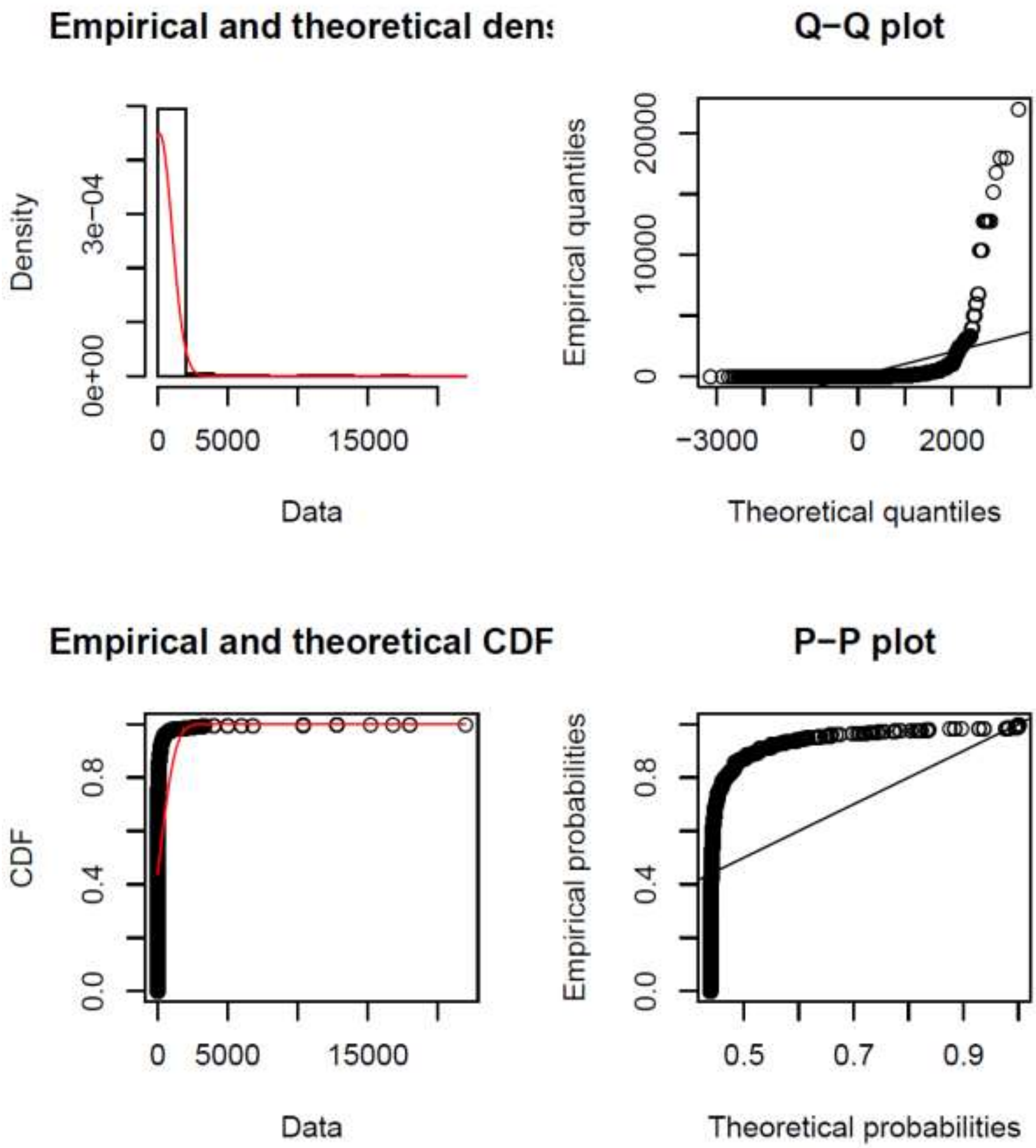
Although outcomes from Easyfit already demonstrate that even a Weibull distribution did not result in an appropriate fit, a second analysis was made with R. This only confirmed that no appropriate fit could be found. Therefore, it has been decided that only empirical demand data will be used instead.

R script:

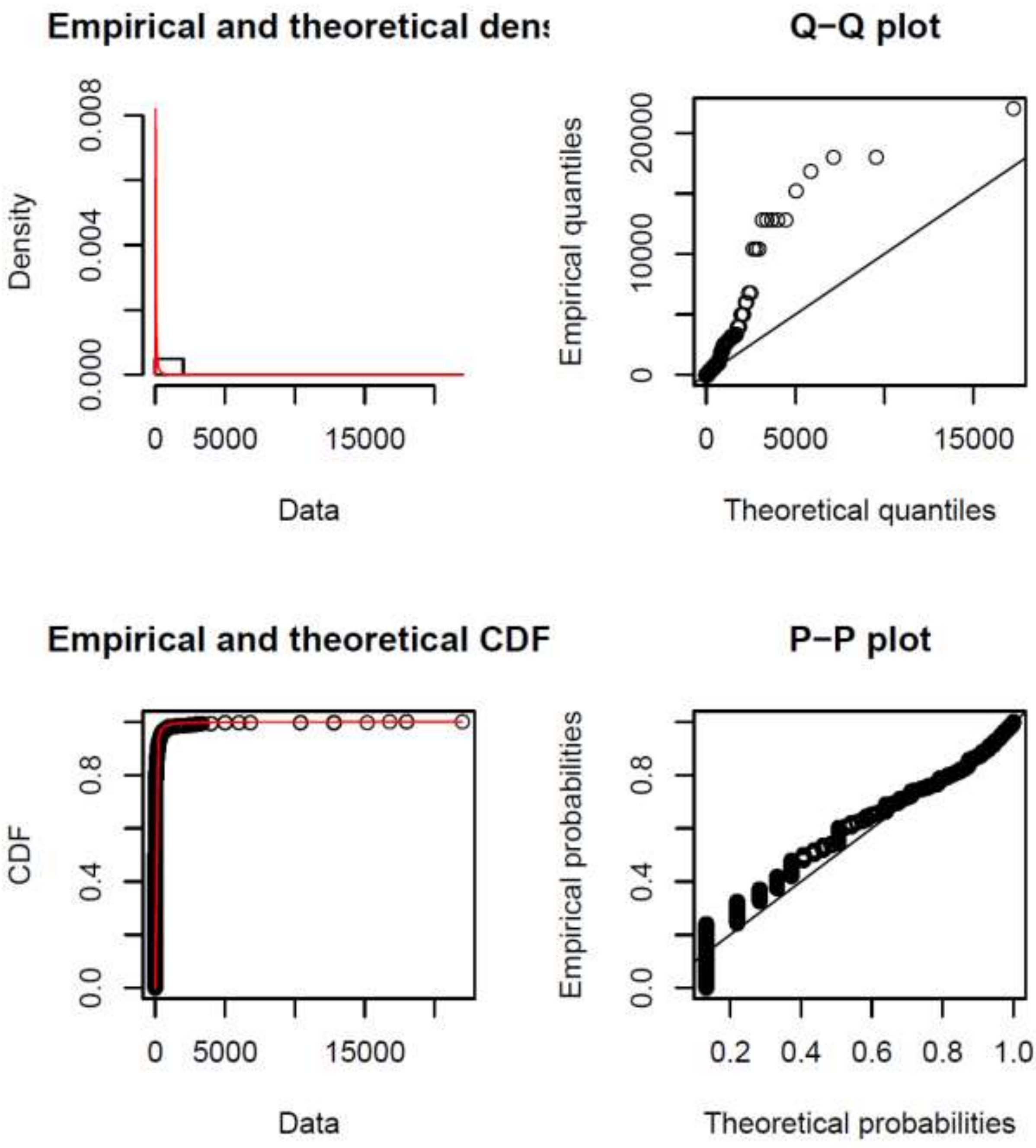
```
> setwd("myworkdirectory")

> library(fitdistrplus)
> library(logspline)
> library(survival)
> library(MASS)
> library(moments)

# read the data
Demand_history <- read.csv("Sales orders.csv", header = TRUE, row.names = NULL, nrows =
4277)

> summary(x)
       Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
        1.0     2.0     6.0   137.8    36.0 22000.0

> descdist(x, discrete = FALSE, boot = 5000)

       summary statistics
       ------
       min:  1   max:  22000
       median:  6
       mean:  137.7816
       estimated sd:  889.9189
       estimated skewness:  15.10891
       estimated kurtosis:  273.7145
```



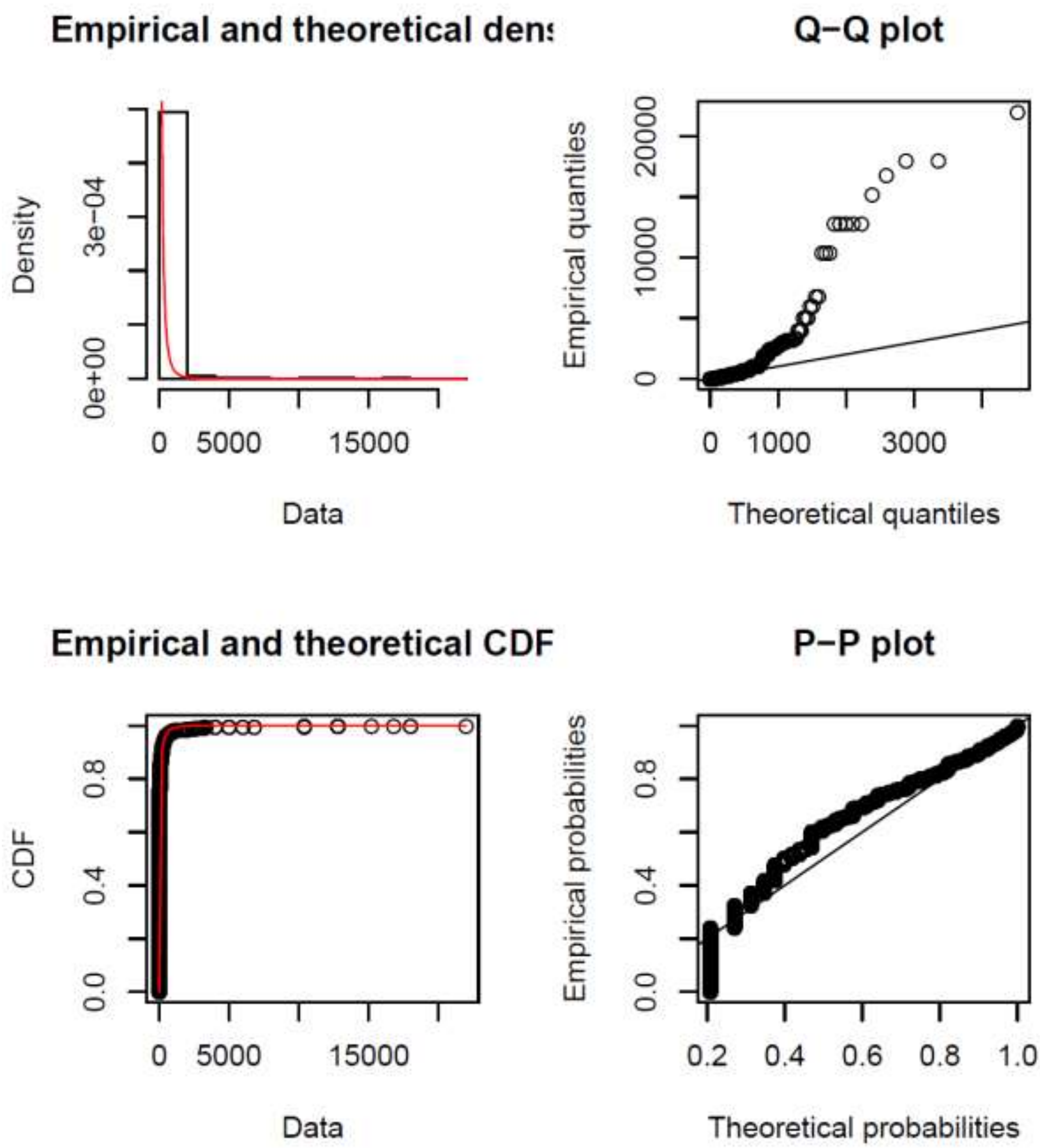
```r
# Based on the previous plot we try different distributions

fit_n <- fitdist(x, "norm")
summary(fit_n)
plot(fit_n)
```



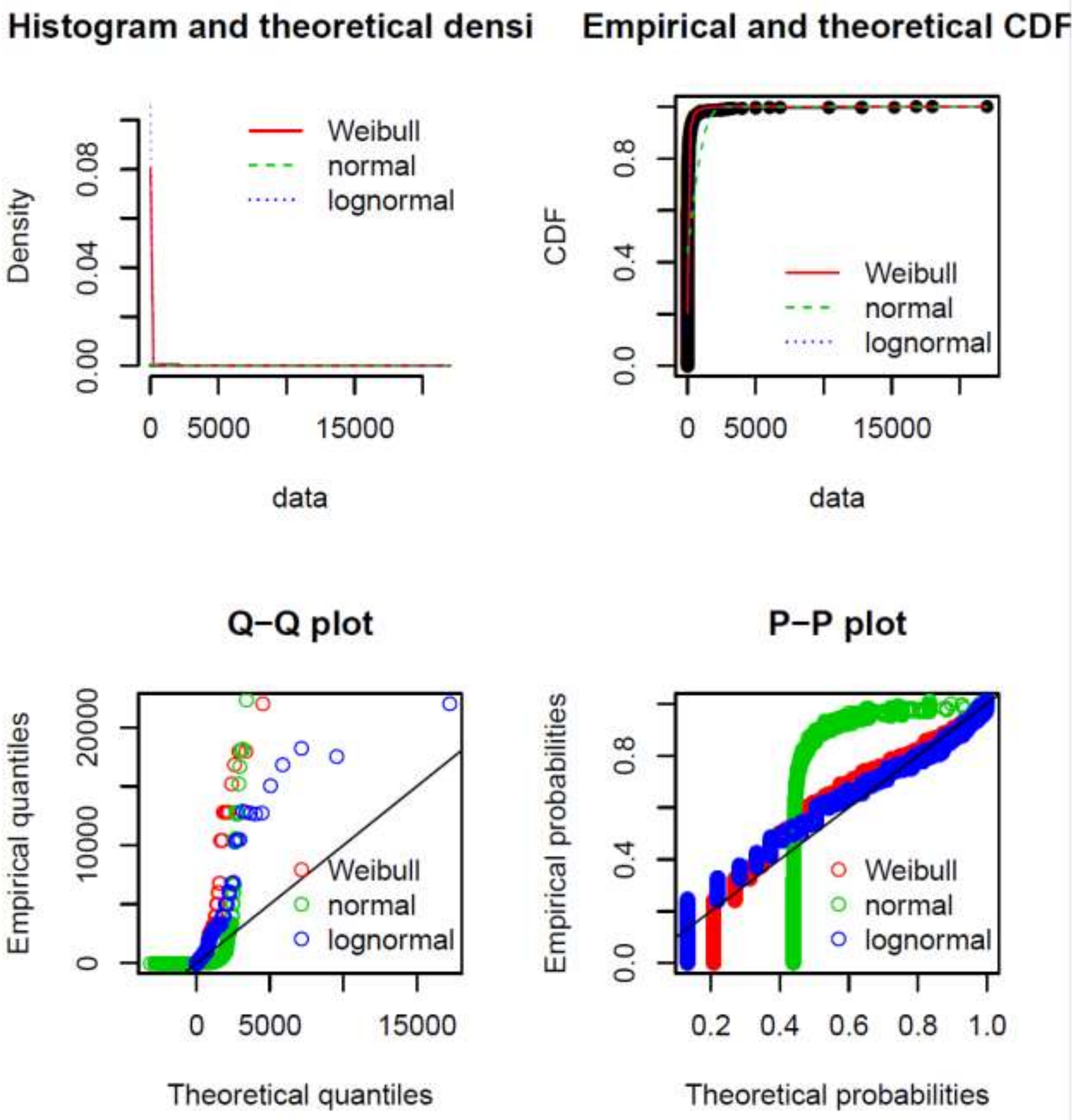
```
fit_ln <- fitdist(x, "lnorm")
summary(fit_ln)
plot(fit_ln)
```



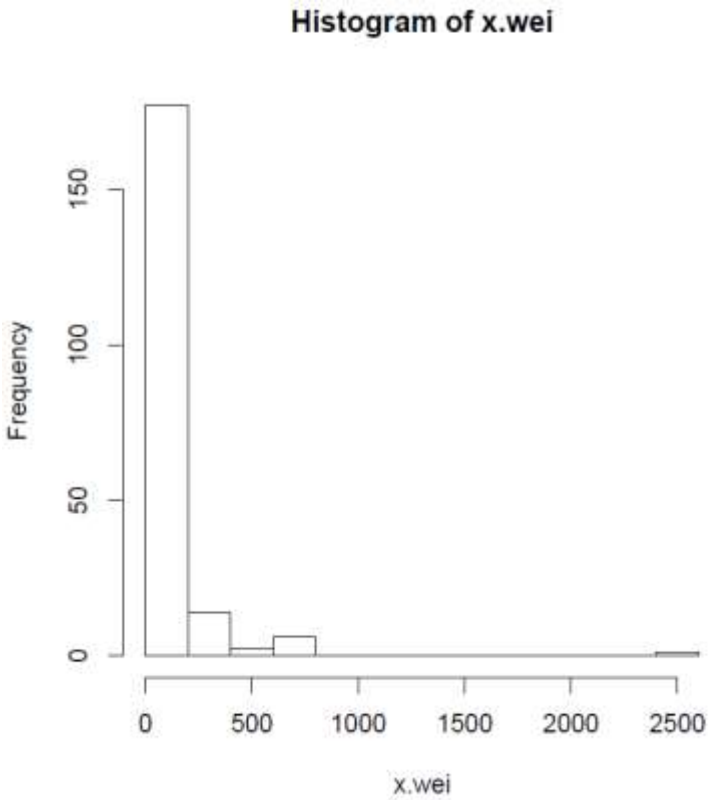
```
fit_w <- fitdist(x, "weibull")
summary(fit_w)
plot(fit_w)
```



```
par(mfrow = c(2, 2))
plot.legend <- c("Weibull", "normal", "lognormal")
denscomp(list(fit_w, fit_n, fit_ln), legendtext = plot.legend)
cdfcomp(list(fit_w, fit_n, fit_ln), legendtext = plot.legend)
qqcomp(list(fit_w, fit_n, fit_ln), legendtext = plot.legend)
ppcomp(list(fit_w, fit_n, fit_ln), legendtext = plot.legend)
```



```
# looking at preliminary results we fit Weibull

> fitdistr(x, densfun = dweibull, start = list(scale = 1, shape = 1), lower = 0.001)
           scale          shape
       28.442211507    0.434676672
      ( 1.064625817) ( 0.004557428)

# simulate a Weibull distribution with parameters shape = 0.434676672 and scale =
28.442211507
x.wei <- rweibull(n = 200, shape = 0.434676672, scale = 28.442211507)

# familiarize with the data
hist(x.wei)
```




```
# assess the symmetry (skewness), and tailed-ness (kurtosis) relative to a normal
distribution
> skewness(x.wei)
       [1] 7.19385

> kurtosis(x.wei)
       [1] 71.77632



# check whether the simulated data follows a Weibull distribution
> ks.test(x.wei, "pweibull", 0.434676672, scale = 28.442211507)

       One-sample Kolmogorov-Smirnov test

              data:  x.wei
              D = 0.064372, p-value = 0.3786


# store the simulated demand
write.csv(x.wei,"simulated_demand.csv")
```

F Processing time variability

To analyze processing variability for each item, at each workcenter, on average 600.000 cycles were analyzed for each machine where on average approximately 200 distinct programs were used.

To summarize the results, plots are shown in Figure 38, Figure 39, and Figure 40. Roughly all average cycle times are under 40 seconds for these workcenters. Variances diverge, especially for those jobs with only a small number of cycles, for example trial-shots for items in prototype phase. A part of the data is also represented in Table 18, wherein a snap shot is included of the available data on cycle times.

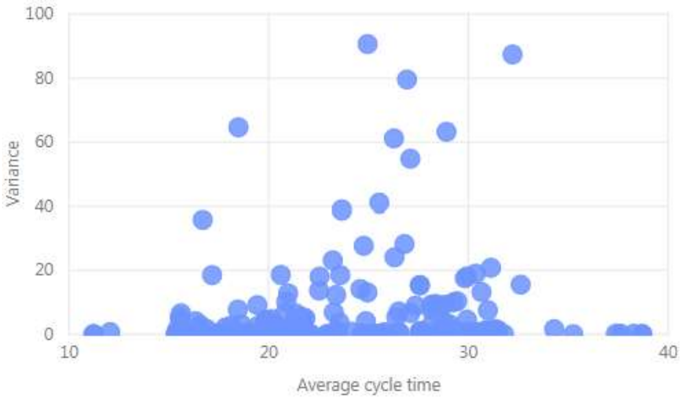


Figure 38: Cycle time analysis workcenter 1

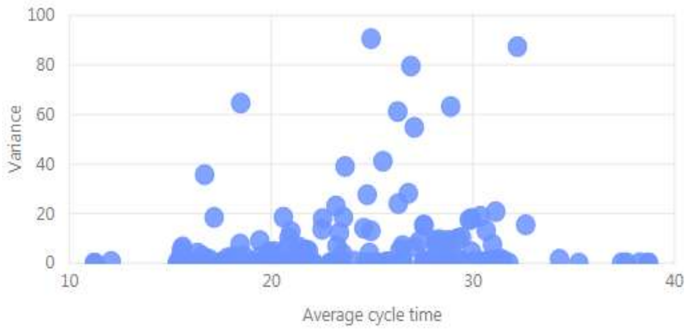


Figure 39: Cycle time analysis workcenter 2

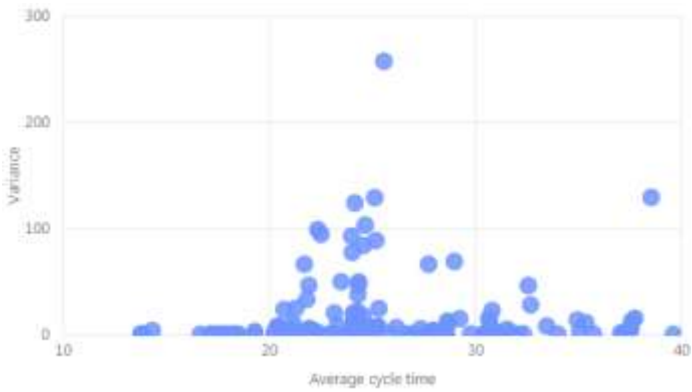


Figure 40: Cycle time analysis workcenter 3

Program + timestamp	Average cycle time	Variance cycle time	Count cycle time
pp_2015_12_29__11_31_29.txt	37,38596154	0,143332729	208
pp_2015_12_29__18_31_15.txt	27,67170732	1,41582E-05	246
pp_2015_12_30__08_22_15.txt	30,87179775	1,293908004	178
pp_2015_12_30__09_58_52.txt	30,4354057	0,107323667	14888
pp_2016_01_08__15_00_25.txt	17,42037316	7,37053E-05	11684
pp_2016_01_18__13_54_07.txt	19,95744512	0,001864801	10568
pp_2016_01_22__14_45_10.txt	20,145902	0,054568953	8082
pp_2016_01_25__13_57_27.txt	30,33792427	0,59031946	4384
:	:	:	:

Table 18: Snapshot of cycle time data

G Starting inventories

To initiate model calculations and generate feasible order proposals, starting inventories are applied. Starting inventories reduce large capacity requirement at the start of the simulation. Since the demand stream which is used as input, is based on sales orders from a certain time interval, nearly all items have to be produced in the first 30 days if no inventory would be assumed. Table 19 provides an overview of applied starting inventories for a selection of items. In total 120 items of the 221 items in total are assigned with starting inventory.

Item	Item number	Router	Months of stock	Average monthly demand	Starting inventory
6487-1100-3100	6	A-1	1,00	26,91	27
6309-1200-8904	214	C-1	1,00	1367,27	1367
6309-1603-4101	213	A-2	1,00	1352,73	1353
6432-1000-2906	102	A-2	1,00	237,45	237
6731-1601-7101	46	B-1	2,00	108,00	216
6500-1100-4304	95	A-1	1,50	224,36	337
6001-1303-0101	32	B-2	0,25	88,36	22
6527-1200-4100	150	A-1	0,25	383,64	96
6516-1500-9400	185	B-1	0,50	571,64	286
6564-1200-1504	123	A-1	0,50	311,64	156
6655-1301-9907	126	A-1	0,25	314,91	79
:	:	:	:	:	:
6525-1701-1900	186	A-1	0,50	577,45	289
6500-1100-5704	66	B-1	0,50	153,09	77
6309-1600-0500	107	B-1	1,00	265,82	266
6309-1600-2600	18	B-1	0,50	60,73	30
6309-1300-5800	181	A-1	0,25	539,64	135
6475-1400-0800	41	A-1	0,25	94,91	24
6001-1333-6200	207	C-1	0,50	1263,64	632
6500-1400-5400	98	B-1	0,50	226,18	113
6731-1601-7201	165	A-1	0,50	444,00	222
6596-1200-8302	161	B-1	0,50	414,18	207
6516-1400-3500	189	B-2	0,50	605,82	303
6731-1601-7201	165	A-1	0,50	444,00	222

Table 19: Starting inventories

H Numerical examples:

H.1 Example 1: V-CLIP

In this example, a numerical example is considered where an upstream operation has released a production order that will be due on 10-04-2018. The target quantity contains 96 pieces of which only 90 pieces are delivered. Let's assume the remaining pieces where rejected due to unconformities. Due to the process characteristics such as long setup times, the manufacturer's upstream operations generally produce in larger batch sizes than the organization's downstream operations such as assembly for example (see Table 21). This implies that the produced quantity from upstream supply chain operations ($\boldsymbol{pq_j}$) is consumed partially over time by downstream operations ($\boldsymbol{dq_{partial,j}}$). Ultimately downstream operations will recognize a shortage of 6 items which will be considered as backorders ($\boldsymbol{B_j}$) (see Table 22). The examples are based on a Uniform distribution to all tardy deliveries ranging between 1 until 10 days tardy. The formula increases penalty when tardiness increases and also penalizes for those products that are backordered.

$\widehat{pq}_j$	96 items
pq_j	90 items
d_j	10-04

Table 20: Numerical example - planned and actual order quantities

$r_{partial,j}$	$pq_{partial,j}$
07-04	24
09-04	24
12-04	24
13-04	18

Table 21: Upstream production/ delivery schedule

$c_{partial,j}$	$dq_{partial,j}$	B_j
11-04	32	0
13-04	32	0
17-04	32	6

Table 22: Downstream consumption schedule

When on-time delivery performance according $V - CLIP_j$ is measured by equation (2), and the cumulative distribution function of a Uniform distribution is applied, performance of 83% is found (see calculation below).

Delivery performance V-CLIP

Input: $\hat{q}_j\ q_{partial,j}\ T_{partial,j}$
Output: $V\ CLIP$

$$Delivery\ performance = \frac{48}{96} + \frac{24}{96} * (1 - \big(F(2)\big) + \frac{18}{96} * (1 - \big(F(3)\big) = \ 83\%$$
$$= 50\% \ + \ 20\% \ + \ 13\% \ = \ 83\%$$

When the matter is considered from an inventory management perspective the assessment of on-time delivery performance can be taken a step further. By reviewing whether late partial deliveries are actually causing delays downstream, different delivery performance would result. Strictly speaking, downstream production is not disrupted as long as items are delivered in sufficient quantity and before the planned consumption date downstream ($\boldsymbol{c_{partial,j}}$). This logic is also graphically depicted in Figure 11. To express this logic mathematically a new variable is included, the inventory position ($\boldsymbol{I_{partial,j}}$). Each time a new partial delivery is received or a partial delivery is consumed, the inventory position will be updated. Based on the inventory position and possibly backorders, it can be determined whether a planned production batch downstream is delayed or not. To complete the example, it is assumed the last 6 pieces are delivered with 1 day tardiness, at 18-04. Based on the example on-time delivery performance of either 99.4% on item level, or 96.7% on batch level are found.

Delivery performance on item level

Input: $I_{partial,j}$ $r_{partial,j}$ $q_{partial,j}$ $c_{partial,j}$ $dq_{partial,j}$ B_j
Output: *Delivery performance on item level*

---

1. $Set\ I_{partial,j}(0) = 0$
2. $I_{partial,j}(t) = \sum I_{partial,j}\ (t-1) + q_{partial,j}(t) - dq_{partial,j}(t)$

$$\begin{aligned}
I_{partial,j}(07-04) &= 24 \\
I_{partial,j}(09-04) &= 24 + 24 = 48 \\
I_{partial,j}(11-04) &= 48 - 32 = 16 \\
I_{partial,j}(12-04) &= 16 + 24 = 40 \\
I_{partial,j}(13-04) &= 40 + 18 - 32 = 26 \\
I_{partial,j}(17-04) &= 26 - 32 = -6 \\
I_{partial,j}(18-04) &= -6 + 6 = 0
\end{aligned}$$

3. $Delivery\ performance = \frac{90}{96} + \frac{6}{96} * (1 - \left(F(1)\right) = 99.4\%$

Delivery performance on batch level

Input: $I_{partial,j}$ $r_{partial,j}$ $q_{partial,j}$ $c_{partial,j}$ $dq_{partial,j}$ B_j
Output: *Delivery performance on batch level*

---

1. $Set\, I_{partial,j}\ (0) = 0$
2. $I_{partial,j}(t) = \sum I_{partial,j}\ (t-1) + q_{partial,j}(t) - dq_{partial,j}(t)$

3. $Production \coloneqq \begin{cases} Batch\ produced\ if \quad dq_{partial,j} \le I_{partial,j}\left(r_{partial,j}\right), else \\ Batch\ produced\ when \quad dq_{partial,j}(t) \le I_{partial,j}\ (t) \end{cases}$

4. $Delivery\ performance = \frac{32}{96} + \frac{32}{96} + \frac{32}{96} * (1 - \left(F(1)\right) = 96.7\%$

Although the penalty for delaying a whole production batch seems harsh, delayed production of the whole batch with all its related consequences is a realistic scenario. However, we will not further apply the above mentioned metrics since relating the consumed quantity to the partially delivered quantities leads to a more inventory management related perspective on the problem. This would be out of scope of this research.

H.2 Example 2: Generate order proposals

Example by numerical enumeration of items 20, 21, and 22 (see Table 23). These items were selected because each item is categorized in a different 'volume group'. Item 20, has a high average demand (>500), item 21 has a moderate average demand ($251 < q_{21} < 500$), item 22 has a low average demand (<250). For a description of volume categories and lot-sizing decisions, please see Figure 15 and Table 5 presented in Section 3.4.2. Note that this example follows lot-size scenario 2.

Item	PT's item description
:	:
20	6829-1800-0700
21	6724-1400-7300
22	6500-1100-2405
:	:

Table 23: Numerical enumeration: Generate order proposals

>>> *read downstream demand* $\triangleright\ \forall\, i \in \{\, 20,21,22 \,\}$

```
# determine date difference and covert to months
```

>>> $months_i$ = *(downstreamdemand['Requested date'].max() - downstreamdemand['Requested date'].min()).months()*

Order reservation	Requested date	Requested quantity
23	03-01-2018	68
427	15-01-2018	768
621	23-01-2018	14
749	30-01-2018	2
906	02-02-2018	10
1071	09-02-2018	60
1308	22-02-2018	2
1409	28-02-2018	16
1464	01-03-2018	30
1539	05-03-2018	36
1606	06-03-2018	16
1588	06-03-2018	60
1783	12-03-2018	4
1995	20-03-2018	24
2050	22-03-2018	2
2127	27-03-2018	2000
2337	06-04-2018	200
2928	16-05-2018	10
3302	15-06-2018	20

Table 24: Downstream demand item 20

Order reservation	Requested date	Requested quantity
48	03-01-2018	10
212	08-01-2018	2
226	08-01-2018	2
247	08-01-2018	40
457	16-01-2018	6
569	19-01-2018	76
555	19-01-2018	10
649	24-01-2018	10
1862	14-03-2018	80
1908	15-03-2018	2
2036	22-03-2018	2
2063	22-03-2018	2
2867	09-05-2018	1380
2977	18-05-2018	2
3043	24-05-2018	2
3116	31-05-2018	6
3127	31-05-2018	2
3258	13-06-2018	8

Table 25: Downstream demand item 21

Order reservation	Requested date	Requested quantity
55	03-01-2018	2
240	08-01-2018	2
342	11-01-2018	2
702	26-01-2018	50
1222	19-02-2018	180
1228	19-02-2018	4
1400	28-02-2018	54
1585	06-03-2018	32
1659	08-03-2018	30
2503	16-04-2018	2
2512	16-04-2018	2
2514	16-04-2018	36

Table 26: Downstream demand item 22

sum requested downstream demand per item

>>> *average monthy demand* $(\bar{q}_i) = downstream\_demand.groupby(item).sum(quantity) \,/\, months_i$

$q_{20} = 3322 \,/\, 5 = 644$

$q_{21} = 1634 \,/\, 5 = 327$

$q_{22} = 396 \,/\, 5 = 79$

>>> Lotsize(2,(q_i)) $\rhd \ \forall\ i \in \{\ 20{,}21{,}22\ \}$

For element(20) in downstream_demand:
If 644 <= 250:
lh_{20} *= 20*
elif 644 <= 500:
lh_{20} *= 10*
else:
lh_i *= 4*
return lh_{20} *= 4*

For element(21) in downstream_demand:
If 327 <= 250:
lh_{21} *= 20*
elif 327<= 500:
lh_{21} *= 10*
else:
lh_{21} *= 4*
return lh_{21} *= 10*

For element(22) in downstream_demand:
If 79 <= 250:
lh_{22} *= 20*
elif q_i *<= 500:*
lh_{22} *= 10*
else:
lh_{22} *= 4*
return lh_{22} *= 20*

$>>>(s_{i,j}) = \min[requested\ delivery\ dates\ of\ downstream\ demand_i]$ # determine due date

$s_{20,j} = 03 - 01 - 2018$

$s_{21,j} = 03 - 01 - 2018$

$s_{22,j} = 03 - 01 - 2018$

$>>>(ls_{i,j}) = s_{i,j} + lh_i$ # determine planning horizon by due date + lot size defined in weeks

$ls_{20,j} = 03 - 01 - 2018 + \text{to\_timdelta}(ls_{20} * 7, unit =' d') = 31 - 01 - 2018$

$ls_{21,j} = 03 - 01 - 2018 + \text{to\_timdelta}(ls_{21} * 7, unit = 'd')$

$ls_{22,j} = 03 - 01 - 2018 + \text{to\_timdelta}(ls_{22} * 7, unit = 'd')$

$>>>(\widehat{pq}_{i,j}) = [requested\ downstream\ demand_i < ls_{i,j}].sum(q_i)$ #determine planned quantity job j

$\widehat{pq}_{20,j} = [requested\ downstream\ demand_i < 31 - 01 - 2018].\text{sum}(q_i)$

Order # (upstream)	Start date	Planning horizon length	Planned quantity
20	03-01-2018	31-01-2018	852

Table 27: Planned order item 20

$\widehat{pq}_{21,j} = [requested\ downstream\ demand_i < 14-03-2018].\mathrm{sum}(q_i)$

Order # (upstream)	Start date	Planning horizon length	Planned quantity
21	03-01-2018	14-03-2018	236

Table 28: Planned order item 21

$\widehat{pq}_{22,j} = [requested\ downstream\ demand_i <].\mathrm{sum}(q_i)$

Order # (upstream)	Start date	Planning horizon length	Planned quantity
22	03-01-2018	23-05-2018	396

Table 29: Planned order item 22

generate new jobs until all demand for item 20 is covered

while $\widehat{pq}_{20} < [requested\ downstream\ demand_i].sum(q_i)$:

$j = j+1$

$s_{20,j} = \min[requested\ delivery\ dates\ of\ downstream\ demand_i > ls_{j-1}]$

$ls_{20,j} = s_j + lh_{20}$

$\widehat{pq}_{20,j} = [d_{i,j} < requested\ downstream\ demand_i \leq ls_{i,j}].sum(q_i)$

269	02-02-2018	02-03-2018	88
270	01-03-2018	29-03-2018	2172
271	06-04-2018	04-05-2018	200
272	16-05-2018	13-06-2018	10
273	15-06-2018	13-07-2018	20

Table 30: Planned orders item 20

while $\widehat{pq}_{21} < [requested\ downstream\ demand_i].sum(q_i)$:

$j = j+1$

$s_{21,j} = \min[requested\ delivery\ dates\ of\ downstream\ demand_i > lh_{j-1}]$

$ls_{21,j} = s_j + lh_{21}$

$\widehat{pq}_{21,j} = [d_{i,j} < requested\ downstream\ demand_i \leq ls_{i,j}].sum(q)$

274	15-03-2018	24-05-2018	1388
275	24-05-2018	02-08-2018	18

Table 31: Planned orders item 21

while $\widehat{pq}_{22,j} = [requested\ downstream\ demand_i <].\mathrm{sum}(q_i)$

-

H.3 Example 3: Load balancing

Example by numerical enumeration of items 165, 26, and 219 (see Table 32). These items are selected because they consist of different routers, A-2, B-1, and C-1 respectively. For a description of all routers, please see Table 6. Note that this example follows lot-size scenario 2.

Item	PT's item description
:	:
165	6527-1200-4402
26	6731-1601-7404
219	6001-1444-7800
:	:

Table 32: Numerical enumeration: Load balancing

>>> *sort jobs ascending by* s_j $\triangleright\ \forall\, j \in \{J\}$

```
        # generate new set 'Jobs' after index is reset
Jobs = sort_values(by =['Start_date']).reset_index(drop=True)
```

>>> *categorize jobs by* J_k $\triangleright\ \forall\, k \in \{K\}$

```
        # 4 sets are generated for 4 workcenters
SET_Wc1= Jobs.loc[Load['Router'].isin(['A-1','A-2'])]
```

Item	PT's item description	Order #	Start date	Planned Quantity	Router
:	:	:	:	:	:
16	6432-1000-2906	16	08-01-2018	1302	A-2
165	6527-1200-4402	165	09-01-2018	1852	A-2
168	6505-1200-1700	168	10-01-2018	758	A-1
:	:	:	:	:	:

Table 33: Selection of jobs @ Wc1

```
SET_Wc2= Jobs.loc[Load['Router'].isin(['B-1','B-2'])]
```

Item	PT's item description	Order #	Start date	Planned Quantity	Router
:	:	:	:	:	:
52	6505-1500-1000	29	19-01-2018	10	B-1
26	6731-1601-7404	26	20-02-2018	18	B-1
50	6159-1101-2803	50	20-01-2018	502	B-2
:	:	:	:	:	:

Table 34: Selection of jobs @ Wc2

SET_Wc3= Jobs.loc[Load['Router'].isin(['C-1','C-2'])]

Item	PT's item description	Order #	Start date	Planned Quantity	Router
:	:	:	:	:	:
88	6527-1101-0700	88	15-01-2018	944	C-1
219	6001-1444-7800	219	16-02-2018	188	C-1
148	6731-1601-7304	562	18-06-2018	26	C-2
:	:	:	:	:	:

Table 35: Selection of jobs @ Wc3

SET_Wc4= Jobs.loc[Load['Router'].isin(['A-2','B-2','C-2'])]

Item	PT's item description	Order #	Start date	Planned Quantity	Router
:	:	:	:	:	:
165	6527-1200-4402	165	09-01-2018	1852	A-2
:	:	:	:	:	:

Table 36: Selection of jobs @ Wc4

$>>> required\ capacity_{j,k} = \hat{f}_{j,k} + \widehat{pq}_{i,j} * \widehat{cc}_{j,k}$

```
# order 165, cycle time wc1 = 26 seconds per piece, quantity order 165 = 1852 pieces
48151,98 = SET_Wc1.loc[Jobs['Order #'].isin([165])]['Daily_Load'].sum())
55560 = SET_Wc4.loc[Jobs['Order #'].isin([165])]['Daily_Load'].sum())
```

Index	Material	Order #	Date	Daily_Load_Wc1	Daily_Load_Wc4
165	6527-1200-4402	165	09-01-2018	8025.33	0.0
1705	6527-1200-4402	165	10-01-2018	8025.33	0.0
1706	6527-1200-4402	165	11-01-2018	8025.33	0.0
1707	6527-1200-4402	165	12-01-2018	8025.33	0.0
1708	6527-1200-4402	165	13-01-2018	8025.33	0.0
1709	6527-1200-4402	165	14-01-2018	8025.33	0.0
1710	6527-1200-4402	165	15-01-2018	0.0	13890.0
1711	6527-1200-4402	165	16-01-2018	0.0	13890.0
1712	6527-1200-4402	165	17-01-2018	0.0	13890.0
1713	6527-1200-4402	165	18-01-2018	0.0	13890.0

Table 37: Average daily capacity requirements at workcenter during lead time of job 165

```
# order 26, cycle time workcenter 2 = 33 seconds per piece, quantity order 26 = 184 pieces
6072 = SET_Wc2.loc[Jobs['Order #'].isin([26])]['Daily_Load'].sum())
```

26	6731-1601-7404	26	03-01-2018	766.67	0.0
868	6731-1601-7404	26	04-01-2018	766.67	0.0
869	6731-1601-7404	26	05-01-2018	766.67	0.0
870	6731-1601-7404	26	06-01-2018	766.67	0.0
871	6731-1601-7404	26	07-01-2018	766.67	0.0
872	6731-1601-7404	26	08-01-2018	766.67	0.0

Table 38: Average daily capacity requirements at workcenter during lead time of job 26

```
# order 219, cycle time workcenter 3 = 29 seconds per piece, quantity order 26 = 188 pieces
5452 = SET_Wc3.loc[Jobs['Order #'].isin([219])]['Daily_Load'].sum())
```

Index	Material	Order #	Date	Daily_Load_Wc3	Daily_Load_Wc4
219	6001-1444-7800	219	16-02-2018	681.5	0.0
705	6001-1444-7800	219	17-02-2018	681.5	0.0
706	6001-1444-7800	219	18-02-2018	681.5	0.0
2051	6001-1444-7800	219	19-02-2018	681.5	0.0
2052	6001-1444-7800	219	20-02-2018	681.5	0.0
2053	6001-1444-7800	219	21-02-2018	681.5	0.0
2054	6001-1444-7800	219	22-02-2018	681.5	0.0
2055	6001-1444-7800	219	23-02-2018	681.5	0.0

Table 39: Average daily capacity requirements at workcenter during lead time of job 219

>>> *determine gross available capacity* $= l_k * C_k$

```
# For an overview of standard lead times, based on routers, see Table 6
# order 165
172800 = Jobs.loc[Jobs['Order#'].isin([165])&(Jobs['Daily_Load']>0)]['Capacity_Wc1'].sum())
86400 = Jobs.loc[Jobs['Order#'].isin([165])&(Jobs['Daily_Load']>0)]['Capacity_Wc4'].sum())

# order 26
216000 =Jobs.loc[Jobs['Order#'].isin([26])&(Jobs['Daily_Load']>0)]['Capacity_Wc2'].sum())

# order 219
172800 = Jobs.loc[Jobs['Order#'].isin([219])&(Jobs['Daily_Load']>0)]['Capacity_Wc3'].sum())
```

Item	Material	Router	Lead time IM	Lead time PPS
:	:	:	:	:
16	6432-1000-2906	A-2	6	4
165	6527-1200-4402	B-2	6	4
168	6505-1200-1700	C-1	8	0
:	:	:	:	:

Table 40: Item parameter overview

Date	Available cap. Wc1	Available cap. Wc2	Available cap. Wc3	Available cap. Wc4
:	:	:	:	:
16-02	43200	43200	28800	28800
17-02	43200	43200	28800	28800
18-02	43200	43200	28800	28800
19-02	43200	43200	28800	28800
20-02	43200	43200	28800	28800
21-02	43200	43200	28800	28800
:	:	:	:	:

Table 41: Available capacity per day for each workcenter

>>> *set:* $e_{j,k} = d_{j,k}$

```
# order 165
14-01-2018 =Jobs.loc[Jobs['Order #'].isin([165]) &
(Jobs['Daily_Load_Wc']>0)]['Due_date']
18-01-2018 =Jobs.loc[Jobs['Order #'].isin([165]) &
(Jobs['Daily_Load_Wc']>0)]['Due_date']
```

```
# order 26
08-01-2018 =Jobs.loc[Jobs['Order #'].isin([26]) &
(Jobs['Daily_Load_Wc']>0)]['Due_date']

# order 219
23-02-2018 =Jobs.loc[Jobs['Order #'].isin([219]) &
(Jobs['Daily_Load_Wc']>0)]['Due_date']
```

```
# End date needs to be re-calculated when prior job finishes later.
# If so, calculate net available capacity and determine new end date.
```

while $e_{164,1} > e_{165,1}$:

Available capacity during lead time($l_k\ d_{j,k}\ e_{j,k}\ C_k$)

$available\ capacity_{165,1} = (d_{165,1} - e_{164,1}) * C_1$

$0 = (14\text{-}01\text{-}2018 - 14\text{-}01\text{-}2018) * 43{,}200$

$net\ available\ capacity_{165,1} = available\ capacity_{165,1} - required\ capacity_{165,1}$

$-48{,}151.98 = 0 - 48{,}151.98$

End date($net\ available\ capacity_{j,k}$)

if $net\ available\ capacity_{165,1} < 0$:

$e_{165,1} = e_{165,1} + (\ capacity\ shortage_{165,1} / C_1)$

$16-01-2018 = 14-01-2018 + (48{,}151.98 / 43{,}200)$

else

$e_{165,1} = e_{164,1} + (\ required\ capacity_{165,1} / C_1)$

Since wc4 follows wc1, it is also checked when wc1 finishes ($e_{164,1}$)

while $e_{164,4} > e_{165,4}$:

Available capacity during lead time($l_k\ d_{j,k}\ e_{j,k}\ C_k$)

$available\ capacity_{165,4} = min(d_{165,4} - e_{164,4},\ d_{165,4} - e_{164,1}) * C_4$

$0 = (18\text{-}01\text{-}2018 - 18\text{-}01\text{-}2018) * 28{,}800$

$net\ available\ capacity_{165,4} = available\ capacity_{165,4} - required\ capacity_{165,4}$

$-55{,}560 = 0 - 55{,}560$

End date($net\ available\ capacity_{j,k}$)

if $net\ available\ capacity_{165,4} < 0$:

$e_{165,4} = e_{165,4} + (\ capacity\ shortage_{165,4} / C_4)$

$20-01-2018 = 18-01-2018 + (55{,}560 / 28{,}800)$

else

$e_{165,4} = e_{164,4} + (\ required\ capacity_{165,4} / C_4)$

while $e_{25,1} > e_{26,1}$:

Available capacity during lead time($l_k\ d_{j,k}\ e_{j,k}\ C_k$)

$available\ capacity_{26,1} = (d_{26,1} - e_{25,1}) * C_1$

$43{,}200 = (08\text{-}01\text{-}2018 - 07\text{-}01\text{-}2018) * 43.200$

$net\ available\ capacity_{26,1} = available\ capacity_{26,1} - required\ capacity_{26,1}$

$37{,}128 = 43.200 - 6{,}072$

End date($net\ available\ capacity_{j,k}$)

if $net\ available\ capacity_{26,1} < 0$:

$e_{26,1} = e_{26,1} + (\ capacity\ shortage_{26,1} / C_1)$

else

$e_{26,1} = e_{25,1} + (\ required\ capacity_{26,1} / C_1)$

$08\text{-}02\text{-}2018 = 07\text{-}01\text{-}2018 + (6{,}072 / 43{,}200)$

while $e_{218,1} > e_{219,1}$:

Available capacity during lead time($l_{j,k}\ d_{j,k}\ e_{j,k}\ C_k$)

$available\ capacity_{219,1} = (d_{219,1} - e_{218,1}) * C_1$

*57,600 = (23-02-2018 − 21-02-2018) **28,800

$net\ available\ capacity_{219,1} = available\ capacity_{j,k} - required\ capacity_{j,k}$

57,148 = 57,600 – 5,452

End date($net\ available\ capacity_{j,k}$)

if $net\ available\ capacity_{219,1} < 0$:

$e_{219,1} = e_{219,1} + (\ capacity\ shortage_{219,1} / C_1\ )$

else

$e_{219,1} = e_{218,1} + (\ required\ capacity_{219,1} / C_1\ )$

22-02-2018 = 21-02-2018 + (5,452 / 28,800)

H.4 Example 4: Performance measurement (V-CLIP)

This example contains numerical enumeration of item 133 (job 696), item 199 (job 578), and item 197 (job 258). These jobs were selected because performance is calculated differently for each job. Job 696 is produced on-time and therefore has on-time performance of 100%. The two jobs which are produced late are different in the sense that job 578 is produced partly before and partly after due date and job 258 is started late such that the full delivery was late. Note that this example follows lot-size scenario 2.

Item	PT's item description	Job
:	:	:
133	6655-1302-2706	696
199	6309-1200-1504	578
197	6726-1500-0300	258
:	:	:

Table 42: Numerical enumeration: V-CLIP

Item	Job	Due date	End date	Tardiness	V-CLIP	Router
:	:	:	:	:	:	:
133	696	05-08-2018	05-08-2018	0 days	100%	A-1
199	578	08-07-2018	12-07-2018	4 days	84,5%	A-1
197	258	10-03-2018	14-03-2018	4 days	68,2%	A-1
:	:	:	:	:	:	:

Table 43: Lateness

$$\textit{determine Lateness}\,(L_j) = \textit{Due date}\,(d_j) - \textit{End date}\,(e_j)$$

$$L_{696} = 0 = 05\text{-}08\text{-}2018 - 05\text{-}08\text{-}2018$$
$$L_{578} = 4 = 08\text{-}07\text{-}2018 - 12\text{-}07\text{-}2018$$
$$L_{258} = 4 = 14\text{-}03\text{-}2018 - 10\text{-}03\text{-}2018$$

$$\textit{determine Tardiness}\,(T_j) = [L_j]^+$$

$$T_{696} = 0 = [0]^+ = max[0, 0]$$
$$T_{578} = 1 = [1]^+ = max[0, 1]$$
$$T_{258} = 3 = [4]^+ = max[0, 4]$$

$\textit{categorize jobs by workcenter}\ (I_k)$ $\qquad \rhd\ \forall\ k \in \{K\}$

Item	Job	Router
:		:
133	696	A-1
199	578	A-1
197	258	A-1
:	:	:

Table 44: Wc1

Item	Job	Router
:	:	:
220	14	B-1
67	15	B-1
188	22	B-2
:	:	:

Table 45: Wc2

Item	Job	Router
:	:	:
170	46	C-1
59	13	C-2
68	55	C-1
:	:	:

Table 46: Wc3

Item	Job	Router
:	:	:
188	22	B-2
59	13	C-2
173	16	A-2
:	:	:

Table 47: Wc4

$determine\ required\ days\ of\ production\ for\ job\ (z_j) = required\ capacity_{j,k}\ /\ C_k$

$z_{696} = 3{,}070\ /\ 43{,}200 = 0.071\ days$

$z_{578} = 227{,}280\ /\ 43{,}200 = 5.26\ days$

$z_{258} = 49{,}976\ /\ 43{,}200 = 1.16\ days$

for j **do:** $\triangleright\ \forall\ j \in \{J\}$

if $T_j == 0:$

$z_{696} = 3{,}070\ /\ 43{,}200 = 0{,}071\ days$

$VCLIP = 1$

else:

$VCLIP\ (T_{578}, z_{578})$

$VCLIP\ (T_{258}, z_{258})$

function: VCLIP (T_{578}, z_{578})

if $z_{578} \le T_{578}$

$diff = T_{578} - z_{578}$

for x **in range** $(diff\ , T_{578}):$

$VCLIP = VCLIP + (C_1 /\ required\ capacity_{578,1} * (1 - nbinom.cdf(x, 1{,}0.08755)))$

else:

for x **in range** $(0\ , T_j):$

$diff = z_j - T_j$

$1.26 = 5.26 - 4$

if $x == 0:$

$processed = \max[diff * C_1, C_1]$

$VCLIP = \max[diff * C_1, C_1] /\ required\ capacity_{578,1}$

$0.38 = \max[2 * 43{,}200, 43{,}200]\ /\ 227.280$

else:

$today = min[C_1, required\ capacity_{578,1}, required\ capacity_{578,1,} - processed)$

$processed = processed + today$

$VCLIP = VCLIP + (today /\ required\ capacity_{578,1} * (1 - nbinom.cdf(x, 1{,}0.08755)))$

$0.538 = 0.38 + (43{,}200\ /\ 48{,}378 * (1 - nbinom.cdf(1{,}1{,}0.08755)))$

$0.682 = 0.538 + (43{,}200\ /\ 48{,}378 * (1 - nbinom.cdf(2{,}1{,}0.08755)))$

$0.814 = 0.682 + (43{,}000\ /\ 48{,}378 * (1 - nbinom.cdf(3{,}1{,}0.08755)))$

$0.845 = 0.814 + (11{,}280\ /\ 48{,}378 * (1 - nbinom.cdf(4{,}1{,}0.08755)))$

function: VCLIP (T_{258}, z_{258})

if $z_{258} \le T_{258}:$

$diff = T_{258} - z_{258}$

$2.84 = 4 - 1.16$

for x **in range** $(diff, T_{258}):$

$(3, 4):$

$VCLIP = VCLIP + (C_1 /\ required\ capacity_{1,258} * (1 - nbinom.cdf(x, 1{,}0.08755)))$

$0.596 = 0 + (43{,}200\ /\ 49{,}976 * (1 - nbinom.cdf(3{,}1{,}0.08755)))$
$0.682 = 0{,}596 + (6{,}776\ /\ 49{,}976 * (1 - nbinom.cdf(4{,}1{,}0.08755)))$

else:
  for x **in range** $(0\ , T_{258})$:
    $diff = z_{258} - T_{258}$
      if $x == 0$:
        $processed = \max[diff * C_1, C_1]$
        $VCLIP = \max[diff * C_1, C_1] /\ required\ capacity_{258,1}$
      else:
        $today = min[C_1, required\ capacity_{578,1,} arequired\ capacity_{578,1,} - processed)$
        $processed = processed + today$
        $VCLIP = VCLIP + (C_1 /\ required\ capacity_{258,1} * (1 - nbinom.cdf(x, 1{,}0.08755)))$

I Description of all variables & parameters

d_j:	due date of the job (confirmed delivery time)
s_j:	start date of the job
e_j:	end date of the job
c_j:	confirmation date, time at which the job is registered as finished by warehouse
q_i :	demand quantity item i
$dq_{partial,j}$:	downstream consumption quantity (partial)
$c_{partial,j}$:	downstream consumption date (partial)
$\widehat{pq}_j$:	planned production quantity of job j
pq_j:	produced quantity of job j, i.e. delivered quantity
$pq_{partial,j}$:	produced quantity of job j, i.e. delivered quantity
r_j:	confirmed delivery date of the job i.e. delivery date
l_j:	lead time of the job, expressed in days
sc:	scenario
L_j:	Lateness of the job; $c_j - d_j$
E_j:	Earliness of the job; $\min(0, d_j - c_j)$
T_j:	Tardiness of the job; $\max(0, L_j)$
lh_i:	lot-size horizon for item i
ls_j:	lot-size interval for job j
V_j:	Volume performance of the job; $\frac{pq_j}{\widehat{pq}_j}$
C_k:	available processing capacity at workcenter (k), expressed in seconds
I:	set of all items (i), in the case company's context, items are referred to as PNs
I_k:	set of all items (i) produced on workcenter (k)
I_O:	set of all items (i) produced at operation (O)
$IP_i\ (t)$	Inventory position for item i
B:	backordered demand
H:	planning horizon

F: frozen interval

R: replanning interval

hr: hourly rate for machine availability, expressed in EUROS

hr_{extra}: hourly rate for extra availability, expressed in EUROS

fc: setup costs, expressed in EUROS

cr: carrying ratio for inventory carrying costs, expressed in percentage

$avai(t)$: planned machine availability for time period t, expressed in hours per day

$avai_{extra}(t)$: planned extra machine availability time for time period t, expressed in hours per day

z_j: required capacity of job j

cc_j $(\widehat{cc}_j)$: cycle time (norm) of job j

f_j $(\hat{f}_j)$: setup time (norm) of job j

$scen$: scenario

m: Bill Of Material-level

n: echelon level

x: number of workcenters

ρ_k: utilization at workcenter k

J Standard model parameters

To approximate the actual scenario, ERP parameters and historic order sizes are analyzed. With the insights from this analysis, a simulation can be developed wherein a scenario is created that is close to the actual planning model. Figure 41 provides the frequency distribution of lot-sizes parameters. Table 48 presents the lot size parameters by a numerical overview.

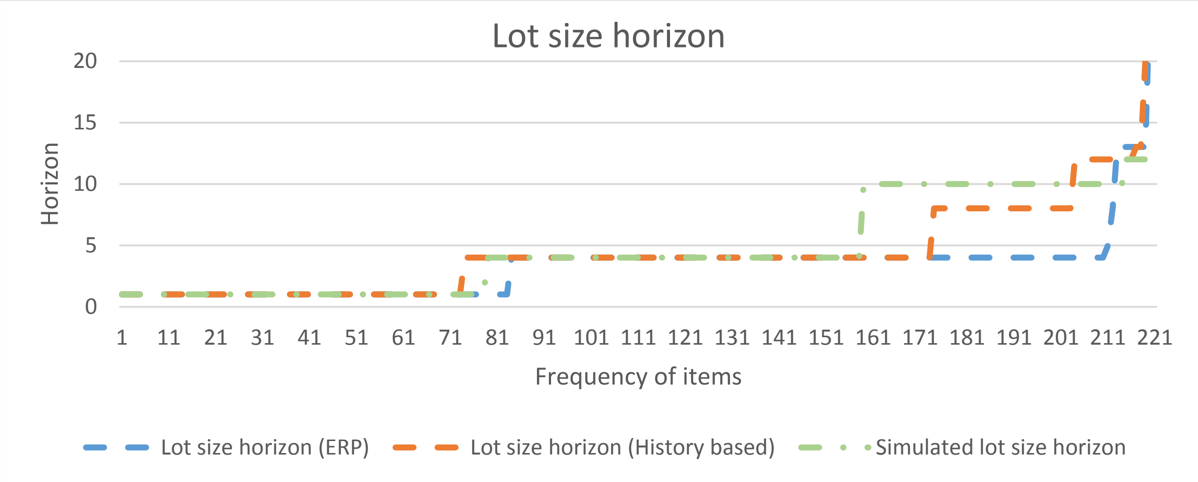


Figure 41: Frequency distribution of lot-size horizons

Item	Lot size horizon (ERP based)	Lot size horizon (History based)	Simulated lot size horizon
1	1	1	1
2	1	1	1
3	1	1	1
4	1	1	1
5	1	1	1
6	1	1	1
7	1	1	1
8	1	1	1
9	1	1	1
10	1	1	1
11	1	1	1
:	:	:	:
211	5	12	10
212	8	12	10
213	13	12	10
214	13	12	10
215	13	12	12
216	13	12	12
217	13	13	12
218	13	13	12
219	13	20	12
220	26	26	12
221	26	26	12

Table 48: Lot size horizons versus simulated lot size horizons