

MASTER

Improving tactical buffer management and operational control under uncertainties in assemble-to-order systems an exploratory case study in the real-life complex supply chain of VDL ETG

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Improving tactical buffer management and operational control under uncertainties in assemble-to-order systems

An exploratory case study in the real-life complex supply chain of VDL ETG

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"The important thing is not to stop questioning. Curiosity has its own reason for existing."

-Albert Einstein-

Abstract

Companies in assemble-to-order environments face many different uncertainties, but it is unclear how to control operations and determine buffers in order to improve overall supply chain efficiency and control. In this master thesis we study this problem for the real-life supply chain of VDL ETG. We design two general models which contribute to the insights and understanding of operational control and buffer management in dynamic order-driven assembly systems, and which support buffer norm setting. We introduce a new mathematical concept called 'hidden inventory', which allows for analyzing customer order due date uncertainty under order-driven control as demand uncertainty in an inventory model. We apply the model to three real-life cases, showing the potential to reduce system nervousness. Secondly, we develop a planned lead time model which supports the analysis of safety time buffers (planned lead times) in order-driven assembly systems under lead time uncertainty. Via discrete event simulation we show that important cost and cycle time savings are possible by using smart heuristics to determine planned lead times. Finally, based on our modeling and analysis, in combination with support tools which have been developed, we 'design' important directions for improving operational control and buffer management at VDL ETG.

Management summary

In this thesis report we present the results of our study on tactical buffer management and operational control in multi-item multi-echelon assemble-to-order (ATO) systems. As a case study, the real-life complex supply chain of VDL Enabling Technologies Group Eindhoven (VDL ETG) has been selected.

Problem statement

VDL ETG is active in the field of complex, innovative mechatronic systems. The company is a tier-one contract manufacturing partner for original equipment manufacturers (OEM's) of complex, high-tech products (e.g. AMSL and FEI). The environment in which these companies operate is very complex in terms of high demand and supply uncertainty; low volumes; complex bill of material structures and dependencies; expensive materials; rapid technological developments; capacity restrictions; and customer lead times which are shorter than integral throughput times.

Based on an extensive problem analysis, we constructed a cause and effect diagram and we formulated several projects to address the key problems. Using dependencies between the projects and the priorities of key stakeholders at VDL ETG, a roadmap towards improvement of efficiency and control in VDL ETG's supply chain has been developed. We focus on one of these projects, which concerns buffer management and control in the ATO/MTO supply chain. Despite the considerable progress in developing analytical models for such systems, there is still much room for new theoretical developments, especially concerning the application of knowledge and models from classical inventory theory in order-driven assembly environments. In order to address this promising gap for extending the existing literature and to investigate the possibilities for improving supply chain efficiency and control at VDL ETG, the following main research questions was defined:

How should VDL ETG manage buffers and control operations in its dynamic ATO/MTO environment, such that the supply chain efficiency and controllability is improved?

Analysis of key supply chain features in the real-life complex supply chain

In order to gain understanding of important aspects to take into account for improving operational control and buffer management in the design phase of our research, we first analyzed key strategic, tactical and operational features in the as-is situation at VDL ETG. Flexibility and responsiveness have been discussed as two important strategic features. We argued that, from an integral planning and control perspective, we might consider required responsiveness as 'given', reflected by the target customer service levels and lead times. In terms of tactical features, we discussed capital investment risk and customer commitment. In the supply chain of VDL ETG, we basically identify three types of stock related investments: 'inventory', 'work in progress' and 'purchasing'. Investments in all three classes can be order-driven (i.e. 'project investments') or forecast-driven (i.e. 'anonymous investments'). From a risk perspective, it is mainly anonymous inventory which creates a high risk exposure for VDL ETG. In order to protect against these risks, VDL ETG has forecast commitments with its customers. Finally we identified planning stability and nervousness as two important operational features of supply chain planning in real-life complex supply chains. We argued that nervousness is mainly a symptom of bad or deficient control and planning. Hence the design and evaluation of alternative buffer norms and control rules should also be considered in relation to system nervousness.

Supply chain uncertainties and current buffer methods

Qualitative and quantitative analysis revealed the existence and magnitude of three main classes of uncertainty from an integral planning and control perspective in the supply chain of VDL ETG: supply

uncertainty, manufacturing process uncertainty, and demand uncertainty. Concerning the supply and manufacturing process uncertainty, our analysis showed that besides stochastic yield, especially lead times create much uncertainty. Demand uncertainty in the order-driven supply chain of VDL ETG can be considered from both a time and quantity perspective. We showed that not only forecasts create uncertainty about future demand, stochastic customer order due dates do provide significant uncertainty about future period demand as well.

In order to protect against the uncertainties, VDL ETG uses different types of buffers at different moments and places. We identified and discussed consignment stock, a week buffer between internal and external customer due dates, safety time and MPS smoothing as the most prevalent buffer options. Our research revealed that the application of buffers is mainly operationalized based on employees' experiences (from planners, factory engineers, etc.). There is a lack of explicit performance feedback loops and control with regard to uncertainties and methods used to buffer against them. This makes it hard to create a solid understanding of the existence and especially the impact of uncertainties (on decisions already made as well as decisions to be made), let alone on how to buffer against them (parameter setting) and control production in the most efficient and effective way.

Design for understanding and analysis

In the first part of our design phase, we therefore designed two general models which support understanding and analysis of buffering against the two main classes of uncertainty in order-driven assembly systems: demand uncertainty and lead time uncertainty. We argued that, in order to allow for robust and effective planning at the integral level, an explicit decoupling between demand and lead time uncertainty is needed.

Stochastic (hidden) inventory model – buffering and control under demand uncertainty

Firstly, based on mathematical expressions, we hypothesized that service in a single-item single-echelon inventory system can be 'explained' by the average inventory level and average order size as system outcomes, and that this service is relatively insensitive from specific control parameters which are used. Numerical analysis and empirical analysis for three real-life examples provides support for our hypothesis, at least in the high-tech environment of VDL ETG, characterized by high service levels, long lead times and low volumes.

In order to validate our hypothesis for real-life examples in the order-driven supply chain of VDL ETG, we introduced a new modeling concept. Analysis of cumulative demand uncertainty (see Figure) revealed that cumulative forecasts orders (blue line) do generally exceed cumulative real demand (red line). Production (in the form of scheduled receipts, green + orange bars) is initially planned based on cumulative orders. Under the order-driven

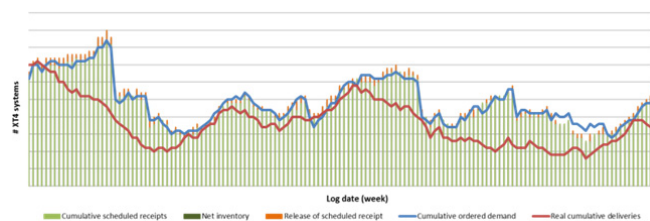


Figure: Example of MPS cumulative demand uncertainty in relation to production planning for the ASML XT4 system (see page 28 for normal size and more explanation)

control at the MPS level, actual receipts are generally matched with real customer demand. Since this real demand on average is lower than the ordered demand (customer rescheduling), a difference between scheduled and actual receipts arises. Mathematical expressions for these differences under order-driven MRP control at the MPS level have been formulated. We name the new concept which includes these differences 'hidden inventory'. We show that this concepts provides the explanation of a striking observation: VDL ETG's extremely high service level under high demand volatility, while there is no (or very little) inventory at the final stock

point. More generally, the concept allows for analyzing buffering against order due date uncertainty in an order-driven system as buffering against demand uncertainty in a make-to-forecast inventory system. Hidden inventory can be considered as a kind of inventory which is hidden/kept in the work in progress. This inventory is spread in the pipeline in such a way that there is enough hidden inventory which can quickly enough be converted in real stock in order to cope with the stochastic demand from customer side, thereby obtaining a certain service level.

Stochastic planned lead time model – buffering and control under lead time uncertainty

In order to understand and analyze buffering against lead time uncertainty, we developed a planned lead time model based on the two-stage assembly structure of a customer system produced by VDL ETG. We implemented the model in a discrete event simulation tool, and empirically validated it with historical data. Analysis revealed that the current planned lead time settings (average lead time plus safety time) are similar to using a so-called Fractile method. We introduced three alternative methods to determine planned lead times. Via our discrete event simulation tool we quantified the improvement potential of each of the alternative methods. It turned out that rather ‘easy’ Critical Chain concepts can result in a reduction of both the cycle time and stock investments. A more sophisticated Newsvendor heuristic (Atan et al.,2015) can result in major efficiency improvements: 4-5% cycle time reduction associated with 11% cost reduction in case of high target service levels (on-time delivery performance, OTD) and relatively low added value in the final assembly stage (which characterizes the main customer systems produced by VDL ETG).

Table: Discrete event simulation results showing the improvement potential of three alternative methods to set planned lead times

Scenario: high target service level and 10% added value during final assembly stage					
Method	OTD service level	Cycle time		Stock investment	
Fractile method	89,9%	103,9	100,0%	39.975	100,0%
Critical Chain	90,0%	100,7	96,9%	35.910	89,8%
Critical Chain Extreme	89,9%	97,5	93,8%	37.780	94,5%
Newsvendor heuristic	90,0%	99,4	95,7%	35.510	88,8%

We expect these two mathematical models and related insights to apply to real-life, complex ATO supply chains in general. Together, the stochastic inventory model and the stochastic planned lead time model provide a powerful concept for understanding two important classes of uncertainties in order-driven assembly systems: due date uncertainty and lead time uncertainty. Companies can use the stochastic inventory model to support the determination of important inventory buffers under due date uncertainty, and methods based on the Critical Chain concepts or a more sophisticated Newsvendor heuristic can be used to determine important time buffers under lead time uncertainty. Both aspects are important for efficient and effective buffer management and control in what we can regard as ‘make to order-driven stock’ supply chains.

Design for improvement

After the major part of our design phase, in which we designed models to improve crucial understanding of buffering in the complex order-driven supply chain of VDL ETG, we ‘designed’ directions and options for improvement based on our analyses and supporting tools which have been developed. Amongst others, we discussed (in Chapter 6): the visualization and management of the hidden inventory buffer in order to reduce system nervousness and ease (capacity) planning and control; the exploration of the effect of lower target service levels on possible reduction of the required inventory buffer size; the decoupling between demand uncertainty and lead time uncertainty to allow for robust and effective planning at the integral level; the investigation of the planned lead time model and Newsvendor heuristic for more systems, in order to quantify the improvement potential for those systems; the use of new planning performance metrics to allow for explicit production control and feedback loops; the use of the new Stock Investment Report structure to measure and monitor stock-related capital investments.

Preface

This report is the result of my master thesis project, which I conducted at the VDL Enabling Technologies Group in Eindhoven. It does not only conclude my Master in Operations Management and Logistics, it also is the end of five magnificent years at one of the most beautiful and inspiring universities in the world: Eindhoven University of Technology.

During these years I have learnt incredibly much in many different areas. During the courses, internships, study trips and many more activities I had the opportunity to meet many incredible people. What I will never forget is all the fun and inspiring conversations we had.

I would like to thank a number of people for their role in my master thesis project. First of all, I would like to thank Ton de Kok, not only as my first supervisor but also as a great coach. I'm extremely honored that I got the chance to experience at first hand why he is one of the best professors at our university and in our field of research. Ton, every meeting and discussion we had has been very inspiring, and I'm thankful for learning about your vision and ideas on science, supply chains and in particular on how to manage them. I think it is not by chance that my time at the university literally started with your introductory lecture notes about stochastic inventory control and my time actually ends with the same inspiring field of research.

Secondly, I would like to thank my second supervisor, Zümbül Atan. Zümbül, I'm very glad that I got the chance to work with you from the very beginning of my time at VDL ETG. I really appreciated your feedback, suggestions and support through the entire project.

Next I would like to express my gratitude to both my company supervisors, Jeroen Zwiep and John Langenhuysen. You made it possible for me to conduct my research project in the inspiring environment of VDL ETG, and you made me feel at ease right from the beginning. Thanks for creating the flexibility to shape my own research and for your support throughout the entire project. Jeroen, your analytic view and role as innovation manager really helped me taking an integral perspective when needed, and really contributed to the justification and application of the findings. John, your operational perspective really helped me to keep focus on delivering useable results and tools, and I appreciated your practical view on managing complexity in real life supply chains. The dual supervision by both of you has been very valuable and pleasant.

Moreover, I would like to thank my colleagues at VDL ETG for their input, support, and suggestions. Thanks for dedicating time to answer my (probably annoying) questions and for creating a very pleasant working atmosphere.

During the first half year in preparation for my real thesis project I had the chance to work together with two colleague students. Tom, it has been very valuable to work with you on the development of the supply chain roadmap. You really helped me to get acquainted with VDL ETG's supply chain environment quickly. It was very interesting to be involved with the intelligent things you have been working on. Bas, I would like to thank you for the nice collaboration on our shared literature review. Performing a literature review is often considered as one of the most boring tasks for graduating, but working together with you on our atypical literature study was both challenging and funny.

I would also like to thank my friends and housemates for the enjoyable time next to the working hours at the university and VDL ETG. It was very nice just to share thoughts with you about my study and thesis project, but most important of all just to laugh often and make much fun.

Last but not least, I would like to express my gratitude to my family. To my special grandparents, Jaap and Cis. Your open interest in and proud of everything I was doing at the university really enriched me. More than once didn't I have to travel home by train, as one of you would drive an hour to pick me up by car so I would be in time for my football training at Stormvogels'28. And finally, to my parents and sister. I cannot imagine that there is someone that goes home during the weekend and gets such a warm support for his study and life as I have received. Andries, Corina and Guusje, I cannot thank you enough for the unconditional support you provided, not only at the moments of sharing enthusiasm and happiness, but especially at the moments those were far away. I'm so grateful to have you in my life!

Jaap Arts

Eindhoven, July 2015

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List of abbreviations

ATO	Assemble-to-order
BOM	Bill of materials
CLIP	Committed line item performance
CODP	Customer order decoupling point
ECLIP	Earlier (than) committed line item performance
GFC	Goods flow control
MRP	Material requirements planning
MPS	Master production scheduling
MTO	Make-to-order
MTS	Make-to-stock
NPI	New product introduction
OEM	Original equipment manufacturer
PU	Production unit
R4V	Release for volume
RLIP	Requested line item performance
SCOP	Supply chain operations planning
VDL ETG	VDL Enabling Technologies Group (Eindhoven)

Introduction

"Life is really simple, but we insist on making it complicated" -Confucius-

In this report we present our study on tactical buffer management and operational control in multi-item multi-echelon assemble-to-order (ATO) supply chains, conducted at VDL Enabling Technologies Group Eindhoven (hereafter 'VDL ETG'). VDL ETG is active in the field of complex, innovative mechatronic systems. The company is a tier-one contract manufacturing partner for original equipment manufacturers (OEM's) of complex, high-tech products (e.g. AMSL and FEI). The environment in which these companies operate is very complex in terms of high demand and supply uncertainty; low volumes; complex bill of material structures and dependencies; expensive materials and rapid technological developments.

A very important feature of this type of environment is the long internal throughput time of products compared to the lead times required by customers. Companies active in the supply chain manufacture and/or assemble customer-specific products from modules and components in multiple production (and test) steps. Moreover, these components and modules might be used for multiple customer orders, possibly in different combinations and/or with optional features. This creates many challenging tasks, and urges the companies to keep improving their supply chain operations efficiency and control. A lack of good efficiency and control can cause unnecessary high investments in inventory and can lead to supply chain nervousness in terms of rescheduling production plans (De Kok & Fransoo, 2003; De Kok & Inderfurth, 1997).

In the past decades, there has been a growing interest in supply chain operations planning and control in multi-echelon systems (De Kok & Fransoo, 2003; Song & Zipkin, 2003). Following the definition of the first-mentioned authors, we can define the objective of supply chain operations planning as: "to coordinate the release of materials and resources in the supply network under consideration such that customer service constraints are met at minimal cost."

Despite the considerable progress in developing analytical models for these systems, there is still much room for new theoretical developments, especially concerning the application of knowledge and models from classical inventory theory in ATO environments. This thesis therefore addresses this promising gap for extending the existing literature by focusing on the following problem:

Companies in ATO environments face many different uncertainties, but it is unclear how to control operations and determine buffers in order to improve the overall supply chain efficiency and control.

The remainder of this chapter is organized as follows: after a discussion of the research methodology in the next section, we provide an introduction to VDL ETG in Section 1.2. In Section 1.3 we discuss the problem context and summarize the key elements of a roadmap which has been developed to structure a series of master thesis projects at VDL ETG. Based on the problem analysis, we formulate the research questions in Section 1.4. Thereafter, the scope of the research is discussed in Section 1.5. We conclude this chapter by outlining the remainder of this report in Section 1.6.

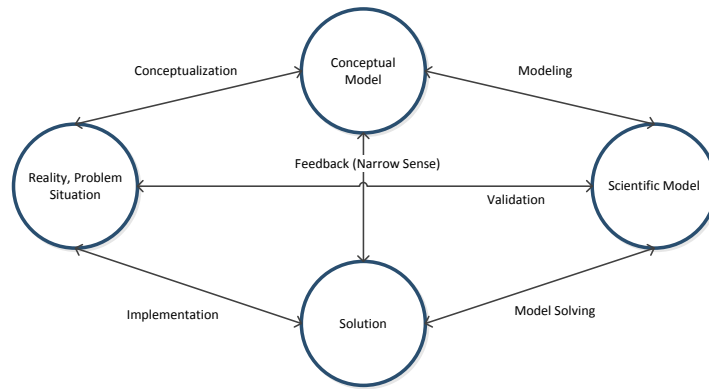


Figure 2: Quantitative research model (Mitroff et al., 1974)

Concerning the research methods, we practically used:

Desk research including the use of academic literature as well as company documents and databases, in order to retrieve insights and support the generation of new design knowledge.

Interviews have been used to validate quantitative results as gathered from VDL's databases, as well as to discuss current problems and important issues to consider when investigating new concepts for buffer norm setting and material control.

Modeling is required to support the design phase of the project. This concerns the development of mathematical models and quantitative concepts to understand existing processes and to analyze important decision functions.

Simulation, finally, is used to test the performance of alternative methods for norm setting and operational control, and to investigate the improvement potential compared to the current situation.

1.2. Company introduction

VDL Enabling Technologies Group (VDL ETG) is part of the large international, family owned business VDL Group. The VDL Group consists of more than 83 companies, with more than 10.000 employees working in 19 different countries around the world. It is a collection of flexible, independently operating companies, each with their own specialism. The VDL Group focuses on the development, production and sale of semi-finished products, busses and complex end-products, and on assembly of cars (VDL Annual Report, 2013).

VDL ETG is active in the field of complex, innovative mechatronic systems. In 1900, it all started as Philips Machinefabrieken and during the 20th century it became a worldwide operating company, supplying integrated systems and solutions to Philips as well as other companies. In 2000, the name changed into Philips Enabling Technologies Group and in 2006 it was taken over by the VDL Group.

VDL ETG focuses on systems integration and supply chain management of mechatronic (sub)systems for OEM's of complex, high-tech products. This is reflected in their mission statement:

"To reach global leadership as tier-one contract manufacturing partner, by outperforming in delivering mechatronic solutions."

VDL ETG has different divisions, with general management being located at the headquarters in Eindhoven. The company has a special division named VDL ETG Research, focusing on engineering and prototyping. Moreover, the division VDL ETG Technology & Development takes care of the product

and technology development. In addition, there is a special division called VDL ETG Projects, which focuses on producing one-off, customer specific modules and systems. Finally, the company offers its main serial production and assembling services characterized by high complexity and low volumes, being performed in 4 different locations: VDL ETG Almelo, VDL ETG Eindhoven, VDL ETG Singapore and VDL ETG Suzhou. Unless stated otherwise, when using the term VDL ETG we refer to VDL ETG Eindhoven (Acht). The other three production sites, each with their own characteristics and planning and control structures, are outside the scope of this project.

The modules produced by VDL ETG (and its customers) are used in different markets: semiconductor, analytical systems, solar, medical and aerospace. The major part of VDL ETG’s turnover is attributable to customers active in the lithography/semiconductor industry. As shown by Figure 3, this market has grown over the past decades, but meanwhile has a high volatility. This volatility in demand is further amplified upstream in the supply chain. VDL ETG faces this effect, being highly subject to the economic cycles and demand patterns.

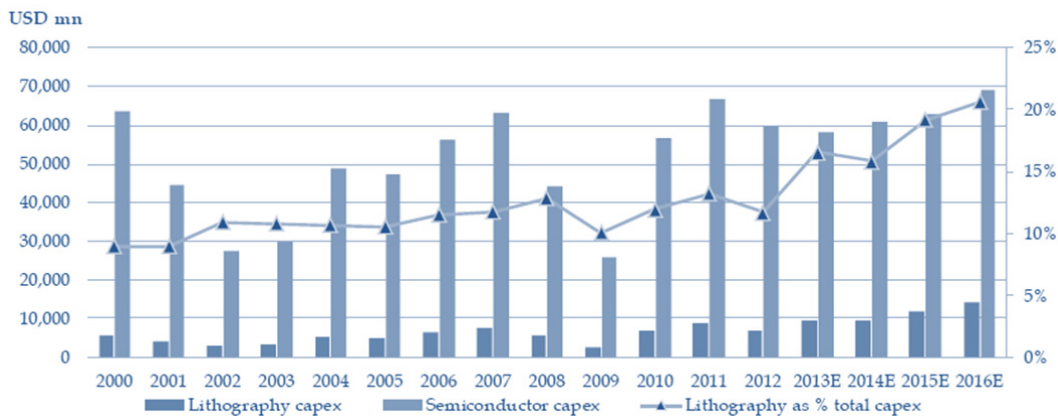


Figure 3: Lithography market trend and semiconductor capital expenditures (Berenberg, 2013)

1.2.1. VDL ETG’s supply chain

The core activity of VDL ETG is the assembly and integration of modules and systems, which is controlled by the Systems department. Components used for the assembly and integration are either produced internally by the Parts department or sourced from external suppliers. Parts is characterized by job-shop planning, detailed production schedules and routings, set-up times and machine utilization level control. Employees working on the Parts floor are highly specialized, i.e. they have specific skills to perform operations on only one or very few machines. Components produced by Parts are used for the assembly activities of Systems as well as to fulfill external customer demand. Compared to Parts, Systems has a higher flexibility in terms of capacity. Within Parts, machines are the critical resources and cause bottlenecks, whereas the most important capacity within Systems is people. Due to rather generic nature of the assembling activities, Systems has a higher resource flexibility. Assembly capacity can be scaled up due to the nature of the work, but this cannot be done quickly. Hence, capacity constraints are present over a short planning horizon, whereas for the long run often infinite capacity is assumed.

The customer order decoupling point (CODP) lies at different places for different customers and final systems. Some systems have an assemble-to-order (ATO) structure, while others have a make-to-order (MTO) structure. In the first case, the CODP lies before assembly; in the case of MTO, the CODP is before VDL ETG.

Considering the current planning and control structure of the supply chain, we identify a structure as shown in Figure 4.

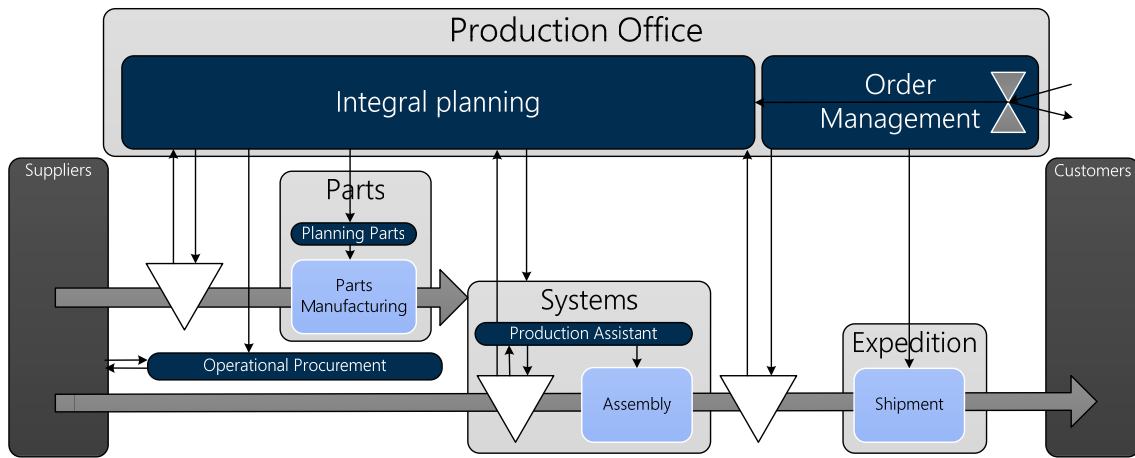


Figure 4: Supply chain planning and control structure VDL ETG

Integral production planning is performed by Integral Planning. A master production schedule (MPS) is created based on the demand plan of customers. The MPS is disaggregated/exploded by Baan (VDL ETG's internal ERP system) and a suggested MRP production schedule is provided by the system. Integral planners then critically review the suggested schedule and make adjustments in case they think this is needed. This results in the customized planning schedule, according to which the planners release procurement and production orders. Due to multiple reasons, a.o. customers which change their order due date or suppliers which do not deliver on time, rescheduling might be needed. In this case, Integral Planning takes care of the rescheduling of production and procurement orders. Rescheduling contributes significantly to the workload of the planners and often causes problems for production planning, an issue which we will address later.

Operational Procurement is responsible for the supply of materials and components from external suppliers (both for the stock point just in front of Parts as well as the stock point just before Systems). When they receive a procurement order from Integral Planning, they verify and check the suggested order, especially considering the buying prices and lead times of suppliers.

The Parts department mostly operates independently from Production Office, i.e. Parts receives production orders from Integral Planning and is responsible for its own production schedules. The performance of Parts on this aspect, however, can be improved. Agreed planned lead times are often unmet, causing a delay in the arrival of certain components, which delays the start of the assembling process or results in disturbances during assembly execution.

Within Production Office, there is a special unit Order Management which takes care of balancing demand with supply. The order managers are responsible for the communication with the customers (i.e. Customer Support) and, in addition, communicate with Integral Planning about the possibilities to accept future customer orders. Moreover, as they are responsible for direct contact with the customers, Order Management also receives modified orders and/or forecasts from the customers and communicates this with Integral Planning. Finally, Order Management is also responsible for releasing orders towards Expedition, with information regarding the delivery process and schedules for end products ready to be sent to the customers.

Finally, we briefly point out to a special group within the supply chain which has been created in January 2014: Repair Spare parts & Service (RS&S). This group is especially dedicated to the control and management of incoming demand for components and materials as required for spare parts and service. When a component or (semi-)finished module is needed, they inform Integral Planning about this 'demand'. Integral Planning then checks if they can satisfy this demand by releasing available inventory. If this is the case, the demand is satisfied. In case the demand cannot be satisfied immediately, RS&S is responsible for the procurement and production of the materials needed. About 5% of the sales volume of VDL ETG is represented by the RS&S chain. RS&S's contribution to the profit of VDL ETG is somewhat higher (about 10%), due to higher profit margins on these products compared to general components and modules (Kamps, 2015).

1.2.2. VDL ETG's supply chain planning and control processes

Within the supply chain as shown in Figure 4, operational control is organized according to separate 'chains'. In general, a chain refers to a specific customer, e.g. FEI or Philips. Considering ASML (being a very important and large customer for VDL ETG), a chain refers to a specific system class, e.g. the wafer handler system. Each chain has its own employees occupying the main functions related to operational planning and control: account manager(s), integral planner(s), operational buyer(s) and order manager(s). Next to these chain specific functions, there are also more general functions (being allocated to a set of multiple chains): parts planners and production assistants.

Besides the main classification in different 'chains', there is another supply chain classification focused on the final system level. This deals with the difference between so called 'Programs' and 'NPI Projects'. Initially, when a new system for a (new) customer is put into production, the production activities start as a 'New Production Introduction' (NPI) project. These projects are characterized by an experimental character of production operations and planning, low production volumes and they have a dedicated project leader. When time passes, the production and demand plans become more certain. A special checklist then is used to check if the project can be 'Released For Volume' (R4V), thereby becoming a 'Program'. Programs are characterized by controlled and released production processes, higher demand and production volumes, regular production planning and they have dedicated program managers.

Finally, we briefly make an important note about the term 'order' at the demand side (MPS-level): this can be either a 'real customer order', or a so called 'management order'. This latter type of order is an order which is created if production has to start while a 'real customer order' is lacking. In this case, management has to sign the 'management order', thereby agreeing to be aware of the potential risk of the 'order'.

To indicate the time dependencies between the main planning and control processes discussed above, we constructed a so called 'swimming lane diagram', see Appendix A.

1.3. Problem context

Since this research project actually marks the shared start of a series of research projects which will be conducted in collaboration between VDL ETG and students from Eindhoven University of Technology, an extensive problem analysis at VDL ETG has been performed. Based on this problem analysis, a roadmap has been developed to structure and plan the series of projects which share an overarching goal: improving the supply chain efficiency and control at VDL ETG.

In this paragraph we summarize the key elements of the roadmap, we refer to Kamps and Arts (2014) for the full report.

1.3.1. Challenging business environment

As discussed in the introduction, the business environment in which VDL ETG operates is very challenging. We have identified nine 'features' that together create the complexity faced by companies like VDL ETG when managing their supply chain:

- Complex Bill of Materials (BOM) structures (a final system typically consists of hundreds or thousands of items, some of which can be used in multiple successor items)
- Low demand volumes and short life cycles
- High value of components
- Uncertainty in the lead time of suppliers
- High, early customization (chains are MTO or ATO organized)
- Significant yield issues (products can be rejected during production and assembly processes)
- Capacity restrictions at (Parts) manufacturing
- Customer lead times shorter than integral throughput times
- Demand due date uncertainty (customer can advance or delay order delivery dates)

Although these features do not necessarily create complexity individually, it is the combination which does (Figure 5).

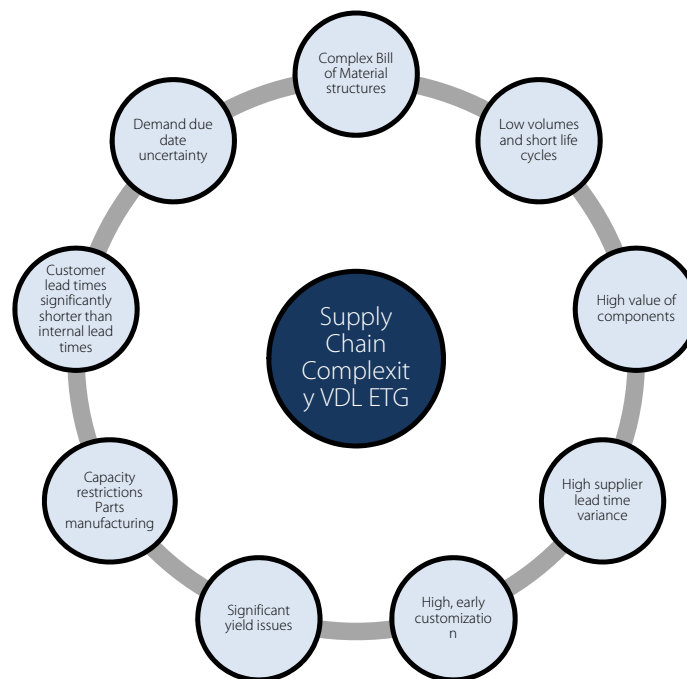


Figure 5: Factors contributing to VDL ETG's supply chain complexity

1.3.2. Problems and causes

In order to better understand the real problems and issues which VDL ETG faces, we organized a semi-structured session with some of the key actors who are closely involved in the operational decision making processes (Coppens et al., 2014). Based on this session along with process observations and individual discussions, an extensive cause-and-effect diagram has been constructed (see Figure 28 in Appendix B). We derived that the general 'problem' which is experienced and considered to be subject for improvement is actually threefold: the capital investment in inventory and work in progress is high,

the planning workload due to rescheduling activities is high, and finally the customer responsiveness is low.

In order to validate the problems and causes, we extended the qualitative analyses with some general quantitative analyses. Since we will provide a more extensive discussion on the quantitative analyses related to the key issues for our study later on in this report, we refer to Kamps and Arts (2014) for the support of the identified problems and causes via more general quantitative analysis.

1.3.3. A roadmap towards improvements in VDL ETG's supply chain

To address the problems as identified in the previous section, several projects have been constructed. The projects have been prioritized based upon their expected impact (cost savings, inventory reduction, performance improvement, etc.) and required effort (time, resources, supervision of project, etc.). Hereafter the projects have been positioned in time, resulting in a roadmap towards improvement of the controllability and efficiency in VDL ETG's supply chain. In Appendix B we provide a graphical representation of the roadmap along with more information about the individual projects.

1.4. Project selection and research questions

Our development of the roadmap actually started in a September 2014, being the starting point for a series of master thesis projects. As shown by the roadmap (see Figure 30) the route towards improvements begins with 'Project 4'. This project has meanwhile been finished by Tom Kamps, which resulted in the publication of his final master thesis (Kamps, 2015). This project focused on customer delivery date uncertainty and the efficiency of different rescheduling methods to cope with it.

A topic which is closely related to the study of Kamps (2015) is the topic of stock control of components and final systems, and the buffer strategy to cope with uncertainties in the supply chain, a.o. delivery date uncertainty. It addresses other valuable options to improve the performance of the supply chain and to be responsive in a dynamic and uncertain MTO/ATO environment. This second step in the roadmap ('Project 6+10') actually fits within the high-level type of problem we introduced in the introduction of this chapter.

So, since it nicely relates to our high-level problem selection and since it continues with the research study performed by Kamps, we selected 'Project6+10' as the subject for our research.

1.4.1. Research question

The objective of the study is to extend scientific knowledge and to develop solution concepts that enable VDL ETG to become more pro-active and responsive to opportunities and risks created by its customers and suppliers. The knowledge and solution concepts concern the coordination of the planning and control activities in the ATO/MTO supply chain, with a focus on norm setting in terms of safety stock and safety time.

Following the analyses and objective discussed so far, we formulate our main research question:

How should VDL ETG manage buffers and control operations in its dynamic ATO/MTO environment, such that the supply chain efficiency and controllability is improved?

1.4.2. Sub questions

We define 6 sub research questions to answer the main research question and to structure the development of (generic) design knowledge.

1. What are key strategic, tactical and operational features in the supply chain of VDL ETG?

2. What are the different types of uncertainty and their magnitude in the supply chain of VDL ETG?
3. How does VDL ETG currently deal with uncertainties in its supply chain and what can be learned from this?
4. How can operational decision making and control within VDL ETG's supply chain be improved?
5. How should VDL ETG set norms for buffers in materials and time such that demand is met effectively (on time) and more efficiently (with less costs and nervousness)?
6. How can VDL ETG use and implement the new insights?

1.5. Scope of the project

Below we outline the scope of our project by framing our research in a theoretical model and by discussing the practical scope within VDL ETG.

1.5.1. Framing our main research question in the planning hierarchy

First of all we briefly want to frame our research according to a framework which is presented by De Kok and Fransoo (2003). This framework (see Figure 6) positions supply chain operations planning (SCOP) in the planning hierarchy (cf. Bertrand, Wortmann & Wijngaard, 1990).

De Kok and Fransoo (2003, p.597) define the objective of SCOP as “to coordinate the release of materials and resources in the supply network under consideration such that customer service constraints are met at minimal cost.” The operations planning and control part of our research question relates to the SCOP layer in the hierarchy, which can be considered as the function currently performed by the Integral Planning department within VDL ETG. On the other hand, the buffer norm setting relates to the Parameter Setting function in Figure 6, which needs to “coordinate the safety stock, leadtime and workload parameters of the supply chain.” Our research question thus integrates the tactical characteristic of norm setting with the operational character of operations planning in multi-echelon supply chain systems, which are typically closely related (Graves and Willems, 2003).

We focus on the operational control and parameter setting at the integral level, i.e. we do not consider detailed material and resource coordination and parameter setting at the level of detailed Production Unit (PU) control. Note that we will use the terms ‘integral level’, ‘SCOP level’ and ‘Goods Flow Control level’ (Bertrand et al., 1990) interchangeable in the remainder of this report to denote our perspective.

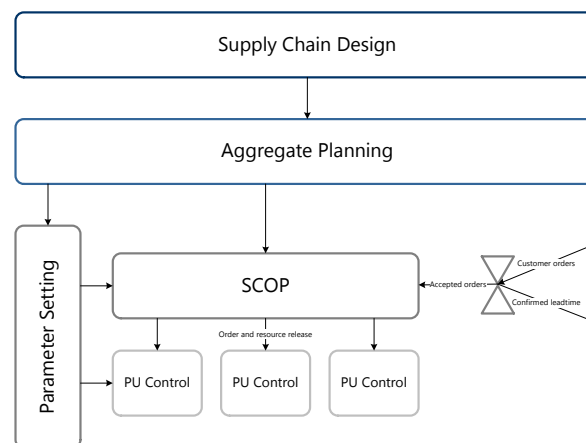


Figure 6: Supply chain operations planning in the planning hierarchy (De Kok and Fransoo, 2003)

1.5.2. Practical scope within VDL ETG's supply chain

More practically, we can make a few other notes about the scope of our research within VDL ETG. Since the research project will mainly address integral operations planning and control, with a focus on buffering against uncertainty, of course the Production Office (see Figure 4) is included within the scope. This department consists of both Integral Planning as well as Order Management. The order acceptance function (i.e. setting/negotiating delivery dates with customers, etc.) is excluded from the scope of our research.

Operational control and buffering at suppliers, as well as extensive operational supply chain integration with suppliers or customers (except for sharing demand forecasts, etc.) is not included within our scope.

We consider Parts as one of the suppliers of materials and components for assembly at Systems. We thus won't explicitly address production planning and control activities within the Parts department (e.g. routings, machine allocations and machine utilization control). As mentioned before, there are several significant issues at Parts which have a high improvement potential. This, however, will be the focus of the research study related to 'Project 7/8/9' (see Figure 30) which is planned to start in September 2015. The control within the RS&S department is excluded from the scope too. This department is responsible for the repair spare parts and service requirements. Tactical decisions as setting inventory levels, developing policies for preventive or reactive maintenance, and operational decisions like item procurement ordering are outside our scope.

For our quantitative modeling and analysis, we will only consider critical items such as customer specific modules, system components and expensive standard items. Items in the category glue and 'bolts and nuts' are left out. These items are controlled 'manually' (two-bin) and their inventory levels are kept high on purpose due to their small cost value.

Finally, note that we will focus on the R4V customer systems and exclude customer systems in the NPI phase. Planning and control of modules and systems in this NPI phase has a 'project' (one-off) character, changes per new project and is actually subordinate to the testing and mechanical engineering activities. Once the systems are released for volume, they are put into ongoing production and their operations planning and control becomes vital.

1.6. Thesis outline

The next two chapters of this thesis present the results of multiple analyses of the as-is situation within VDL ETG. In Chapter 2 we describe several key strategic, tactical and operational features in the dynamic ATO/MTO supply chain, taking a planning and control perspective. An extensive analysis of the main uncertainties observed in the supply chain along with an identification of the current buffer methods is provided in Chapter 3. In Chapter 4 we present some insightful preparative analyses and conceptual discussions which are important for the development of appropriate models to support our design phase. Two general quantitative models that support the evaluation and analysis of buffer management are designed in Chapter 5, along with the results of their application to real life examples in VDL ETG's supply chain. In Chapter 6 we present the second part of our design phase, as we 'design' directions and options for improving operational control and buffer management. In Chapter 7 we provide our main conclusions and insights by answering the research questions and discussing recommendations for further research within VDL ETG. We conclude this thesis in Chapter 7 by improving design knowledge based on a reflection on our case study at VDL ETG, and we provide recommendations for further scientific research.

Analysis of key strategic, tactical and operational supply chain features

"Seek first to understand and then to be understood" -Stephen Covey-

In this chapter we describe several key strategic, tactical and operational features in the supply chain of VDL ETG, taking a planning and control perspective. The focus of this chapter is on the analysis and description of the as-is situation within VDL ETG. We start with a discussion on the strategic role of flexibility and responsiveness in Section 2.1. Two related tactical aspects are capital investment risk and customer commitment, which are discussed in Section 2.2. In Section 2.3 we briefly discuss planning stability and nervousness as two important operational features. We conclude this chapter with an overview of the main planning and control objectives currently used by VDL ETG.

2.1. Flexibility and responsiveness

Across industry sectors, the concept of responsiveness has been receiving increasing attention in the operations management literature. It has been advanced as one of the key themes in recent supply chain research (Reichhart & Holweg, 2007). Reichhart and Holweg (2007) claim that a key shortcoming of definitions, however, has been the unclear separation from the definitions of flexibility. In their synthesis of the existing literature, these authors define and frame supply chain responsiveness in relation to flexibility.

Following Reichhart and Holweg, flexibility can be defined as "the ability of any system to adapt to internal or external influences, thereby acting or responding to achieve a desired outcome." In addition, a system's flexibility is based on internal resources that can be used to achieve different types of internal flexibility, which in turn can support the system's ability to demonstrate external flexibility to its environment. We refer to Bertrand (2003) for an extensive discussion of flexibility from an investment and tactical point of view, i.e. which flexibility to use and how to design it in a system.

Following Reichhart and Holweg (2007), the responsiveness of a manufacturing or supply chain system can be defined as "the speed with which the system can adjust its output within the available range of the four external flexibility types: product, mix, volume and delivery, in response to an external stimulus, e.g. a customer order". These authors identify a lack of distinction between factors that require supply chains to be responsive and factors that enable them to be responsive. In their article, they develop a framework for the conceptualization of supply chain responsiveness (see Figure 7). We now structure our discussion of the need for and applicable determinants of responsiveness in the supply chain of VDL ETG according to this framework, taking an integral planning and control perspective. In the remainder of this report, we will use the term responsiveness and thereby refer to the external flexibility of the supply chain which can be demonstrated towards customers based on internal flexibility.

According to Reichhart and Holweg (2007), the four main areas which create the need for supply chains to become responsive are: demand uncertainty, demand variability, product variety, and lead-

time compression. Note that in the high-tech customer order driven business-to-business (B2B) environment of VDL ETG, except for product variety, all factors are present.

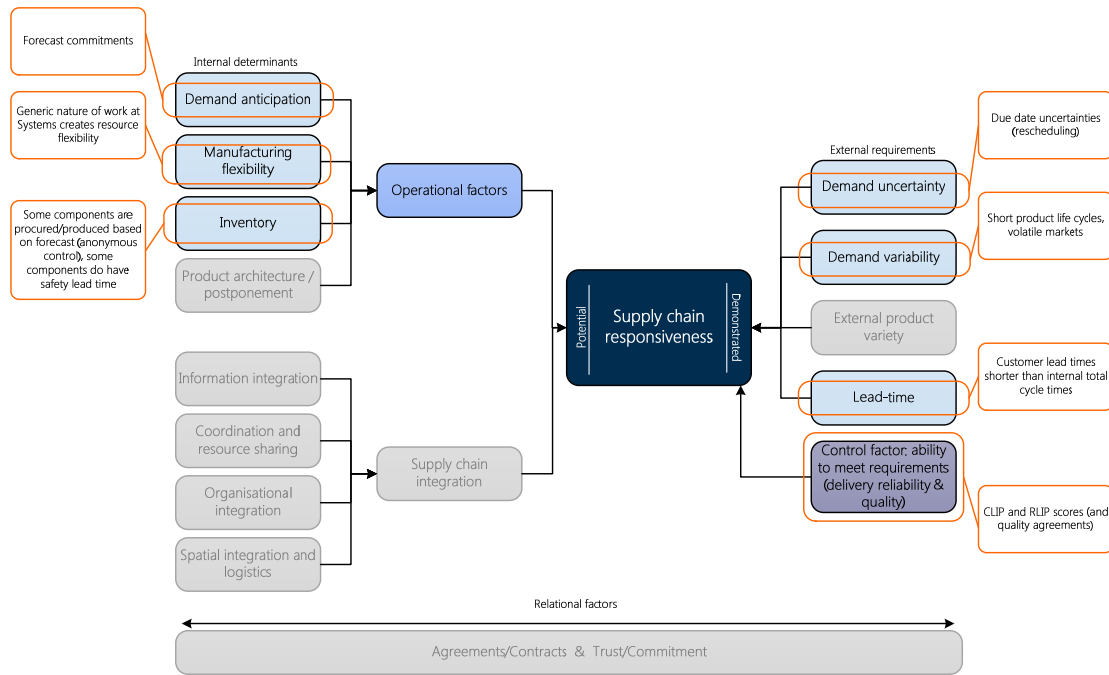


Figure 7: Supply chain responsiveness framework (Reichart & Holweg, 2007) applied to VDL ETG

Demand uncertainty is often regarded as the main reason for being responsive (Fisher, Hammond, Obermeyer & Raman, 1994). In addition to demand uncertainty (schedule instability), demand variability (schedule variability) plays a role with regard to responsiveness too. Product variety is the third factor which drives the need for responsiveness. Demand uncertainty is typically amplified by product variety, as the same aggregated demand is split over more stock keeping units. As mentioned before, this type of uncertainty is not of direct great (and manageable) concern in the complex, business to business supply chain of VDL ETG, with customer specific items. It is rather the short product life cycle of customer specific items which create many challenges. Finally, lead time compression increases the need to be responsive, because the firm or supply chain is given less time to respond to new orders or changes in existing ones.

Of the internal enablers of supply chain responsiveness, we briefly discuss the factors which are relevant concerning VDL ETG's supply chain characteristics. We focus on the first type of internal factors, which are the operational factors applying to individual organizations/systems within a supply chain. The second type, which covers the factors that deal with the integration of different supply chain partners, is outside the direct scope our research project. Hence we refer to Reichhart and Holweg (2007) for a detailed discussion of these factors. Demand anticipation is one of the most obvious enablers for a supply chain to be responsive. Improving demand anticipation can be achieved via different ways. Within the business to business environment of VDL ETG, close relationships exist with the customers. These customers provide forecasts to VDL ETG, which are associated with certain degrees of commitment. Manufacturing flexibility within VDL ETG's supply chain mainly relates to the issues with flexibility of the Parts department. As mentioned before, throughput times are very long and often include many different types of slack. A decrease in the throughput time of items which are internally produced can be achieved by various measures. Resource flexibility, however, is limited due

to the limited machine capacities and very specific skill requirements for the worker(s) operating a certain machine. Therefore, planning within Parts is based on a limited capacity. Within the Systems department, however, there is relatively high (resource) flexibility (cf. Section 1.2). Assembly activities in the Systems department are planned under the assumption of infinite capacity (Langenhuysen, 2015a).

Reichhart and Holweg (2007) note that despite a tendency across industries to become “lean” and operate with less stock, inventory buffers still exist in many places in supply chains and these allow for higher supply chain responsiveness. Product architecture is closely related to the concepts of modularization and postponement. Within the context of VDL ETG, this issue is mainly part of the NPI phase of a customer chain. Once items are released for volume (R4V), the product architecture is basically considered as fixed. It is therefore outside the scope of our research project.

We also briefly point to the control factor in the framework, which is the delivery reliability and quality requirement. VDL ETG measures its delivery reliability towards customers via the Committed Line Item Performance (CLIP) and Requested Line Item Performance (RLIP) measures. The CLIP score denotes the percentage of customer orders which are delivered on or one day before the (latest) confirmed delivery date, whereas the RLIP score denotes the percentage of customer orders which are delivered on or one day before the (latest) requested delivery date. Quality requirements are captured in detailed contractual agreements.

Finally, note that the framework includes some relational factors too. These are neither external requirements nor pure internal determinants, but can be influenced by both parties and impact upon the need, as well as the ability, to be responsive. These aspects mainly apply to the (long-term) strategic relationships with customers, and are typically less relevant from an operations planning and control perspective.

2.2. Risk and customer commitment in relation to capital investments

Closely related to the three external requirements in Figure 7 is the issue of inventory risk. As mentioned before, in the high-tech industry in which VDL ETG and its customers operate, the process of rapid technological developments and advancements goes on. Customer specific products which VDL ETG produces typically are sold to the customer for a period of about 1-2 years. Given this short product life cycle, the high demand uncertainty, and the high value of the products, one could imagine that the inventory which is kept by VDL ETG creates a high risk exposure.

2.2.1. Supply chain capital investments

Three important types of stock related capital investments can be identified in VDL ETG’s supply chain:

Inventory: this can be inventory of components and modules in the warehouses of VDL ETG or consignment stock located at the customer’s site.

Work in Progress: these are components and modules which are in progress within VDL ETG, e.g. released for production but waiting in a queue in front of a machine.

Purchasing: this refers to purchasing orders which are already released but which have not arrived at VDL ETG’s warehouses yet.

Taking a control perspective, each of these types can be split up into two categories: ‘anonymous’ or ‘project’. The first category refers to capital investments based on forecasts (i.e. the forecast-driven part

of the supply chain), while the second category refers to capital investments based on customer orders (i.e. the order-driven part of the supply chain).

Figure 8 shows the relative size of each of the three main types of capital investments. Note that VDL ETG considers 'project' inventory as a type of work in progress. For monitoring and reporting purposes, VDL ETG currently doesn't make an explicit distinction between 'project' and 'anonymous' work in progress or purchasing. Note that due to confidentiality, the vertical axis is hidden.

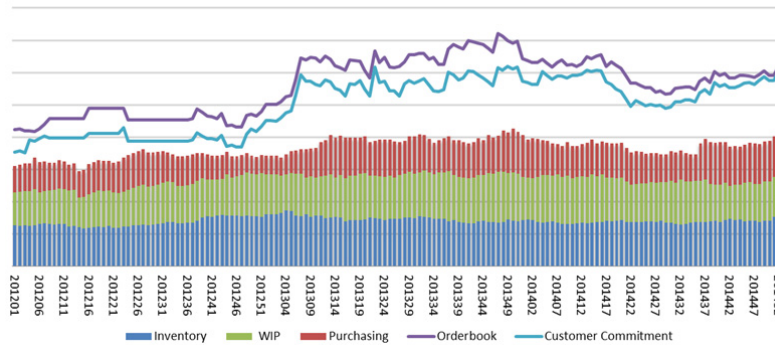


Figure 8: Supply chain capital investment VDL ETG (performance report 2015 week 2)

2.2.2. Capital investment risk and risk management

Basically, any inventory which is held by VDL ETG creates a risk exposure as discussed above. Given the different types of inventory and taking an integral planning perspective, we can say that it is mainly the anonymous inventory which creates (obsolescence) risk (note that VDL ETG considers an item as obsolete if it hasn't 'moved' for 4 months). In addition, the work in progress creates some risk too, since it also includes some anonymous work in progress. The fraction of the work in progress which is anonymous, however, is rather small (aggregate value of 1/6).

Note that we explicitly mentioned the integral planning perspective above. For the integral planning department both customer orders and management orders (see Section 1.2) are simply considered as an order, and planned and controlled accordingly. Inventory which is held for an order is considered as project inventory, although it thus may actually stem from a management order. This type of order, however, creates risk for the company VDL ETG just as forecast-driven anonymous inventory does.

Finally note that, despite the fact that project inventory generally creates no risk exposure, it still is associated with holding costs in terms of opportunity cost of capital and storage costs.

Inventory in the MTO chains is generally kept for real customer orders. For the ATO chains, anonymous inventory is basically the result of a customer lead time for a final system which is shorter than the internal total cycle time, as agreed in close collaboration with the customer (Van Wandeloo, 2015). Hereby some of the components in a final system's BOM have to be kept on stock, i.e. these have to be procured or produced based on a forecast instead of a real order.

In order to minimize and control the risk associated to this forecast-driven inventory, VDL ETG uses two different options:

- For long-lead-time-items, VDL ETG asks the customer for full commitment to start producing or procuring these items. It thus can be considered as a kind of real customer order for a certain long-lead-time component of the final system.

- In general, customer agreements include forecast commitments. Customers are committed to the order amount of their forecasts to a certain level, and the level of commitment increases as the time to the required delivery date decreases.

Concerning the second option, different structures exist. For example, for end items produced for FEI a structure with four equal commitment zones is used. In other words, the total integral lead time is split up into four equal zones. Right from the beginning the customer is committed for 25% to the forecast it provides. Once 75% of the integral lead time has passed, this customer is 100% committed to the order amount (Van Oosterhout, 2015).

For the biggest customer, ASML, a more basic forecast commitment structure is used. One with two different zones: a full 100% commitment zone of X weeks, and a limited Y% commitment zone of Z weeks, where the X,Y and Z values differ per final product (Botden, 2015).

2.3. Planning stability and nervousness

De Kok and Inderfurth (1997) note that the performance of control policies and parameter settings are traditionally evaluated with respect to the costs they cause, and in case of avoiding estimation of shortage costs, with regard to the service degree they provide. These authors mention a third criterion in addition to the traditional performance which can be of high performance. This is the level of planning stability that can be achieved in a rolling horizon planning framework. In the case of VDL ETG, planning instability is represented by rescheduling of production and procurement plans (e.g. due to demand rescheduling, see Kamps (2015) for a detailed discussion). De Kok and Inderfurth (1997) note that especially in a multistage production environment ruled by an MRP system, nervousness on the top level (MPS –level) is propagating throughout the system. Due to MRP time-phasing and deterministic assumptions, even future planning instability enforces present replanning actions. Following the reasoning of De Kok and Inderfurth, we will treat planning stability as an independent attribute for assessing an inventory control system, similar to the attribute of customer service which cannot be replaced by cost or profit values in most practical situations. So, since nervousness matters, operations control rules and control parameters (buffer stock and planned lead times) will be discussed under additional consideration of their stability effects.

Buffers can be installed to tackle this nervousness. Buffers are currently installed by VDL ETG via safety times (and in some cases safety stock). De Kok (2015), however, claims that nervousness is typically a symptom of bad or deficient planning and control procedures. We will, therefore, also shed light on how the improvement of buffer management and operational control can support the reduction of the supply chain nervousness.

Finally, we identify two important reasons why nervousness and rescheduling matter in the supply chain of VDL ETG. First of all, rescheduling activities are labor intensive (we refer to Kamps (2015) for a cost analysis of these activities). Secondly, taking a supply perspective, nervousness is propagated towards suppliers (and Parts production) via rescheduling messages. This creates demand uncertainty and planning instability observed by suppliers (and Parts production), which in turn may decrease their supply reliability towards VDL ETG. As De Kok (2012) shows, also downstream links in the supply chain suffer from the bullwhip effect, i.e. variability not only amplifies as one moves upstream the supply chain, the bullwhip also returns.

2.4. Supply chain planning and control objectives

We conclude this chapter with a brief discussion about the objectives for integral supply chain planning and control within VDL ETG (Langenhuysen, 2015a).

First of all, we note that VDL ETG carefully monitors and controls its performance reliability, i.e. the service levels, towards customers. The target service level (CLIP score) equals 95%. This service level should be considered particularly as a requirement which need to be satisfied, it is not an explicit goal to maximize this service level.

Secondly, inventory plays a central role in the management and evaluation of VDL ETG's supply chain planning and control activities. Since the investment in inventory (and work in progress) is associated with costs and risks, the inventory levels are monitored continuously. Contrary to the service level for which an explicit objective value is defined, there are no hard targets for the inventory values. VDL ETG, however, aims to keep the investments in inventory as low as possible.

As mentioned in the previous section, the planning workload in general and the rescheduling workload in particular are of concern for VDL ETG, too. Compared to inventory and service levels which are carefully monitored and controlled, rescheduling workload is not monitored explicitly. However, management is aware of the burden (and direct and indirect costs) this places on the integral planning and control activities. We therefore identify the reduction of the rescheduling workload as a third type of supply chain planning and control objective.

Finally, we briefly mention some other aspects which we came across during the interviews and desk research. First of all one might argue that products should not only be delivered on time, they should also be of the right quality. Since this typically is a manufacturing / factory engineering issue, we do not consider this as a planning and control objective explicitly. Instead, we will incorporate these quality issues in our analysis via yield. In addition, cycle time reduction could improve the performance of the supply chain and could therefore be seen as a separate objective. This is typically a responsibility of the supply chain engineers, and mainly design-related. Considering the scope of our research, we will consider the lead times and their variability as given, and focus on the improvement of the supply chain efficiency via better norm setting and control. Of course, if smarter buffer management would allow for lead time reductions, this would be an important additional benefit.

2.5. Conclusions and insights

In this chapter we described several key strategic, tactical and operational features in the supply chain of VDL ETG, taking a planning and control perspective. We discussed the strategic role of flexibility and responsiveness, and argued that these affect operational planning and control only indirectly. In addition, we discussed capital investment risk and customer commitment as two related tactical aspects. Moreover, we mentioned planning stability and nervousness as two important operational features. Finally we provided an overview of the main planning and control objectives currently used by VDL ETG. The insights presented in this chapter provide us with an important understanding of aspects to take into account and they provide directions for improving operational control and buffer management in the design phase of our research. In the next chapter we will continue our investigation of the as-is situation with both qualitative and quantitative analyses of supply chain uncertainties and methods currently used by VDL ETG to buffer against them.

Three

Analysis of supply chain uncertainties and current buffer methods

"Uncertainty is a very good thing: it's the beginning of an investigation, and the investigation should never end" -Tim Crouch-

In this chapter, we identify and analyze the different types of uncertainties which are present in the supply chain of VDL ETG. In addition, we discuss the options currently used to buffer against them. In order to improve control and reduce the impact of these uncertainties in the design phase of our research, we must first understand their sources and relative impact (Davis, 1993; Lee & Billington, 1992).

A general introduction about uncertainty and system performance will be presented in Section 3.1. We then structure our discussion of the different types of uncertainties according to the classification of Davis (1993). This author identifies three types of uncertainties in a supply chain: supply, process and demand uncertainty. The key results of our quantitative analysis of these types will be provided in Section 3.2, Section 3.3 and Section 3.4, respectively. In Section 3.5 we attempt to relate the different types of uncertainty and frame them from an integral supply chain perspective. After the discussion of the key types of uncertainties and their 'size' in VDL ETG's supply chain, we will discuss the current buffer options in Section 3.6.

3.1. Uncertainty and system performance

Ho (1989) identifies two different classes of uncertainties that affect production processes: environmental uncertainty and system uncertainty. Environmental uncertainty includes uncertainties beyond the production process, such as demand uncertainty and supply uncertainty. System uncertainty is related to uncertainties within the production process, such as operation yield uncertainty, production lead time uncertainty and changes to product structures. Davis (1993) identifies three different sources of uncertainty that plague supply chains: suppliers, manufacturing and customers. Note that suppliers and customers together constitute the environmental uncertainty discussed by Ho (1989), while manufacturing uncertainty is identical to the system uncertainty. In the remainder of this document, we will use the high-level classification of Davis (1993), i.e. we will discuss and analyze different types of supply, manufacturing process and customer demand uncertainty.

To conclude this short introductory paragraph, we briefly refer to two related laws out of a series of insightful laws developed by Hopp and Spearman (2000) on variability (the term they use for both variation and uncertainty) and trade-off buffering:

Variability law: increasing variability always degrades the performance of a production system

Variability buffering law: variability in a production system will be buffered by some combination of inventory, capacity and time.

This stresses the relevance of our analyses and investigation of the different types of uncertainties. We structure our discussion of the results according to Figure 9. As represented by this figure, we focus on the uncertainties from the perspective of supply chain operations planning and control, e.g. currency

uncertainty, purchase price uncertainty and the risk of a supplier going bankrupt are not considered within our analyses. Our quantitative discussions will be focused on probability density functions, for that is the nature of uncertainty (Davis, 1993). Finally note that we will use the terms variability and uncertainty interchangeably in this chapter.

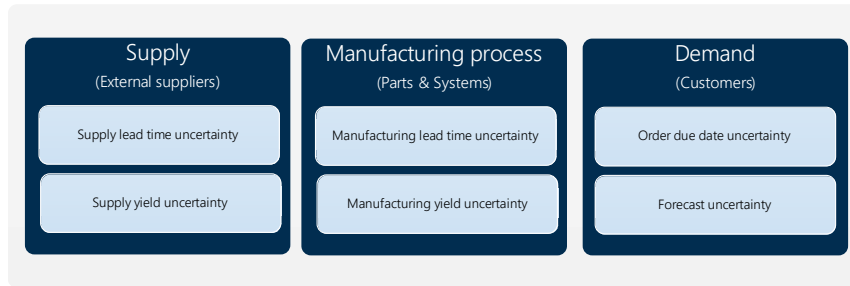


Figure 9: Framework of uncertainties at VDL ETG

3.2. Supply uncertainty

For these analyses, we used ERP-based historical data, filtered on delivery dates between 01-01-2014 and 28-02-2015. This eventually resulted in 15.633 purchasing order lines for Parts, and 19.394 purchasing order lines for Systems. Note that due to confidentiality, the vertical axis is hidden in all figures.

3.2.1. Supply lead time uncertainty

The time needed to receive a component from an external supplier may differ from expected. As with random demand, lead time uncertainties may provoke either some shortages or surplus in inventories. In the context of VDL ETG, the supplier lead time reliability is measured via the CLIP score. VDL ETG considers an order to be delivered 'on time' if it has been delivered 'on or no more than 4 working days earlier than the committed date'. In addition, there is '1 working day late margin for delay in VDL ETG receipt' (Klein, 2015).

Figure 10 visualizes the supplier lead time uncertainty (over all different customer chains). The results are highly similar for Parts and Systems, with the majority of the purchasing orders delivered on time, but still quite a large amount delivered too late. Following the definition of VDL ETG as introduced above, we derive that the total CLIP performance towards Parts and Systems is about 69,1%, respectively 69,8%. For Parts, the average supply lead time deviation is 0,39 days, with an associated standard deviation of 45,9 days. For Systems, the average supply lead time deviation is -0,90 days, with an associated standard deviation of 26,0 days. Note that this analysis considers a kind of additive lead time deviation, focusing on the absolute deviation in days. In other words, we do not consider the multiplicative deviation in terms of a percentage of the planned lead time.

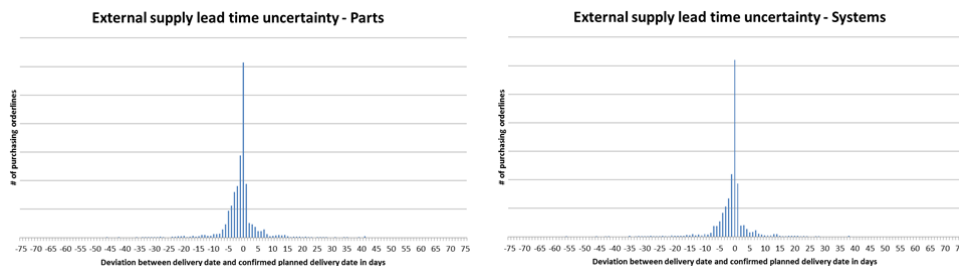


Figure 10: External supply lead time uncertainty Parts and Systems

3.2.2. Supply quantity uncertainty

Besides uncertainty of the supply lead time, there might also be a deviation between the ordered and delivered quantity of purchasing items: supply quantity uncertainty. Here we can make a same note regarding the focus on the distribution of the quantity error instead of the quantity itself.

The deviations between delivered quantities and confirmed order quantities are shown in Figure 11. The percentage of purchasing order lines delivered with the right order quantity (whether or not delivered on time) towards Parts and Systems is 98%, respectively 98,3%. For Parts, the average quantity error equals 0,4 units with an associated standard deviation of 45,8 units. For Systems, the average quantity error is 0,1 units and the standard deviation equals 10,1 units.

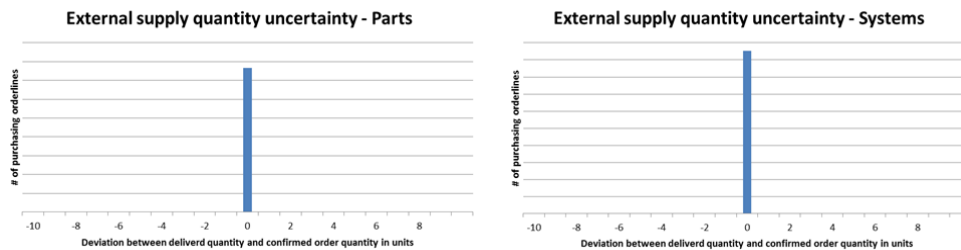


Figure 11: External supply quantity uncertainty Parts and Systems

Although we use no formal expression to compare lead time uncertainty with supply quantity uncertainty, the results above demonstrate that it is especially the supply lead time which requires special attention. Moreover, at VDL ETG supply yield uncertainty is never a reason to order more than actually needed, e.g. ordering 11 units at a supplier since it is expected that the delivered quantity equals 10 units. If suppliers cannot deliver the requested quantity, let's say 10 units, on time, two options are possible: either the supplier informs VDL ETG that it only has 9 units available and waits for the final unit, with the result that it delivers 10 units too late; or the supplier informs VDL ETG and the operational buyer decides to split the order, so 9 units are delivered on time, and other single unit is delivered later but (hopefully) on the confirmed separate delivery date too (Klein, 2015).

Finally note that we do not yet (aim to) provide statements about how to model the supply quantity (yield) uncertainty. We refer to Yano and Lee (1995) for a discussion of different types of yield models and their applicability. The analyses as discussed above, however, are a type of 'additive yield': if an order of size Q is placed, then the yield (quantity actually received) is equal to $Q+Y$, with Y a (continuous) random variable.

3.3. Manufacturing process uncertainty

For these analyses, we used ERP-based historical data, filtered on delivery dates between 01-01-2014 and 28-02-2015. In addition, we excluded RS&S production orders and order lines with internal product rejections. This eventually resulted in 9.088 production order lines for Parts, and 6.577 production order lines for Systems. Note that due to confidentiality, the vertical axis is hidden in all figures.

3.3.1. Manufacturing lead time uncertainty

Figure 12 visualizes the manufacturing lead time uncertainty (over all different customer chains). Again, we focus on the production finish date error in order to analyze the manufacturing lead time uncertainty, see our discussion about the supply lead time uncertainty in Section 3.2. For Parts, the average finish date deviation equals -0,02 working days, with an associated standard deviation of 37,98 working days.

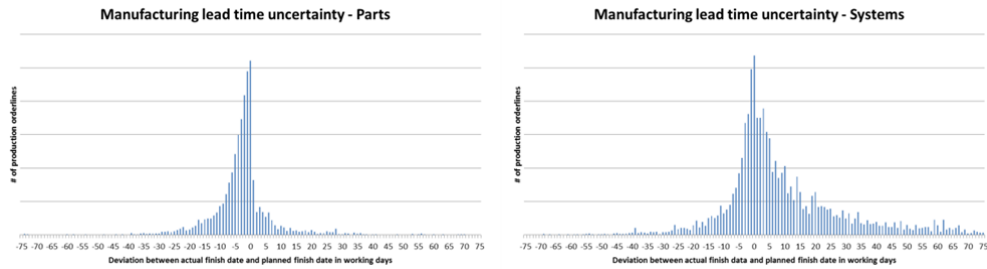


Figure 12: Manufacturing lead time uncertainty Parts and Systems

We should make an important note regarding the manufacturing lead time uncertainty within the Systems department. For Systems, the key performance indicator typically is the final CLIP performance offered towards customers. Internally, production order finish dates are often exceeded, but not only due to material shortages or due to exceeding the throughput time. Often, planners or employees working on the assembly operations know that certain items are not immediately needed but only near the end of the assembly operation (e.g. at day 5 of the total 5 days assembly operation). Moreover, an assembly operation can be started for a production batch of 10 units. Since not all 10 units are needed at the finish date as stated in the planning system, the assembly of some units will be delayed (without updating their requested delivery date). Finally, if customers delay their order then assembly can delay its operations too, but the planned finish dates of modules is not updated in the ERP system.

The lead time analysis for Systems therefore should be considered differently compared to the analysis for the Parts manufacturing operations. For Parts, the majority of the production orders actually is a kind of customer order which should be delivered to Systems. Hence, the CLIP performance measures of Parts do typically represent the true manufacturing process lead time uncertainty (Nas, 2015a). We explicitly note that the lead time uncertainty analysis and probability density function for Systems still clarify an important thing: actual assembly operations differ from the production plans, either on purpose or due to material shortages and planning deficiencies. Moreover, the CLIP measures are not suitable for planning and control decisions, an issue we will discuss later on.

3.3.2. Manufacturing quantity uncertainty

We start with a brief discussion of two aspects related to quantity uncertainty from a manufacturing process perspective within VDL ETG. First of all, items can get a 'waste% factor' for certain operations within Parts, which is the standard percentage of the production order quantity which needs to be manufactured in addition to the order quantity, mainly due to set-up items which are needed (e.g. the first item is used for calibrating a machine setting and becomes waste). These waste% factors, however, cannot be observed in VDL ETG's production order lines data. In other words, if for example 10 units of a certain item are needed, the data file shows an order quantity of 10 (and hopefully a delivered quantity of 10). These waste% factors differ per item per routing and are estimated based on the experience of the Factory Engineers (Leenders, 2015).

From a supply chain planning perspective, we identify the real quantity uncertainty: the deviation between the delivered (produced) quantity and the confirmed (production) quantity. In other words, if 10 units of a product are needed, uncertainty arises if the produced quantity deviates from the requested quantity (whether a constant yield factor was taken into account or not). More specifically, if there is a constant/deterministic yield for all items, this would have been accounted for via the yield factors, and the delivered quantity would always equal the requested quantity. Buffering, however, is intended to cope with unexpected deviations and thus mainly relates to the deviations between the requested and delivered production quantity. Figure 13 shows the quantity deviations.

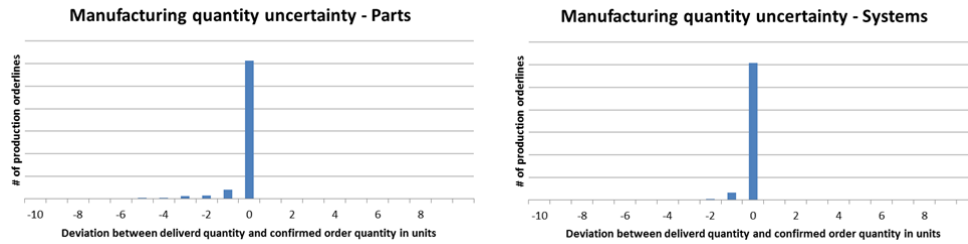


Figure 13: Manufacturing quantity uncertainty Parts and Systems

Finally we note that within Systems, yield plays a different role compared to Parts. For assembly operations, VDL ETG does not decide to assemble 11 products if 10 are actually needed to account for yield issues. It is, however, possible that some items need rework (which can delay the throughput time, which affects the CLIP performance) or items are rejected (then the production order is 'closed', either before or after the planned finish date, and a new production order is released). This again stresses the remark about the caution with which lead times (finish date reliability) of separate production orders within the Systems department should be analyzed (Koops, 2015).

3.4. Demand uncertainty

The final class of uncertainty is related to the demand side, i.e. the uncertainty created by customers. We discuss two different types of uncertainty: demand forecast uncertainty and customer order due date uncertainty.

3.4.1. Taking a 'time perspective': demand due date uncertainty

As discussed in Chapter 1, VDL ETG faces frequent demand due date changes from customers. From a demand uncertainty perspective, this type of uncertainty should be distinguished from forecast uncertainty, since demand due date uncertainty relates to customer orders instead of (customer) forecasts. The demand due date uncertainty is of relevance for the entire MTO chains, as well as for the order-driven part in the ATO chains.

In his thesis report, Kamps (2015) extensively discusses demand due date uncertainty in terms of external rescheduling messages which VDL ETG receives from its customers. We used his data analysis to derive Figure 14, which indicates the existence and extend of order due date uncertainty. We explicitly included a delivery date shift of 0 weeks, i.e. actually no shift, since this provides a fair indication of the customer due date uncertainty. The figure shows that order delays are observed more frequently than order advancements.

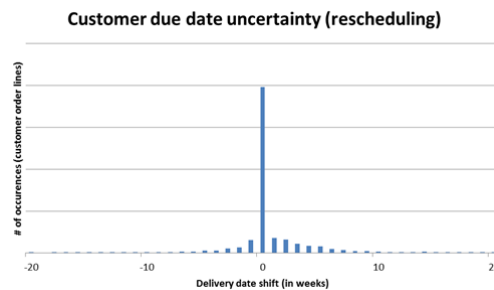


Figure 14: Customer due date uncertainty

3.4.2. Taking a 'quantity perspective': forecast and order error

Besides this 'timing perspective' on demand uncertainty (see previous paragraph), we can also take a 'quantity perspective' on demand uncertainty. In other words, the uncertainty of the required demand in future periods. This consists of both forecasted as well as ordered demand. Note that VDL ETG doesn't forecast customer demand itself, it receives demand forecasts from its customers.

Demand at the MPS-level is initially forecasted (typically with a one year forecast horizon) and once it becomes critical in terms of falling within the integral lead time, there should be an order in the ERP system to start production (either a real customer order or a management order, see Section 1.2). Both the forecasts and orders at the MPS level are stochastic in a rolling schedule environment, i.e. demand for a certain moment in future is thus both forecasted as well as ordered for multiple periods.

In order to get an idea about the existence and extent to which forecast uncertainty is present, we analyzed three important final systems in detail: the ASML NXT3 system, the ASML XT4 system and the FEI Project Assy. These are complex systems in the two biggest ATO chains (ASML Wafer Handler and FEI). These systems are MPS controlled, with long-lead-time-items being procured or produced based on forecasts, while the majority of the (sub) modules is assembled to order. Below we discuss the results for the ASML NXT3 system, for the other two systems we obtained highly similar results.

To get an idea about the relative forecast and order accuracy throughout the forecast and order period, we calculated the average deviation between the forecasted/ordered amount and the final customer delivery ('real demand'), for each number of weeks before delivery. Figure 15 shows that, on average, demand is over forecasted/ordered. Moreover, the accuracy improves as one moves closer to the final delivery date. Note that there is a small overlap between orders and forecasts around 27 weeks before delivery: this is the order lead time, which equals the integral lead time (excluding a few very long-lead-time-items). The bars indicating the number of data points show the overlap. In other words, sometimes an order has been placed by ASML more than 27 weeks before delivery, while there are also instances in which there was only a forecast less than 27 weeks before delivery.

The strange value for the deviation 1 week before final delivery is explained by the fact that within the data (ERP system), the order amount for the next week includes both the customer orders for that specific week, as well as the outstanding/backlog orders concerning internal delivery dates. Because of a one week buffer between the internal and external delivery date, the number of outstanding orders typically varies between 1 and 2 units (weekly demand), which explains the striking data point.

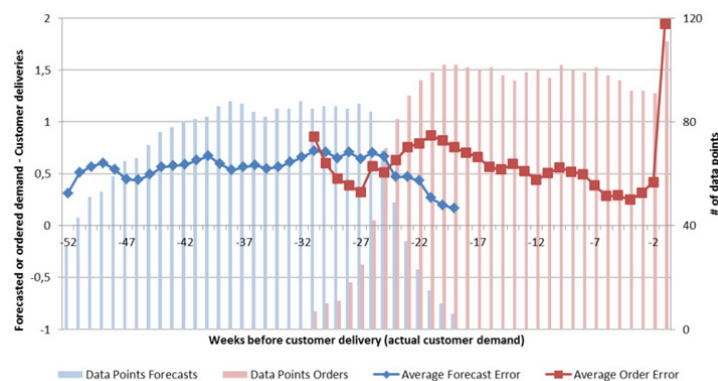


Figure 15: Forecast and order uncertainty ASML NXT3 system

Finally we emphasize the rather isolated character of our discussion of the demand (forecast) uncertainty in this paragraph. Considering the scope of this sub question, the analyses above serve to

indicate the existence of demand uncertainty, from both a time and quantity perspective. In Section 4.1 we analyze demand forecast uncertainty in relation to inventory and buffer control, with a focus on cumulative numbers instead of single period values.

3.5. Towards an integral supply chain perspective

The previous sections discussed the analyses of different types of uncertainty as faced at the integral level within VDL ETG. If we take a broader supply chain perspective, we can extend the uncertainties discussed above with uncertainties which are actually 'propagated through the system' by VDL ETG.

We therefore extended our analysis of uncertainties with an analysis of three other types of uncertainties, which are 'created' by VDL ETG: purchase order due date uncertainty 'sent' to suppliers, internal production order due date uncertainty, and delivery uncertainty 'sent' to customers. The results and some discussions are provided in Appendix C.

Finally we framed the different types of uncertainties which have been discussed above in the supply chain control structure of VDL ETG, see Figure 35 in Appendix C. We do not (aim to) make any claims regarding formal causalities between these types of uncertainties. With Figure 35 we rather aim to provide a more integrated perspective on the different types of uncertainties, by positioning them in the supply chain control structure and indicating likely relations between them. Note that we make a clear distinction between the information flow and related uncertainties on the one hand, and the material flow and related uncertainties on the other hand.

3.6. Current buffer methods

In this section we discuss methods and options which are currently used by VDL ETG to buffer against uncertainties in the supply chain. We aim to identify and briefly explain the different options, an extensive investigation of the underlying procedures and working of the concepts is outside the scope of this section.

As formulated in the 'variability buffering law' discussed in the introduction of this chapter, variability in a system will be buffered by a combination of time, material and capacity. This also applies to the supply chain of VDL ETG, in which safety stock and safety time are used as buffers. In addition to buffering with time and material (which are interchangeable in some way; Chang (1985)), buffering with capacity is a third option. As discussed in Section 1.2, capacity flexibility exists within the Systems department. Hence planning assembly operations in the Systems department is performed while assuming infinite capacity (static planning). Within Parts, (dynamic) capacity buffering is used. For the medium (and long) term, capacity is planned at 80%, i.e. a 20% capacity buffer. For the short term, i.e. next week, capacity is planned at 100%. The buffer is typically used to deal with issues as order advancements, rejections and operator absenteeism (De Vocht, 2015).

Since we take an integral material planning and control perspective in this chapter, we won't consider production unit capacity buffering explicitly in the remainder of this section. Still, it is a promising avenue for further research and improvement especially within Parts, and therefore formulated as a separate research project which will be started in the second half of this year (cf. Figure 30).

3.6.1. Master production scheduling and buffering

In VDL ETG's MRP planning environment, customer forecasts and orders are translated into a master production schedule (MPS). The MPS in this case is typically not completely identical to the demand forecast. Planners aim for smooth production schedules, and by doing so actually create buffers to cope with uncertainties (of any type, but especially demand uncertainties). Based on their experiences,

planners also buffer against expected order advancements from customers, etc. Note that MPS planning is typically performed with a rolling planning horizon of 1-2 years, and MPS's are not frozen (Rosenau, 2015; Nas, 2015b).

3.6.2. Item safety stock and safety time buffers

Except for only a few critical (high uncertainty, low cost value, etc.) items, safety stock is not used (only 48 items out of total 22.065 active items). Safety time is used for 1642 items (out of total of 22.065 active items). The safety times for these items relative to their lead times are shown in Figure 16. Note that safety times are typically a multiple of 5 working days (one week). The average of the safety time divided by the lead time is 0,42 for Parts, 0,34 for Systems.

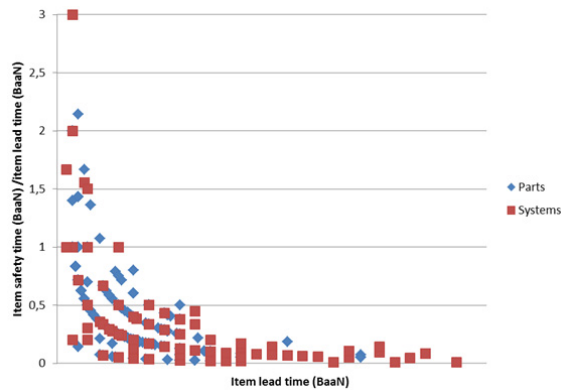


Figure 16: Safety time MRP items

3.6.3. Buffer between external and internal customer due date

Generally, VDL ETG uses one week difference between the external and internal customer due date, implemented in BaaN by the Order Managers. This creates some buffer, but is not necessarily fixed. In other words, planners can and do decide to skip or deviate from this buffer week for various reasons, e.g. if a customer order is received within integral lead time (Nas, 2015b).

3.6.4. Consignment stock

The final buffer option which can be observed in VDL ETG's supply chain is consignment stock. This is stock which is actually located at the customer, but still owned by VDL ETG (with the risks associated to it). The most eminent example of this option can be observed in the chain of Philips. VDL ETG produces final systems based on forecasts provided by Philips, in combination with predefined lower and upper inventory levels as agreed between both parties.

3.7. Conclusions and insights

In this chapter, we identified and analyzed the different types of uncertainties which are presented in the supply chain of VDL ETG and the options currently used to buffer against them. Understanding the sources and relative impact of these uncertainties helps us to improve control in the design phase of our research (cf. Davis, 1993; Lee & Billington, 1992). Taking an integral planning and control perspective, we summarize the main insights we derived from our qualitative and quantitative analysis below.

Three main classes of uncertainties which VDL ETG faces are: supply, process and demand uncertainty. In terms of the supply and manufacturing process classes, it is especially lead time uncertainty which is

important. In terms of demand uncertainty, we identify both forecast and order uncertainty in terms of requirements for future periods (which actually captures the demand due date uncertainty).

Uncertainty generally is buffered with a combination of time, material and capacity. Capacity buffering is only used at planning within Parts. Systems plans under the assumption of infinity capacity. Other options currently used to buffer against uncertainty are: safety stock, safety time, MPS planning with buffers, buffer of one week between external and internal due date, and consignment stock.

Within VDL ETG, there is a strong focus on and monitoring of material related uncertainties and performance metrics, e.g. CLIP suppliers, inventory levels, CLIP towards customers. In contrast, there is much less understanding and monitoring of information related uncertainty, e.g. forecast uncertainty, internal rescheduling and lead time modelling. People are aware of related issues, but the real impact and causes are not really known. Different types of buffers are used at different moments and places. The application of buffers is mainly operationalized based on employees' experiences (from planners, factory engineers, etc.). There is a lack of explicit performance feedback loops and control with regard to uncertainties and methods used to buffer against it. This makes it hard to create a solid understanding of the existence and especially the impact of uncertainties (on decisions already made as well as decisions to be made).

This provides an interesting avenue for improvement: improving the understanding of uncertainties and their buffer management, which allows for performance improvement from a more integral supply chain operations planning and control perspective. Moreover, it will enable VDL ETG to become pro-active (robust planning, awareness and insights about forecast uncertainties, etc.) instead of re-active (cost accounting afterwards, underpinning inventory levels after production projects are closed, etc.). We further elaborate on this promising option for improvement in Chapter 6.

Pre-design phase

"We cannot solve our problems with the same thinking we used when we created them" -Albert Einstein-

In Chapter 2 and Chapter 3 we extensively analyzed the current situation in the supply chain of VDL ETG by taking an integral planning and control perspective. Before we continue with the design of quantitative models which support the analysis and determination of buffer norms, we first introduce some important preparative analyses and conceptual discussions.

In Section 4.1. we analyze customer demand uncertainty in relation to material planning at the MPS level. In the previous chapter we already discussed forecast uncertainty with a focus on the volatility of forecasts and the forecast error per period. In this chapter we consider cumulative forecast uncertainty in relation to inventory positions, which will provide us with important information for our design phase. Hereafter, we analyze MPS nervousness in terms of demand plan and production plan stability in Section 4.2. Especially in the multistage MRP-controlled production environment of VDL ETG, uncertainty and nervousness at the MPS level is propagating throughout the system (De Kok & Inderfurth,1997). We continue with MPS uncertainty and nervousness in Section 4.3, as we provide an important conceptual discussion on the role and position of the CODP within VDL ETG. Hereafter in Section 4.4 we discuss the importance of suitable performance metrics in order to support decision making and control.

4.1. MPS forecast uncertainty

In order to study forecast uncertainty in relation to operations planning and control, we analyzed the MPS (ERP based) history for three important MPS items at VDL ETG: the FEI Projector Assy (average demand = +/- 1 system per week, integral lead time = 28 weeks), the ASML NXT3 wafer handler (average demand = +/- 1,5 systems per week, integral lead time = 27 weeks) and the ASML XT4 wafer handler (average demand = +/- 1 per week, integral lead time =17 weeks). We selected these systems since they are important final customer systems in two important ATO chains within VDL ETG: the ASML AWH chain and the FEI chain. Together, these two chains represent about 30% of the total investment in inventory and work in progress and about 60% of the investment in anonymous inventory (see our discussion in Section 2.2).

We retrieved an extensive data file, covering all MPS related historical information for many MPS items, a.o. the items mentioned above. We used this data set for our analyses, in combination with discussions with planners and order managers to validate the data based results. As indicated by De Kok and Fransoo (2003, p.669), "the existence of ERP systems allows for the analysis of transactional data over time, from which we can obtain insight into the behavior of demand, inventories and lead time. Such research will be time consuming and difficult, due to the fact that the experimental setting cannot be fully controlled. Such research will be rewarding in terms of deeper insights into real-world supply chain operations planning problems and the contribution of quantitative models to its solution."

First of all we analyzed the data from a single-item single-echelon perspective. In other words, we consider the MPS item as a single product (no assembly operations) with a single lead time which is set

equal to the integral planned lead time of the item (L^{cum}) recorded the ERP system (i.e. the longest cumulative planned lead time in the BOM).

In the context of VDL ETG, even customer orders do change and only become ‘final’ at the moment they are actually requested by the customer. Moreover, once a forecast becomes critical in terms of falling within the integral lead time without being a customer order, a management order is created. Planners (and the MPS history files) don’t distinguish between real customer orders and management orders. The above mentioned elements triggered us to make no explicit distinction between orders and forecasts for future moments. In the remainder of this section, we use the notation $\sum_{s=0}^{L^{cum}+R-1} F_t(t+s)$ for the at time t estimated demand during the cumulative lead time plus review period (in general this includes (stochastic) customer orders, but can also include some forecasts; if there was both a forecast quantity as well as an order quantity for a period, we took the maximum value). Without loss of generality, we assume a review period of one time period (week).

We compared the forecasted cumulative demand at each review (log) date [$\sum_{s=0}^{L^{cum}+R-1} F_t(t+s)$] with the real demand (customer deliveries) during the same period [$\sum_{s=0}^{L^{cum}+R-1} D_t(t+s)$]. These indicators serve to illustrate the cumulative demand forecast uncertainty. In addition, we offset these numbers against the ‘state’ of the system at each log date. This state is comprised of the net stock at moment t [I_t] (excluding scheduled receipts which arrive at the start of period t) plus the scheduled receipts for the next cumulative lead time period, i.e. $\sum_{s=0}^{L^{cum}-1} SR_t(t+s)$. Note that this sum includes R periods less than the sum of the forecasted demand. The demand during this final R periods is exactly the decision variable at a certain review date: the order release at the start of period t , i.e. $SR_t(t+L^{cum})$.

Below we discuss the findings of our analysis. We present the detailed results for the ASML XT4 system in Figure 17, similar figures for the ASML NXT3 system and the FEI Projector Assy are provided in Appendix D. Due to confidentiality, the vertical axes are hidden.

The figures show the state of the system right before a release decision as represented by the scheduled receipts (green bars) plus possible on hand inventory/shortage (dark green bars). The amount released is represented by the orange bar, which is actually the scheduled receipt for L^{cum} periods later. Cumulative forecasts are indicated by the blue line, the real customer deliveries during the same cumulative period are represented by the red line.

Note that the L^{cum} rightmost red data points provide a ‘wrong’ indication of the demand. This is due to the lack of customer deliveries during the full cumulative lead time. For example, for 1-3-2015, we can calculate the forecasted demand for the next L^{cum} periods. The customer deliveries, however, are only recorded until the moment of data retrieval (1-4-2015), and therefore significantly lower than the demand forecasts. This explains the decreasing cumulative demand in the final L^{cum} periods.

The figures provide additional support for our earlier conclusion in Chapter 3 about demand uncertainty: demand is typically ‘over forecasted/ordered’ by customers. Moreover, we see that the forecasted cumulative requirements partially match with the ‘state’ of the system as reflected by the scheduled receipts plus net inventory. Note that for the FEI Projector Assy, planners do explicitly plan with some finished goods stock. This is supported by Figure 37 in Appendix D, which shows some ‘over planning’ in terms of scheduled receipts which exceed the forecasts. For ASML, planners generally plan with no finished inventory. ASML’s final systems are typically held as work in progress and only released as finished inventory when they are delivered to the customer, i.e. they are in finished stock for less than a day.

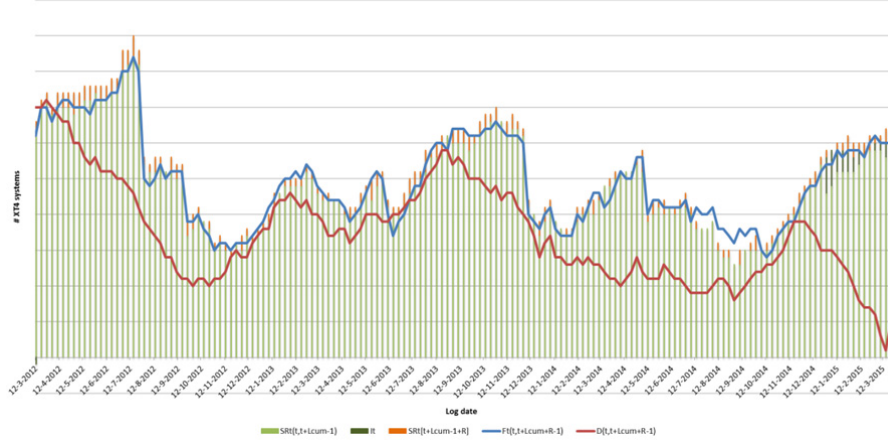


Figure 17: Cumulative demand uncertainty ASML XT4 system

4.2. MPS demand and supply nervousness

In the previous paragraph we analyzed forecast uncertainty from a MPS planning perspective, i.e. focusing on cumulative demand and forecasts in relation to the system's state. In this paragraph we discuss the uncertainty/ volatility of the demand forecasts and the uncertainty/volatility of production planning.

The MPS data set has been used to analyze the forecast revisions (demand plan) and scheduled receipts revisions (production plan) over the entire planning horizon for each of the three MPS items discussed before. We determined any change in the forecast or scheduled receipt for each period over time. Mathematically, we compare:

$$\forall t: F_0(t + L^{cum}) \leftrightarrow F_1(t + L^{cum}) \leftrightarrow \dots \leftrightarrow F_t(t + L^{cum}) \leftrightarrow F_{t+1}(t + L^{cum}) \leftrightarrow \dots \leftrightarrow F_{t+L^{cum}-1}(t + L^{cum})$$

$$\forall t: SR_0(t + L^{cum}) \leftrightarrow SR_1(t + L^{cum}) \leftrightarrow \dots \leftrightarrow SR_t(t + L^{cum}) \leftrightarrow SR_{t+1}(t + L^{cum}) \leftrightarrow \dots \leftrightarrow SR_{t+L^{cum}-1}(t + L^{cum})$$

Note that $\forall i: i < t, F_i(t + L^{cum}) \leftrightarrow F_{i+1}(t + L^{cum})$ relates to possible changes in demand plans outside the lead time, i.e. before production has been started. Similarly, $\forall i: i \geq t, F_i(t + L^{cum}) \leftrightarrow F_{i+1}(t + L^{cum})$ relates to changes within the lead time. Of course, this distinction holds for the changes in scheduled receipts too.

In order to get an idea about the extent to which revisions occur, we first visualized the above changes in the MPS history file. A part of this analysis for the ASML XT4 module is shown in Figure 38 and Figure 39 in Appendix D. The visual analyses revealed the smoothing effect of MPS planning for all three customer systems, i.e. the production plan as represented by the scheduled receipts is more stable than the demand plan as represented by the customer forecasts. Moreover, especially within the lead time this dampening effect can be observed. Outside the lead time there seems to be no dampening effect. It actually seems like the production plan outside the lead time (planned receipts instead of scheduled receipts) is more volatile than the demand plan.

We extended our visual analysis with a quantitative analysis, by investigating all revisions as formulated by the expressions above. The detailed quantitative results are reported in Section D.2 in Appendix D. Below we briefly discuss the general findings.

Our quantitative analysis confirmed the dampening MPS effect within the lead time, where the number of scheduled receipt revisions is about half the number of forecast revisions. Outside the production lead time, the number of production revisions is even larger than the number of forecast revisions for both ASML systems. Regarding the difference between increases and decreases in forecast/production plans, we see that outside the lead time, there are more demand/production increases (about 65%), whereas within lead time there are more demand/production decreases (about 55%). Regarding the link between demand revisions and production revisions, the analysis revealed that (within the lead time) production is more likely to respond to a demand forecast decrease compared to a demand forecast increase.

4.3. The CODP: its role and position within VDL ETG

During our analyses of current planning and control policies and our search for improvement opportunities, we faced different 'problems' evidencing the haziness about the current role and position of the CODP within VDL ETG.

In the existing literature, the CODP is often defined as "the point that indicates how deeply the customer order penetrates into the supply chain. It is the distinction between the order-driven and forecast-driven parts of the supply chain for a particular product market combination" (De Kok & Fransoo, 2003; cf. Bertrand et al., 1990). An important aspect in relation to the CODP point is demand uncertainty. De Kok and Fransoo (2003) state that "all releases downstream of the CODP are based on actual customer orders and thus are not planned under uncertainty of demand (cf. Orlicky, 1995). All releases upstream of the CODP are planned based on dependent demand."

Regarding the penetration of a customer order into the supply chain, we identify both ATO and MTO structures within VDL ETG (see Section 1.2). Assembly operations are only performed based on orders, whereas Parts production orders or purchasing orders can be released based on an order as well as a forecast.

As mentioned before, however, within the highly volatile B2B environment of VDL ETG, customer orders are associated with uncertainty too. Not in terms of the customer buy, but mainly in terms of the moment at which the customer buys. From a MPS planning perspective, this uncertainty is actually demand uncertainty, i.e. the demand for a specific future period is unknown until the moment of real demand. More specifically, as our quantitative analysis in Section 3.4 revealed that customer orders are as uncertain as a (customer) demand forecasts, releasing based on customer orders is actually similar to releasing based on forecasts from an uncertainty perspective. This is contrary to the definition of the CODP as stated above.

Although order driven release decisions can be regarded as forecast driven release decisions from a planning (uncertainty) perspective, one might think of a significant difference in terms of commitment: orders have full customer buy commitment, whereas forecasts are essentially not associated with commitment. But recall from our discussion in Section 2.2 that forecasts are associated with varying levels of commitment too. Moreover, management orders are created if production needs to be released but customer commitment is lacking. For a planner, there is actually no distinction between a real customer order, a commitment order or a management order. So, from a planning perspective, we observe that actually all release decisions are covered by some type of commitment.

These observations triggered us to question the general view of the supply chain as a pure ATO system. We therefore constructed an alternative framework which represents the decoupling situation within VDL ETG, see Figure 18. Release decisions are thus covered right from the beginning of the supply chain. For the MTO product chains as classified by VDL ETG, material is allocated to a customer

order right from the beginning. For the ATO product chain, purchasing and production decisions are taken anonymously, i.e. without an order, and material is only allocated to an order during assembly. Finally, decisions which are made based on uncertain demand information are basically only decoupled from certain demand information at the final product inventory position.

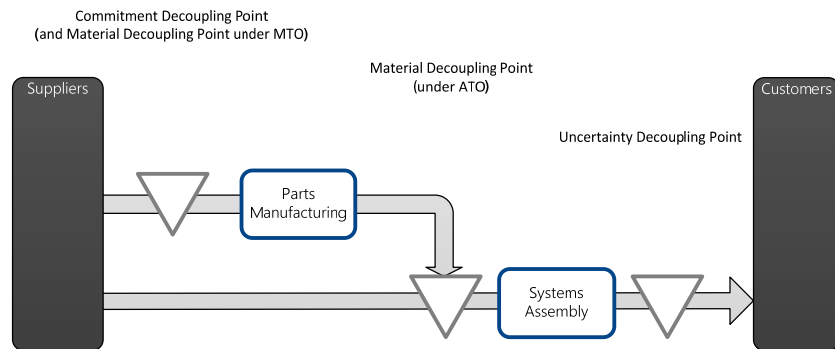


Figure 18: Alternative view on decoupling within VDL ETG

It is interesting to note that in existing literature, inventory models for operations planning and control typically only focus on decisions for items that are kept in stock at and upstream of the CODP (De Kok & Fransoo, 2003). On the other hand, models for stochastic throughput times are only considered in order driven systems, i.e. the part after the CODP, assuming deterministic order due dates.

Buffering is needed to cope with demand and process lead time uncertainty, and both currently exist from the beginning until the end of the supply chain. Considering the main purpose of our next research part, i.e. modeling and analyses to support buffer norm setting, we will initially consider the uncertainty decoupling point as the CODP in typical stochastic inventory models, and the commitment decoupling point as the CODP underlying stochastic lead time models. We further address this aspect in the next chapter during our discussion about the necessity to decouple demand uncertainty from lead time uncertainty.

Given the discussion above, and since our buffering analysis is not so much about the exact position of the CODP but about possible efficient options for decoupling, we will not explicitly refer to 'the CODP' in our upcoming discussions.

4.4. Planning and control performance metrics

VDL ETG currently uses two major service measurements: the RLIP (percentage of orders fulfilled one day before or on the latest requested customer delivery date) and the CLIP (percentage of orders fulfilled one day before or on the latest confirmed delivery date). Both measures are not only used for customer orders, but for procurement and production orders as well.

There currently is a strong emphasis on CLIP delivery measures on customer orders (average service level of about 95%), fed by the strong customer-orientation of this measure. This metric therefore is mainly suited to measure the 'delivery reliability' which VDL ETG obtains at the very final end of its supply chain, i.e. at delivery to the customer. This metric, however, is the only measure which is structurally employed, and it is used during planning meetings, evaluations, etc. (Nas, 2015b; Langenhuisen, 2015b).

Due to different reasons (a.o. the flexibility in terms of modifying order due dates in consultation with the customer, a difference between external and internal due dates and customer deliveries as part of

a yearly order for which the delivery date is only recorded in the system just before delivery), this indicator is a kind of 'intervention dependent metric' and thereby unsuitable for modeling and buffer norm setting (and for true measurement of planning performance).

The RLIP (average service level of about 30%) can be considered as a more suitable alternative to the CLIP indicator, measuring the true supply chain (planning) 'capability'. However, this measure provides some difficulties too. Especially if customers initially place an order with an extremely short, 'unrealistic' order lead time, while accepting the alternative, 'realistic' lead time suggested by VDL ETG afterwards. In addition, the RLIP still is external due date oriented, while (MPS) planning is focused on internal due dates. Besides these issues, the inconsistency of production planning which is initially focused on internal production due dates and the shift to a focus on external customer due dates once issues (e.g. capacity issues, escalations) arise, limits the true control value of CLIP or RLIP monitoring too.

The issues explained above clearly demonstrate that one might argue whether the CLIP (and RLIP) measure are the right or only service measures to focus on. They can be used to measure service offered towards customers, but fail to support operational decision making and control. A detailed investigation and development of alternative service measures, however, is outside the scope of our research. For the quantitative modeling and analysis in the design phase of our research, we will consider more suitable service measures while taking into account the availability of service related data. In Chapter 6 and 7 we return to the issue of control performance metrics as we discuss recommendations for improvement and further research within VDL ETG.

4.5. Conclusions and insights

In this chapter we presented some insightful preparative analyses and conceptual discussions which are important for the development of appropriate models to support our design phase. Analysis of historical demand and production data revealed that, for three important customer systems in the ATO supply chain of VDL ETG, cumulative customer forecasts and orders generally exceed real demand. In addition to uncertainty, demand orders and forecasts are associated with nervousness too. Via leveling in the MPS production plan, an important part of this nervousness is dampened by planners. Since even customer orders provide uncertain (and nervous) information about real demand until the final moment of delivery, we argued that we can (and should) consider the supply chain as a kind of MTS system in order to support buffer norm setting under stochastic demand. There is, however, one important difference with a classical MTS environment: within VDL ETG production is generally only started if there is customer commitment (either via a real customer order or committed forecast), thereby reducing the majority of the risk of stock investments. Production control thereby becomes generally order-driven, but under stochastic lead times and uncertain demand. We should therefore design alternative models to support buffer norm setting against demand and lead time uncertainty.

We split up the design phase of our research in two parts. In the next chapter, we extensively discuss the design of new mathematical models. Since the complex, stochastic current planning and control situation (see discussions above) doesn't allow for the use of standard mathematical models to easily design improved rules, we first design new quantitative models. These models support the understanding and analysis of buffering in order-driven assembly systems with lead time and demand uncertainty. Besides discussing the design of the models, we also discuss their value for understanding the complex reality and we use them to evaluate alternative buffer norm settings. After 'design for understanding and analysis' in Chapter 5, we focus on 'design for improvement' in Chapter 6. In other words, based on the models designed and analyzed in Chapter 5, we also discuss the 'design' of more concrete directions and options for improving operational control and buffer norm setting.

Design for understanding and analysis

"Everything should be as simple as possible, but not simpler" -Albert Einstein-

Based on the analyses and discussions in the previous paragraph, we believe that there is a need and promising option for the design of new and alternative buffer norms and strategies in order to improve operational control and efficiency in the real life complex supply chain of VDL ETG. For the design and complementary quantitative modeling and analysis, we use and extend scientific knowledge on analysis and control of stochastic multi-echelon supply chain systems.

In Chapter 2 we provided an extensive analysis of the different types of uncertainties faced by VDL ETG, and investigated their relative impact. Accordingly, we select two main classes of uncertainties for which we will design quantitative models to support the analysis of buffer norms. This decision will be underpinned in Section 5.1, along with a theoretical discussion of the need for decoupling them for quantitative modeling and analysis. Then in Section 5.2 we discuss the first class of uncertainty: demand uncertainty. The second class of uncertainty, which is lead time uncertainty, will be discussed in Section 5.3. We conclude this chapter with a summary of the main insights.

Note that the focus of this chapter is on the design of quantitative models to support the understanding and analysis of buffer management in the stochastic assemble-to-order supply chain. In the next chapter, we use the insights obtained in this chapter to design directions for improvement.

5.1. Decoupling demand uncertainty from lead time uncertainty

The first class of uncertainty for which we will design quantitative models to analyze buffer settings is demand uncertainty. By taking an alternative perspective to demand uncertainty compared to the current understanding and beliefs within VDL ETG, we will be able to capture both the demand due date uncertainty as well as the forecast/order uncertainty in one model. Next to demand uncertainty, we will model lead time uncertainty. Our analysis in Chapter 2 revealed that, compared to quantity or yield uncertainty, lead time uncertainty is more comprehensive for VDL ETG's control. Here we consider both supplier lead time uncertainty as well process lead time uncertainty, which both simply represent lead time uncertainty which propagates downstream through the supply chain system.

In Section 1.5 we positioned our research in the planning hierarchy (De Kok & Fransoo, 2003; Bertrand et al., 1990). Although we do not aim to provide a comprehensive discussion of all production planning and control concepts, we point to an important design principle for designing production control systems as introduced by Bertrand and Wortmann (1981), and further elaborated on by Bertrand et al., (1990): the separation of Goods Flow Control from Production Unit control. Goods Flow Control, within VDL ETG mainly represented by Integral Planning, coordinates the output of the Production Units and coordinates production with sales. Production Unit control, on the other hand, focuses on detailed control of operations, in an MRP environment often denoted as work centers or shop floors. The objective of detailed Production Unit control then is to realize targets set at the integral level. De Kok and Fransoo (2003) note that a consequence of this approach is that lead times of the various Production Units are fixed and are input to the system rather than output. These lead times are essentially modeled in exactly the same way as in MRP. More specifically, in order to properly coordinate the release of materials and resources while taking into account the random processing

times at work centers (as the result of interactions between materials and resources), the concept of 'planned lead times' emerges. This concept as a result for the need of robust and feasible control of real-life complex production systems, affects our upcoming quantitative modeling and analysis in two ways.

First of all, we will decouple demand uncertainty from lead time uncertainty. If the planned lead times are chosen properly, such that they are consistent with the resource availability and flexibility, we can assume that the lead times are met with a high reliability. Then, (multi-echelon) inventory models, which assume deterministic lead times, can be used to model and analyze buffering against demand uncertainty. In Section 5.2 we will discuss these types of analyses. We start with a basic one-product inventory model and consider a final MPS item as one product with a fixed lead time equal to the integral planned lead time. It turns out that this is a fair representation of VDL ETG's reality, which provides an important basis for the design of improvement options.

Secondly, if we zoom in on the item level, it turns out that planned lead times within VDL ETG are definitely not met with a 'sufficiently high' reliability. Since a high reliability of planned lead times is an important aspect in order to allow for efficient and effective control at the integral level, we will also model and analyze lead time planning within VDL ETG. Hereby the focus will be on the support for the determination of buffer norms (i.e. safety times) in order to improve the overall efficiency and control within the supply chain.

Finally, we briefly underpin our decision to rely on stochastic quantitative modeling for the analysis and design of improved buffer options. Generally, MRP-based planning systems do not provide support for the determination of safety stock and safety time norms to buffer against uncertainty a priori. These parameters therefore are determined based on experience, lacking a clear understanding of their performance and impact, let alone a clear idea of their 'optimal' values. In addition, MRP-based concepts do not provide insights about the impact of demand uncertainty on supply chain capital requirements to achieve required customer service levels (De Kok & Fransoo, 2003). Likewise, VDL ETG's MRP-based planning and control methods do not include uncertainty actively as part of the 'model'. Uncertainty rather is mainly 'controlled' via rescheduling, with very high associated workload, costs and nervousness. By using and extending existing knowledge about stochastic inventory and lead time models, we support the analysis of buffer management and the design of options for improving operational control.

5.2. Demand uncertainty and inventory models

As discussed in the previous section, we rely on stochastic inventory modeling in order to analyze buffering against demand uncertainty in VDL ETG's supply chain. Before we continue with the analysis of specific cases within VDL ETG, we first provide a general, insightful discussion on service performance in a classical single-item single-echelon inventory model.

5.2.1. Explaining service in a single-item single-echelon inventory model

There is a vast literature on inventory control policies for single item single location systems based on stationary stochastic demand (De Kok, 2012). Generally, four different control models for such a system can be identified: a continuous review fixed order quantity policy (s,Q), a continuous review order up to policy (s,S), a periodic review fixed order quantity policy (R,s,Q) and period review order up to policy (R,s,S). In Appendix E we list the general model variables, specific policy variables and the model assumptions which together define the model. Following the notations of De Kok (2010), we formulate expressions for performance measures most frequently used in practice in Appendix E too.

If we consider a certain inventory system, we can make a distinction between exogenous ‘parameters’, control parameters and performance outcomes. Exogenous parameters in this case are the average demand per period, standard deviation of demand per period, average lead time in number of periods and the standard deviation of the lead time. Control parameters define the inventory control policy, i.e. the review period, the reorder level, the order up to level or the fixed order quantity. Other variables as the average inventory, the average order size and the average service level are performance outcomes of a certain policy (e.g. a (R,s,Q) rule) to control the inventory system.

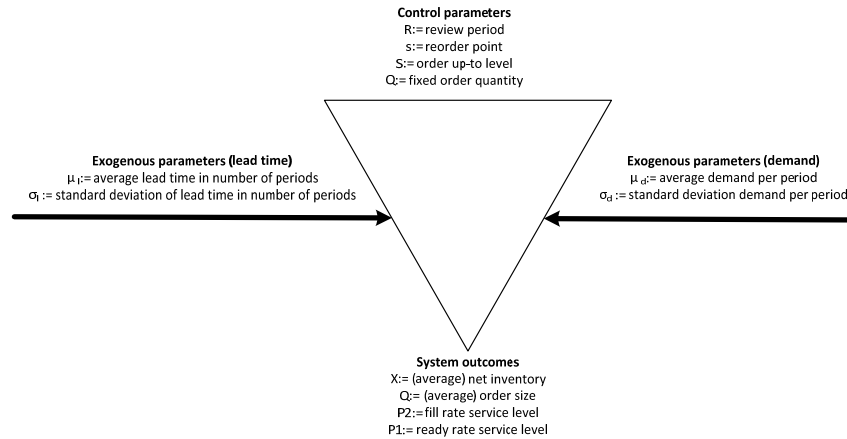


Figure 19: Parameters and variables in the single-item single-echelon inventory model

Based on the expressions in Appendix E and some exploratory analysis, we hypothesize that:

the service level (either the ‘ready rate’ or ‘fill rate’) in a single-item single-echelon system is primarily explained by the average inventory in combination with the average order size, and this service is ‘relatively insensitive’ of the specific control policy which is used.

More specifically, given the external parameters and the average inventory in combination with the average order size as system outcomes, we can approximate the ‘implicitly used’ control parameters under each control rule, which in turn result in a certain service level.

We define:

μ_D := average demand per period

σ_D^2 := standard deviation of demand per period

μ_L := average lead time (in number of periods)

\bar{X} := the average inventory as a system outcome

\bar{Q} := the average order size as a system outcome

Then some mathematical rewriting (details are listed in Appendix E) eventually results in the following estimators of the control parameters for each of the policies:

(s,Q)

$$Q = \bar{Q}$$

$$s = \bar{X} + \mu_D * \mu_L + \frac{\sigma_D^2 + \mu_D^2}{2\mu_D} - \frac{\bar{Q}}{2}$$

(R,s,Q)

$$R = \frac{\bar{Q}}{\mu_D}$$

$$Q = \bar{Q}$$

$$s = \bar{X} + \mu_D * \mu_L + \frac{\sigma_D^2 + \bar{Q} * \mu_D}{2\mu_D} - \frac{\bar{Q}}{2}$$

(s,S)

$$S - s = \bar{Q} - \frac{\sigma_D^2 + \mu_D^2}{2\mu_D}$$

$$s = \bar{X} + \mu_D * \mu_L + \frac{\sigma_D^2 + \mu_D^2}{2\mu_D} - \frac{\bar{Q}}{2}$$

(R,s,S)

$$R = \frac{\bar{Q}}{\mu_D}$$

$$S - s = \bar{Q} - \frac{\sigma_D^2 + \bar{Q} * \mu_D}{2\mu_D}$$

$$s = \bar{X} + \mu_D * \mu_L + \frac{\sigma_D^2 + \bar{Q} * \mu_D}{2\mu_D} - \frac{\bar{Q}}{2}$$

Note that the standard deviation of the lead time does not influence the parameter estimators. It does, however, influence the service level which is obtained.

In addition, note that our discussion in this section and the complementary Appendix E is focused on the formulas which describe the behavior of an inventory system. On the other hand, there is the numerical processing of the formulas. For an industrial engineer, once the formulas have been derived, the numerical processing becomes less interesting (De Kok, 2010). Hence we refer to the Classical Inventory Models tool of De Kok (2010) for analytical evaluation of the expressions and formulas. We adapted the tool to account for modeling demand per period in a continuous review inventory model (instead of considering demand as the combination between an arrival distribution and a quantity distribution per order). In addition, we extended the tool with a section which implements the estimators for the control parameters formulated above. We also included sections for sensitivity analysis. Note that we use the term 'Stochastic Inventory System Tool' for the new tool hereafter.

Our hypothesis actually is twofold. On the one hand, we hypothesize that the average inventory in combination with the average order size (and of course along with the demand and lead time information), 'explain' the service level (either 'fill rate' or 'ready rate'). From a modeling perspective this holds for each control rule separately, since the parameter estimations simply are the result of rewriting the expressions for the average order size and inventory in terms of the parameters. Hence a key aspect of validating this part of our hypothesis is in the empirical validation for real-life examples, which will be performed in the next section.

We can, however, use analytical evaluation in order to investigate the second part of our hypothesis, which is about the 'relative control insensitive' service levels. Below we discuss some key insights obtained from sensitivity analysis which we performed in order to validate this second part of our hypothesis.

Similarity between (r,s,Q) and (r,s,S) policies

First of all note that, given the average order size in combination with the average inventory, analytically estimated service levels (both 'fill rate' and 'ready rate') are equal for an order up to policy and fixed order quantity policy (see Appendix E for quantitative expressions). For our sensitivity analysis, we therefore focused on the comparison of service levels under the (R,s,Q) and (s,Q) control policies (results are highly similar for a comparison between (R,s,S) and (s,S) policies).

Service level and demand distribution

For the sensitivity analysis we focused on the 'fill rate' service measure (often denoted as the P_2 or β service measure), which is "the long-run fraction of total demand, which is being delivered from stock on hand" (De Kok, 2010). Results are highly similar for the 'ready rate', but since the fill rate is most often used in practice and mostly resembles the service measures currently used by VDL ETG, we focus on the fill rate. In addition, analytical evaluation of the fill rate via the Stochastic Inventory System Tool requires a known distribution of the demand, either Gamma or Normal distributed. For our analysis we assume Gamma distributed demand, since negative values are possible when assuming Normal distributed demand, especially in the low-volume environment of VDL ETG.

Influence of lead time

Exploratory analysis revealed that the lead time has a negligible effect on the difference between the service level under (R,s,Q) control and (s,Q) control (see Appendix E for our sensitivity analysis). All other input variables keeping equal, the lead time of course does have an effect on the service level, but this approximately equal for both control policies.

The average inventory and order size in relation to the average demand

Our analysis revealed that the average order size in relation to the average demand has the biggest impact on the difference between the fill rate of a (R,s,Q) and (s,Q) policy. In addition, the average inventory in relation to the average demand does influence the difference between service under the alternative control policies too, only to a smaller extent. In order to illustrate the sensitivity analysis, we illustrate the effect of the average inventory and order size in relation to the average demand for a basic case with $\mu_D = 2, \sigma_D^2 = 1, \mu_L = 10, \sigma_L^2 = 0$.

Figure 20 shows that the service under both policies is equal if the average orders size equals the average demand. An average order size equal to the average demand implies that in a period review system each period an order is placed, which then becomes similar to a continuous review system. If the order size in relation to the average demand becomes larger, the gap between the service under both policies increases (although the difference decreases once the value of the order size divided by the average demand gets 'very' large). Of course, the service under continuous review exceeds the service under periodic review. Moreover, we see that interval in which both service levels are close to each other is larger in case the average inventory in relation to the average demand is larger. Finally note that for very high service levels (above 95%), the difference between service under continuous review policies and periodic review policies is relatively small, especially when the average order size is less than the demand during five periods (difference of 2% point even when the average order size is five times the average demand and the average inventory is five times the average demand).

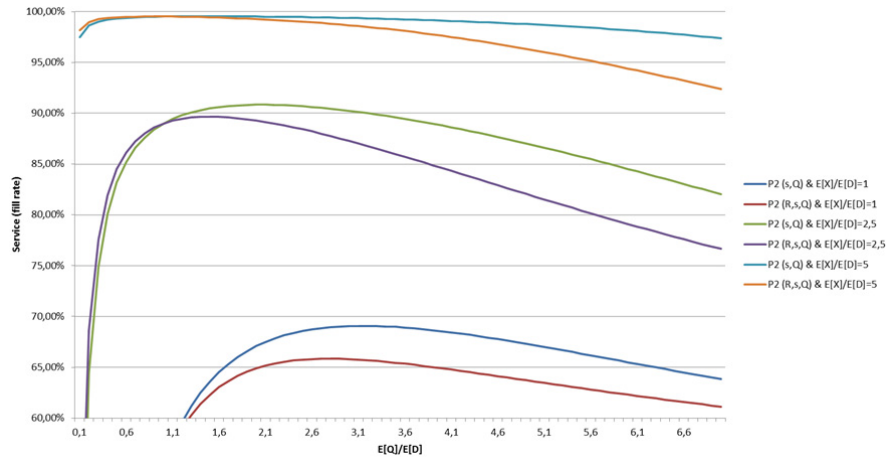


Figure 20: Sensitivity analysis for a basic case

Before we continue with the validation of our hypothesis by applying the model to real-life examples within VDL ETG, we first introduce a new concept which allows for applying a stochastic inventory (MTS) model to an order driven (MTO) supply chain system with stochastic customer due dates.

5.2.2. Introducing a new model concept: hidden inventory

For the empirical validation of the model (i.e. explaining service in a single-item single-echelon inventory system based on the average inventory and order size) with data from VDL ETG, we analyzed historical data of all three important MPS items which have been introduced in the previous chapter: the FEI Projector Assy, the ASML NXT3 wafer handler and the ASML XT4 wafer handler.

First of all, in order to be able to apply the stochastic inventory model to the order-driven supply chain of VDL ETG, we analyzed the historical demand data from a MTS perspective (see our discussion in the previous chapter). More specifically, we analyzed customer demand by considering orders and deliveries per week. We thus neglected the volatility and evolution of individual orders, we only consider stochastic demand (as implied by the latest confirmed delivery dates) and real deliveries per week. By analyzing the percentage of demand which is delivered ‘from stock’, i.e. with no delay, we obtain the service performance in terms of the fill rate. Moreover, we initially considered the MPS item as a single item with a planned lead time which is equal to the integral cycle time (with no uncertainty).

During the analysis we faced a striking inexplicable thing: there was no inventory of finished goods (note that this is the ‘CODP’ under our alternative way of modelling), while the fill rates were between 98%-100%. Some exploratory analysis of the data revealed that the cumulative scheduled receipts (at MPS level) do not equal the cumulative actual receipts in the same period, which is assumed in all classical inventory models. Recall from our analysis of MPS nervousness in Section 4.2 that due dates of MPS production orders are rescheduled, even within the integral lead time window. In order to capture this phenomenon, we formulate mathematical expressions which describe the results of human production control at the MPS level under order-driven control with stochastic due dates. Without loss of generality, we assume a review period of 1 time period (week within VDL ETG). In addition, we assume a deterministic planned lead time, which we further elaborate on later in this paragraph. Note that we follow the same reasoning for deriving an expression for the average inventory as discussed in Appendix E. We use the subscript ‘theory’ to denote our expressions for the expected net inventory based on comparable theoretical models in academic literature.

We define:

$L :=$	<i>planned (integral) lead time of MPS item</i>
$SR(t) :=$	<i>scheduled receipt of MPS item planned to arrive at the start of period (t)</i>
$I_{theory}(t) :=$	<i>'theoretical' net inventory of MPS item at the start of period t (after the arrival of a scheduled receipt)</i>
$IP(t) :=$	<i>inventory position of MPS item at start of period t</i>
$\hat{I}_{theory}(t) :=$	<i>'theoretical' net inventory of MPS item just before the start of period t (before the arrival of a scheduled receipt)</i>
$D(t) :=$	<i>demand for MPS item in period(t)</i>
$E[I_{theory}] :=$	<i>'theoretical' average net inventory (during a replenishment cycle)</i>

We use the following moments in time for our analysis (cf. Appendix E):

$t + L$	<i>moment of arrival of the scheduled receipt released at the start of period t</i>
τ_t	<i>first moment after period t in which a scheduled receipt is released</i>
$t + \tau_t + L$	<i>moment of arrival of the scheduled receipt succeeding the scheduled receipt released at the start of period t</i>

We assume that, in each review period, a production order (scheduled receipt) is released. We derive:

$$IP(t) = I(t) + \sum_{s=0}^L SR(t+s) \quad [5.1]$$

$$I_{theory}(t+L) = IP(t) - \sum_{s=0}^{L-1} D(t+s) = \sum_{s=0}^L SR(t+s) + I(t) - \sum_{s=0}^{L-1} D(t+s) \quad [5.2]$$

$$\hat{I}_{theory}(t+\tau_t+L) = IP(t) - \sum_{s=0}^L D(t+s) = \sum_{s=0}^L SR(t+s) + I(t) - \sum_{s=0}^L D(t+s) \quad [5.3]$$

Now we can derive an expression for the average inventory:

$$\begin{aligned} E[I_{theory}] &= \frac{1}{2} (E[I_{theory}(t+L)] + E[\hat{I}_{theory}(t+\tau_t+L)]) \quad [5.4] \\ &= \frac{1}{2} (E[\sum_{s=0}^L SR(t+s) + I(t) - \sum_{s=0}^{L-1} D(t+s)] + E[\sum_{s=0}^L SR(t+s) + I(t) - \sum_{s=0}^L D(t+s)]) \\ &= E\left[\sum_{s=0}^L SR(t+s) + I(t) - \sum_{s=0}^{L-1} D(t+s) - \frac{1}{2} D(t+L)\right] \end{aligned}$$

An important assumption underlying the expression above, and typically assumed in comparable models in literature (cf. De Kok et al., 2005), is that scheduled receipts arrive according to their planned lead times. From a supply uncertainty perspective, this assumption can be defended since we model the MPS item with a planned lead time which equals the total integral lead time, which is met with such a high reliability that we can neglect lead time uncertainty. From a scheduling/planning perspective, however, we argue that the assumption is violated. Our earlier analysis of nervousness at the MPS level revealed that production orders are rescheduled, especially delayed, within lead time. This implies that the cumulative scheduled receipts do not necessarily represent cumulative actual receipts. More practically, at VDL ETG this is the result of actual receipts which are generally closely matched with real customer demand, and this real demand is significantly lower than the forecasted/ordered demand (cf. Figure 17). Since cumulative scheduled receipts (together with on hand inventory) match with the forecasted demand to a large extent, a difference between scheduled and actual receipts arises.

Hence we modify the above expressions in order to account for 'real' behavior of production planning at the MPS level. We define:

$$\begin{aligned}
 AR(t + s) &:= && \text{actual receipts of MPS item} \\
 I_{real}(t) &:= && \text{'real' net inventory of MPS item at the start} \\
 &&& \text{of period } t \text{ (after the arrival of a scheduled receipt)} \\
 \hat{I}_{real}(t) &:= && \text{'real' net inventory of MPS item just before the start} \\
 &&& \text{of period } t \text{ (before the arrival of a scheduled receipt)}
 \end{aligned}$$

Now we derive the expression for the 'real' inventory levels:

$$I_{real}(t + L) = \sum_{s=0}^L AR(t + s) + I(t) - \sum_{s=0}^{L-1} D(t + s) \quad [5.5]$$

$$\hat{I}_{real}(t + \tau_t + L) = \sum_{s=0}^L AR(t + s) + I(t) - \sum_{s=0}^{L-1} D(t + s) - \frac{1}{2} D(t + L) \quad [5.6]$$

$$E[I_{real}] = \frac{1}{2} (E[I_{real}(t + L)] + E[\hat{I}_{real}(t + \tau_t + L)]) \quad [5.7]$$

$$\begin{aligned}
 &= \frac{1}{2} \left(E \left[\sum_{s=0}^L AR(t + s) + I(t) - \sum_{s=0}^{L-1} D(t + s) \right] + E \left[\sum_{s=0}^L AR(t + s) + I(t) - \right. \right. \\
 &\quad \left. \left. \sum_{s=0}^{L-1} D(t + s) - \frac{1}{2} D(t + L) \right] \right)
 \end{aligned}$$

$$= E \left[\sum_{s=0}^L AR(t + s) + I(t) - \sum_{s=0}^{L-1} D(t + s) - \frac{1}{2} D(t + L) \right]$$

In order to explain the difference and capture the effect of human planning behavior at the MPS level, we define:

$$\Delta_t = \sum_{s=0}^L SR(t + s) - \sum_{s=0}^L AR(t + s) \quad [5.8]$$

Then:

$$E[I_{real}] = E \left[\sum_{s=0}^L SR(t + s) - \Delta_t + I(t) - \sum_{s=0}^{L-1} D(t + s) - \frac{1}{2} D(t + L) \right] \quad [5.9]$$

Under stationary demand, this expressions can be rewritten into:

$$E[I_{real}] = E[I_{theory}] - E[\Delta_t] \quad [5.10]$$

$\Delta_t = \sum_{s=0}^L SR(t+s) - \sum_{s=0}^L AR(t+s)$ thus should explain the difference between the average inventory one would expect to be held in the (inventory) system and the average inventory observed in historical data as a result of (order-driven) planning and control (under stochastic due dates) at the MPS level.

We name this new concept of Δ_t ‘hidden inventory’. Since we explicitly analyzed scheduled receipts (i.e. production orders already released), the hidden inventory can be considered as a kind of inventory which is hidden/kept in the work in progress. This inventory is spread in the pipeline in such a way that there is enough hidden inventory which can quickly enough be converted in real stock in order to cope with the stochastic demand from customer side, thereby obtaining a certain service level. It has a ‘buffer value’ equal to Δ_t items in final stock. This delta is a powerful concept which allows for evaluating human decision making in a stochastic inventory model. More specifically, it captures possible rescheduling decisions at the MPS level under order-driven control with uncertain customer due dates.

Given the possible difference between scheduled and actual receipts, we can regard expression [5.4] for $E[I_{theory}]$ as an expression for the inventory at the final ‘stock point’ plus buffers in the form of hidden inventory upstream in the supply chain. In the next paragraph we will validate our concept by analyzing three real-life examples from VDL ETG.

5.2.3. Empirical validation for three real-life examples from VDL ETG

In order to validate the concept of hidden inventory in combination with the single-item single-echelon inventory model, we used historical data for all three MPS items introduced earlier in this chapter. We initially consider the MPS item as an item in a single-item single-echelon system, with stochastic customer demand per period and a deterministic lead time.

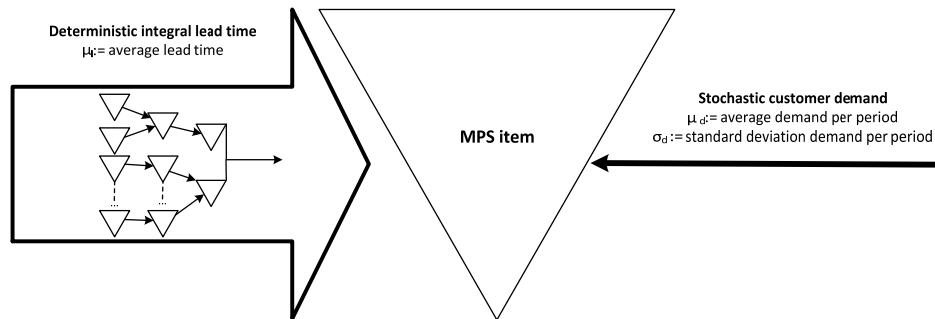


Figure 21: Single-echelon representation of a MPS item

This allowed us to estimate the ‘expected inventory’ via expression [5.4]¹ in combination with historical data about demand, scheduled receipts and actual receipts. Then, along with the average historical order size, we used this expected inventory as input for the single-item single-echelon model discussed in Section 5.2.1 in order to estimate the service level. Concerning the empirical validity of our ‘hidden inventory’ concept as well as the model to explain service, we found that the model-estimated fill rates are close to the historical data-based fill rates. For the ASML NXT3 system and FEI Projector

¹ Note that in a stationary situation, expression [5.4] and the combination of [5.8] & [5.10] should result in the same expected inventory. We estimated the average inventory based on (available) data from the second half in 2013 till the ‘end’ of 2014. In order to capture the dynamics, we use expression [5.4]. More specifically, $[I_{theory}] = \frac{\sum_t [\sum_{s=0}^{L+1} SR(t+s) + I(t) - \sum_{s=0}^L D(t+s) - \frac{1}{2}D(t+L)]}{\sum_t 1}$

Assy, the fill rates are very close, though there is a small discrepancy for the ASML NXT4 system. The results are reported in Table 1. Note that due to confidentiality, we do not report the explicit distinction between ‘real inventory’ and ‘hidden inventory’, i.e. $E[X]$ is the sum of both.

Table 1: Empirical validation for three MPS items (with total integral lead time) within VDL ETG

	Model fill rate estimations								
	μ_D	σ_D	μ_L	σ_L	$E[X]$	$E[Q]$	Cont.Review	Period.Review	Real fill rate
ASML NXT3 system	1,15	0,93	27	0	13,6	1,9	0,990	0,989	0,990
ASML XT4 system	0,8	0,78	17	0	10,2	1,35	0,993	0,992	1,000
FEI Projector Assy	0,91	1,01	28	0	15	1,3	0,981	0,980	0,980

Based on the test for these real-life cases, we derive some relevant insights. First of all, by introducing the concept of hidden inventory, we almost perfectly explain the systems’ service via a single-item single-echelon inventory model. This confirms our hypothesis that, along with demand and lead time input parameters, the average inventory (possibly partially or fully consisting of hidden inventory) in combination with the average order size as system outcomes explain another system outcome: the service level. Moreover, as modeled via the concept of hidden inventory, there is a hidden buffer in the high work in progress levels. Scheduled receipts are based on scheduled due dates of orders. If these are advanced frequently, problems can arise. But since orders are generally delayed, hidden inventory arises. This creates enough buffer flexibility in order to cope with stochastic demand and possible customer order advancements. Still, it likely results in inefficiency since priorities and plans have to be rescheduled.

Secondly, in the environment of VDL ETG, we explain the service without any assumption about the policy used to control the inventory system. In other words, VDL ETG’s context, the service is largely insensitive to the control rule which is used. This provides support for the second part of our hypothesis for the low-volume environment of VDL ETG.

Thirdly, we derive that production planning and control at the MPS level within VDL ETG is quite similar to base-stock control, i.e. continuous review with order multiples of one unit. In Appendix F we proof this claim via formal expressions for ordering decisions at the MPS level in a MRP controlled system and ordering decisions in a base-stock controlled system. Considering our earlier general analysis as represented by Figure 20, we derive that VDL ETG’s environment can be positioned in the area in which the service indeed proves to be relatively insensitive to the control rule used. This provides relevant support for promising options for further improvement of production control (which will be discussed in Section 7.3) and underlies our analysis in the next paragraphs.

5.2.4. Separating final assembly from upstream production: single-item two-echelon model

In the previous paragraph we abstracted from complex BOM structures by considering a final MPS item as a single item with a (planned) lead time equal to the integral lead time. This abstraction allowed us to analyze demand uncertainty at the MPS level in combination with final inventory and hidden inventory in the pipeline. We argued that the hidden inventory is divided over the entire pipeline, apparently in such a way that it can be converted to final inventory quickly enough to cope with stochastic customer demand.

In order to better grasp the concept of the hidden inventory in the supply chain, we extend the single-item single-echelon analysis by explicitly decoupling the final assembly phase from upstream activities. In other words, we model the MPS item in a serial two-echelon system. Based on the planned lead

times retrieved from the ERP system, we can split up the total integral lead time in the lead time of the final assembly plus the lead time of upstream activities.

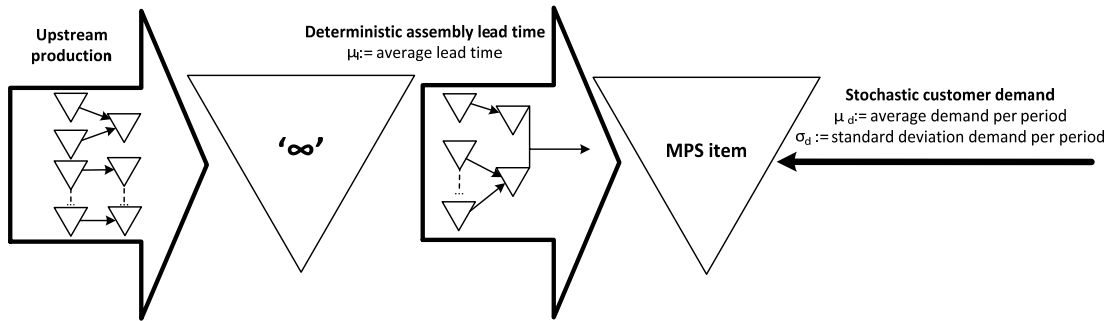


Figure 22: Two-echelon representation of a MPS item

For all three MPS items discussed before, we analyzed the large historical data set again while using a lead time equal to the integral lead time of final assembly. Since production orders are rescheduled during the final assembly window too, again we observe the phenomenon of hidden inventory. By using the same procedures and expressions as formulated in Section 5.2.2, we estimated the final inventory (including some hidden inventory). We used these estimations along with the final assembly lead time, average order size and demand information to estimate the service level via the stochastic single-item single-echelon inventory model explained in Section 5.1.1. The results of the analyses for all three MPS systems are provided in Table 2.

Table 2: Empirical validation for three MPS items (with final assembly window lead time)

	μ_D	σ_D	μ_L	σ_L	$E[X]$	$E[Q]$	Model fill rate estimations		
							Cont.Review	Period.Review	Real fill rate
ASML NXT3 system	1,15	0,93	4	0	6,3	1,9	0,989	0,988	0,990
ASML XT4 system	0,8	0,78	3	0	5,1	1,35	0,990	0,988	1,000
FEI Projector Assy	0,91	1,01	4	0	6,3	1,3	0,976	0,973	0,980

To our surprise, the estimated fill rates based on modeling final assembly as a single-echelon inventory model do quite well match with the historical data-based fill rates, except for a discrepancy for the ASML XT4 system. Similar to our discussion above, we derive that there is hidden inventory which creates an important buffer in the final assembly window too. Since an assumption behind the stochastic single-item single-echelon inventory model is an 'infinite' amount of stock at the external supply side, we thus derive that a limited amount of stock before final assembly apparently suffices to ensure 'infinite' material from a stochastic inventory control perspective. We can regard this as a kind of 'natural' decoupling situation which has originated under the existing planning and control procedures within VDL ETG. So, the upstream activities can be considered as an integral stage which precedes the (final) assembly stage, with a sufficiently high reliability in terms of supplying requested materials to the final assembly stage (cf. Atan, De Kok, Dellaert, Janssen & Van Boxel, 2015).

Note that our discussion of insights above is focused on the understanding, evaluation and explanation of (current) buffering against demand uncertainty in an order-driven system via (hidden) inventory. The high abstraction level allows us to use the concept of planned lead times. At a more detailed level, however, this doesn't hold. We therefore extensively discuss lead time modeling and analysis in Section 5.3. Before we turn to this related class of uncertainty, we first discuss an interesting option for reducing the inventory buffer size in the next paragraph.

5.2.5. The effect of target service levels

In the previous paragraphs we focused on the explanation and evaluation of high customer service levels for three important MPS items within VDL ETG. Since we used a stochastic inventory model with a high abstraction level, the model and analysis are mainly suited for evaluation instead of optimization. A detailed representation and validation of real BOM structures is outside the scope of our research, but we briefly explain in Section 6.1 why the expected gains of detailed inventory modeling are likely to be rather limited.

The analysis in the previous paragraphs provide an empirical validation of our model (for both the single-echelon as well as two-echelon representation), and explains the relation between the size of the (hidden) inventory buffer and the service level (fill rate) which is obtained. We have seen that the service levels for all three MPS items are between 98%-99% if we consider weekly demand. In VDL ETG's environment, one might question if such a high service level is really needed. Especially considering the high value of customers systems and the business-to-business environment (with generally order-driven production), which makes lost-sales very unlikely.

Moreover, we hypothesize that the planners (and order managers) have the capacity to further improve the service performance which would be obtained if the production control methods and concepts are strictly followed. More specifically, we expect that if a certain production control system enables a service level of e.g. 95%, the capacity of planners and smart human intervention makes it possible to obtain a real final service level of e.g. 98%. Of course, this is just a very hypothetical statement which lacks underlying quantitative modeling. In Section 7.2. we propose this as a potentially interesting direction for further scientific research . For now, we briefly discuss the results of a sensitivity analysis which we performed by investigating the effect of the 'target service level' on the required (hidden) inventory buffer.

More practically, we used our valid stochastic single-item single-echelon inventory model in combination with the final assembly window (see Figure 22). Keeping all other parameters equal, we varied the (hidden) inventory buffer such that different fill rate performance levels were obtained. Note that we focused on the fill rates assuming a period review control. We already showed that the differences in the service level explained by assuming period or continuous review are very limited in VDL ETG's environment. However, periodic review best represents VDL ETG's control procedures and also implies a lower bound of the service level. The results are shown in Table 3. We use the model-based estimated service level for the current situation (Table 2) as the benchmark: the size of the (hidden) inventory buffer is normalized at 100% for each MPS item separately.

Table 3: Sensitivity analysis for the effect of target service levels on required inventory buffers

Service Level	ASML NXT3		ASML XT4		FEI Projector Assy	
	Required inventory buffer	Relative size	Required inventory buffer	Relative size	Required inventory buffer	Relative size
99,5%	7,5	119,0%	6	117,6%	8,8	129,4%
99,0%	6,3	100,0%	5,1	100,0%	7,8	114,7%
98,0%	5,7	90,5%	4,6	90,2%	6,8	100,0%
97,5%	5,4	85,7%	4,4	86,3%	6,3	92,6%
95,0%	4,5	71,4%	3,5	68,6%	5,4	79,4%
92,5%	3,9	61,9%	3,1	60,8%	4,7	69,1%

This table shows that lower target service levels are associated with significantly lower inventory buffer requirements. Considering a target service level of 95%, the required inventory buffer size is 25%-30% smaller than the current (hidden) inventory buffer size. In order to visualize this high sensitivity around service levels of about 95%, we show the relation between the inventory size and fill rate for the FEI Project Assy in Figure 23. Again, we stress the exploratory character of this analysis and we note that

setting target service levels rather is a strategic decision instead of an issue for operational supply chain efficiency and control. Still, the analytic results in Table 3 provide an important insight on the relation between service and buffering against demand uncertainty in the supply chain of VDL ETG.

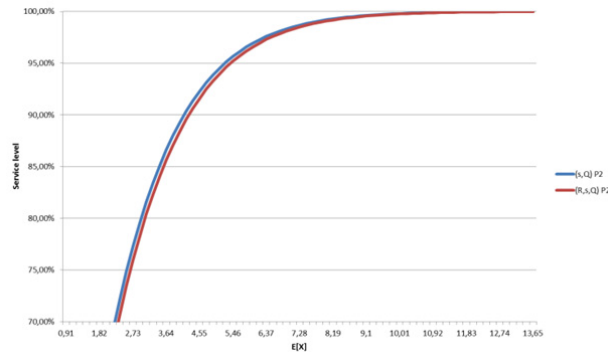


Figure 23: Relation between target service level and inventory buffer size for the FEI Project Assy

Finally, we briefly point to possible operationalization of these target service level insights. Since we proved that the current hidden inventory buffer is the result of customer orders (and forecasts) which generally exceed real demand (i.e. general delay of orders), reducing the inventory buffer directly seems strange to apply in practice. This would imply that certain orders have to be rejected in order to reduce the buffer size, along with a decrease in the service level. An interesting option to indirectly reduce the buffer size, however, is to plan at the MPS level with a shorter planned lead time. For example, if VDL ETG would aim for a lower target service level which is associated with a reduction of X units in terms of the required buffer size, then shortening the planned lead time with L periods will have a similar reduction effect if the average demand during L periods is equal to X units. In Chapter 6 we further elaborate on our recommendations for improving buffering and operational control.

5.3. Lead time uncertainty and planned lead time models

In this section we model and analyze the second class of uncertainty which plays a crucial role for planning and control improvement. In the beginning of this chapter we argued that in order to properly coordinate the release of materials and resources while taking into account the random processing times at work centers (as the result of interactions between materials and resources), the concept of ‘planned lead times’ emerges. In addition, a high reliability of planned lead times is an important aspect in order to allow for efficient and effective control at the integral (Goods Flow Control) level. In this section we investigate the potential of improving supply chain efficiency and control via smarter buffering against lead time uncertainty.

5.3.1. Introduction to planned lead time modeling

Our quantitative analyses in Chapter 2 revealed the significant ‘magnitude’ of lead time uncertainty at the item level, including both external supplier lead time uncertainty as well as manufacturing or assembly lead time uncertainty. Following our reasoning about decoupling demand uncertainty from lead time uncertainty, we derive that after an order release, the only uncertainty to be taken into account is the lead time uncertainty of the supply or manufacturing process.

Holding safety stocks and planning for safety times are two techniques companies use to buffer against uncertainties in demand, supply and manufacturing (Atan et al., 2015). At VDL ETG, buffering with time is preferable to buffering with material. In other words, there is a preference for safety times over safety stocks. Amongst others, two important reasons are the very dynamic environment which

creates a high risk of inventory obsolescence, and the more 'active' behavior of safety times compared to fixed safety stocks under volatile demand. The preference for buffering via safety times in VDL ETG's environment is further acknowledged by different papers. In their well-known paper, Whybark and Williams (1976) suggest that safety times instead of safety stocks are preferred when uncertainties in demand and supply are mostly due to timing rather than quantity. Moreover, Molinder (1997) states that using safety times instead of safety stocks results in lower costs when the variabilities in demand and lead time are high at the same time. In addition, Yano (1987) argues that when all units in a batched order are produced at the same time, the safety stock needs to be as large as the batch size. Hence, using safety times should be a preferred strategy, especially within production environments with high batch sizes (e.g. Parts production at VDL ETG).

Similar to other companies like ASML (Atan et al., 2015), VDL ETG faces the challenging problem of determining planned lead times for control at the integral level. Note that we use the term 'planned lead time' to denote the average lead time plus any safety time. As acknowledged by Atan et al. (2015), the difficulty comes from the interactions among multiple processes. The tardiness of a process might imply delays in the subsequent processes, and eventually, late delivery of final products.

We refer to Atan et al. (2015) for a comprehensive review of earlier work on the problem of determining planned lead times. Gong, De Kok and Ding (1994) show that the problem of determining optimal planned lead times in multi-echelon serial systems is equivalent to the problem of determining optimal base-stock levels in a multi-echelon serial inventory system. For these systems, the optimal echelon base-stock levels can be found by successively solving a series of recursively defined one-dimensional problems. The optimality of the base-stock policies and the decomposition result initially has been derived by Clark and Scarf (1960) and has been extended by Federgruen and Zipkin (1984). For large assembly systems, however, finding exact solutions for the planned lead time problem is very difficult (Axsäter, 2005; Atan et al., 2015). Therefore heuristics are required.

The aim of this section is to investigate the improvement potential of smarter buffering via planned lead times. We therefore start with the formulation of a quantitative model which supports the analysis of planned lead times under lead time uncertainty. We validate the model for a real-life example within VDL ETG and we analyze the improvement potential.

5.3.2. Planned lead times within VDL ETG

At VDL ETG, each item has a specific item *lead time* which is stored in the ERP system. For purchasing items, this *lead time* simply is the agreed delivery time of external suppliers. For manufacturing items, this *lead time* consists of throughput times of multiple operations and possible buffer time in between these operations. For example, a certain module can have a lead time of 10 days, which is comprised of 1 day for picking material in the warehouse, 2 days for washing the material, 3 days for operation on a machine, 1 day buffer time, 2 days for operation on another machine and 1 day for testing. The sum of these times in the routing of an item constitute the item *lead time*. In addition, an item can have a *safety time* to account for any additional disturbances or uncertainties. The sum of the item *lead time* plus the *safety time* can be regarded as the *planned lead time*.

Considering our focus on integral production planning and control (Goods Flow Level), we analyze the problem of determining the *planned lead times* of items given their stochastic *lead times*. Stochastic throughput times of individual operations thus are excluded. This decision is supported by the fact integral planners at VDL ETG work according to item *lead times*, planning at the level of individual operations is performed by production unit control either within Parts or Systems.

Using VDL ETG's ERP system, we gathered lead time related historical data for all production orders (either at Parts or at Systems) since 2013. The *real planned lead time* data (i.e. the difference between the planned start date and end date of production orders) differs considerably from the *standard planned lead times* implied by the sums of the *item lead time* and *safety time* in the ERP system. Next to the *standard planned lead time* and the *real planned lead time*, there is a *real lead time*, i.e. the difference between the real start date and end date of a production order. These three types of lead time related data are visualized in Figure 24, along with the average differences over all production orders for System and Parts.

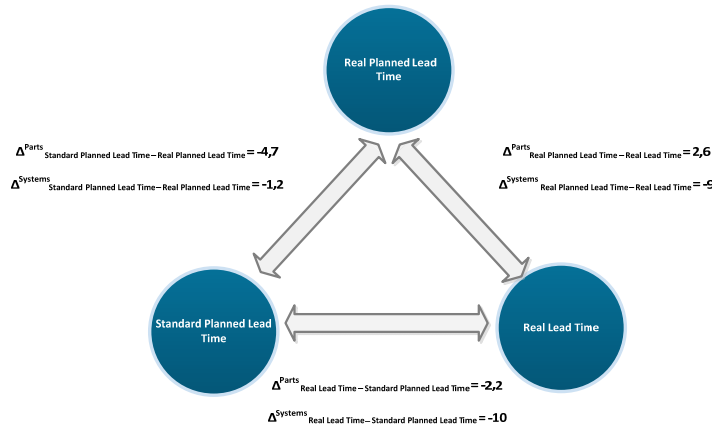


Figure 24: Lead time settings at VDL ETG (average deviations of all production orders)

These results show that planners do deviate from the *standard planned lead time* settings in the ERP system. Although an extensive investigation of all reasons behind this deviation is outside the scope of our research, we name a few: holidays or production plant related schedules, customer orders received within lead time and outdated lead time settings in the ERP system. In order to avoid making life more complex than necessary, we only consider the *real planned lead times* in relation to the *real lead times* and we neglect the *standard planned lead time* for our modeling and analysis. For the ease of reading, we omit 'real' in our discussions below.

With regard to the difference between the planned lead time and the lead time, we should make an important note about data issues. First of all, if customers delay an order, production is often delayed without updating the due date of production orders. This results in lead times which exceed planned lead times, although they actually do not harm the customer service. This happens especially within Systems, and partially explains why at Systems on average the planned lead time is 9 days shorter than the lead time. Secondly, some assembly activities are scheduled in a 'batch' size larger than one (although they are not all produced at the same time). While it is very likely that each item in the 'batch' is completed before the time it is actually needed, the finish date of the production order is set equal to the date at which the final item in the batch is finished. Note that production within Parts also occurs in batches, but since all products in the batch size are typically produced 'at the same time', there is not such an issue about biased lead time data as for Systems.

Similar to most other work in this area, we will focus on the on-time delivery (OTD) percentage as the service level in the planned lead time models. At the final item level, this OTD percentage is similar to the ECLIP measure within VDL ETG: it denotes the percentage of customer orders which is delivered on or before the confirmed time. Note that we will use the term 'on-time delivery performance' and 'service level' interchangeably in our discussions below.

Due to the data issues explained above, the lead time data-based OTD percentage of final customer systems is generally far below the OTD percentage calculated based on data about customer deliveries. An exception to this are final modules or systems which are produced for consignment stock (cf. Section 3.6). An example of the application of this concept is the customer chain of Philips, for which the consignment stock (located at Philips's site, but still owned by VDL ETG) should be between a lower and upper stock level as agreed by both parties. Since under this concept demand uncertainty is generally decoupled from lead time uncertainty, it is suitable for our modeling and analysis of planned lead time settings. More specifically, production plans are generally followed, since demand uncertainty is buffered via consignment stock. The OTD percentage of customer 'deliveries' for consignment items is equal to or close to 100%, since customers just retrieve an item from the consignment stock when needed. The 'production' OTD percentage generally is lower, and can be regarded as the reliability with which customer items are delivered to the consignment stock.

An example of a customer product which is produced under the concept of consignment stock is the Philips U-Arc. Since the rather 'small' product structure of the Philips U-Arc allows us to keep our models and analyses 'manageable', and since production of this module is order-driven, we selected this module as the basis for our modeling and analysis. This will be discussed in the next paragraphs.

5.3.3. Formulation of the model

Based on the full BOM structure for Philips U-Arc, we constructed an assembly system as shown in Figure 25. Note that we omitted 'manually' controlled items (two-bin), since these are outside the scope of integral planning at VDL ETG and they are basically 'always' available.

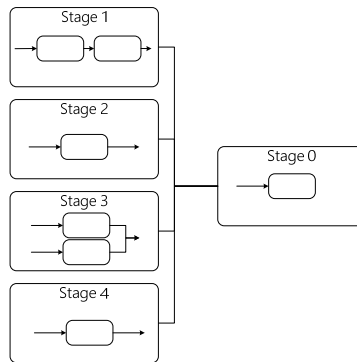


Figure 25: Assembly system Philips U-Arc

The Philips U-Arc is a module which consists of 4 main components for which production is order-driven. Component 1 has an underlying purchasing item, which is purchased based on forecasts. Historical data revealed that the purchase order lead time uncertainty is negligible. In order to take the effect on the total integral lead time into account, we increased both the lead time and planned lead time of Component 1 with an amount equal to the lead time of the purchasing item. Component 3 has two underlying purchasing items, which are purchased based on forecasts. Since historical data revealed that their lead time uncertainty is negligible too, we increased both the planned lead time and lead time of Component 3 with an amount equal to the maximum of the lead times of its predecessors. For the other two components, historical data about starting times revealed that we can assume instantaneous delivery of raw materials to their process. This results in the two-echelon structure shown in Figure 25.

We refer to the process of producing (or assembling) component (or module) i as 'stage' i .

In the remainder of this section we formulate expressions which eventually result in an expression for the service level of the system and the total stock investments (both inventory and work in progress). Note that, similar to the current practice within VDL ETG, we do not aim to include the service performance in the cost expression via penalty costs.

Process expressions

In this section we derive process equations which relate the earliness and tardiness of different stages. We define:

$$\begin{aligned}
 PL_i &:= \text{planned lead time for stage } i, \quad \forall i \in \{0,1,2,3,4\} \\
 \tau_i &:= \text{stochastic lead time for stage } i, \quad \forall i \in \{0,1,2,3,4\} \\
 E_i &:= \text{earliness of stage } i, \quad \forall i \in \{0,1,2,3,4\} \\
 L_i &:= \text{tardiness of stage } i, \quad \forall i \in \{0,1,2,3,4\} \\
 W_i &:= \text{waiting time at stage } i \text{ until the start of stage } 0, \text{ due to the} \\
 &\quad \text{tardiness of other stages} \quad \forall i \in \{1,2,3,4\} \\
 W_0 &:= \text{waiting time of stage } 0 \text{ due to the tardiness of stages } 1 \text{ to } 4 \\
 X^+ &:= \max(0, X)
 \end{aligned}$$

If all components (at stage 1 to 4) are finished on or before time, production of the module in the final stage starts at its planned start date. In other words, we assume that finale module production is hold back in case all previous stages are finished early. Atan et al. (2015) note that this assumption is quite common in literature (cf. Yano, 1987; Axsäter, 2005), often motivated by the fact that cost efficiency is obtained by waiting until the planned start time of successive stages and holding inventory of less costly products (since holding cost increase as more value is added). Moreover, at VDL ETG this policy generally is followed too, mainly because early start of stages will affect capacity planning and can lead to extensive rescheduling later on.

Therefore, we have:

$$W_0 = \max_{1 \leq i \leq 4} L_i \quad [5.11]$$

The waiting time of component stage i due to the tardiness of other components is:

$$W_i = (\max_{1 \leq j \leq 4, i \neq j} L_j - L_i)^+ \quad \forall i \in \{1,2,3,4\} \quad [5.12]$$

Due to the negligible lead time uncertainty of the purchasing items and the instantaneous delivery of material to the production stages, we derive that stages 1 to 4 can always start at the planned start time. We have:

$$E_i = (PL_i - \tau_i)^+ \quad \forall i \in \{1,2,3,4\} \quad [5.13]$$

$$L_i = (\tau_i - PL_i)^+ \quad \forall i \in \{1,2,3,4\} \quad [5.14]$$

Since the start of final module production is delayed for W_0 time units, we derive the following expressions for the earliness and tardiness of the final stage:

$$E_0 = (PL_0 - \tau_0 - W_0)^+ \quad [5.15]$$

$$L_0 = (\tau_i - PL_i + W_0)^+ \quad [5.16]$$

Given that the throughput times at all stages are random, E_i and $L_i, \forall i \in \{0,1,2,3,4\}$, are random variables as well.

Service expression

Let $\mathbb{P}(\theta)$ denote the probability of event θ .

Since we focus on the percentage of customer modules which are finished on (or before) time as the service level in our model, we derive

$$\text{service level} = 1 - \mathbb{P}(L_0 > 0) \quad [5.17]$$

Cost expression

Let $\mathbb{E}[\cdot]$ denote the expectation of a random variable. Furthermore, let \mathbf{PL} be the vector of all the planned lead times and $C(\mathbf{PL})$ be the total expected stock investments in the system as a function of \mathbf{PL} .

Without loss of generality, we set the planned start time of the final module production to 0. We assume that the system incurs a marginal holding cost investment of h_i from the moment production at stage i starts until the final module is finished. In the setting of VDL ETG, this holding cost investment consists of labor and material costs. The final module is finished at $PL_0 + L_0$ and component production at stage $i, \forall i \in \{1,2,3,4\}$, starts at $-PL_i$. Note that actual production at the final stage starts at W_0 . We derive:

$$C(\mathbf{PL}) = \mathbb{E}\left[\sum_{i=1}^4 h_i (PL_0 + PL_i + L_0) + h_0(PL_0 + L_0 - W_0)\right] \quad [5.18]$$

We define $H_0 = \sum_{i=0}^4 h_i$. Then we can rewrite the above expression into:

$$C(\mathbf{PL}) = \mathbb{E}\left[\sum_{i=1}^4 h_i (PL_i + PL_0) + h_0(PL_0 - W_0) + H_0 L_0\right] \quad [5.19]$$

Now the objective is to find the vector \mathbf{PL} that minimizes the total expected stock investments $C(\mathbf{PL})$ under a service level constraint. Before we continue with an analysis of alternative methods to determine the planned lead times, we first validate our model and explain our insights on VDL ETG's current practice of planning lead times in the next paragraph.

5.3.4. Empirical validation for the Philips U-Arc

In order to validate the model and to analyze alternative methods for setting planned lead times, we developed a discrete event simulation tool in Microsoft Excel, which we name the 'Planned Lead Times Simulation Tool' hereafter. This simulation implements the expressions and structures formulated above. More practically, using the planned lead times, the average and standard deviation of the lead time and the cost parameters as input, the Planned Lead Times Simulation Tool returns the service level and average stock investments as output. In Appendix G we provide some more information about the structure of the tool.

Using VDL ETG's ERP system, we retrieved historical data about lead time realizations for the Philips U-Arc. For the final module production stage, we have a set of 150 lead time realizations. For the component production stages, our data consists of a number of realizations between 15 and 45. One might argue that these numbers of realizations are not sufficient for validation. Our model validation, however, does not concern standard statistical modeling where the model is estimated from the data.

We used the historical data to calculate the sample mean and standard deviation of the stochastic lead times. Moreover, we retrieved data about the added value and planned lead time per stage from the ERP system. The parameter values are reported in Table 4. Note that because of confidentiality, we multiplied the original cost parameter values with a certain factor.

Table 4: Model parameter values Philips U-Arc

	Parameter values Philips U-Arc			
	E[τ]	$\sigma[\tau]$	PL	h
Component 1	47,7	8,4	56,0	490
Component 2	32,0	8,0	41,0	170
Component 3	36,0	7,8	42,0	300
Component 4	47,0	8,9	56,0	530
Final module 0	31,0	7,8	39,5	1510

We used these parameters as input for our Planned Lead Times Simulation Tool in order to obtain the average stock investment and service level as output. Note that we rely on fitting a Normal distribution on the historical lead time average and standard deviation in order approximate the distribution of the stochastic lead times (see Appendix G). Concerning the empirical validity of our model, we find that our model-based service level estimate of 75,3% is very close to the actual module on-time performance of 75,1%.

Our historical data analysis revealed that the planned lead time settings for the Philips U-Arc imply an OTD percentage of about 85% at the individual stages. We know from other current research (Atan et al., 2015) that planned lead times at ASML are determined by fitting a Normal distribution on the average and standard deviation of the lead time at each stage, and then using a certain % fractile to select the planned lead time. In order to investigate if the current practice of setting planned lead times at VDL ETG resembles such a concept, we used our Planned Lead Times Simulation Tool to draw an efficient service and cost frontier using the Fractile method. The results in Figure 26 confirm that the current planned lead time settings for the Philips U-Arc indeed resemble the Fractile method (with a 85% fractile).

Based on the above analysis, we conclude that our model (and Planned Lead Time Simulation Tool) provides a valid representation of reality, and it provides a solid basis for the analysis of alternative methods to determine planned lead times. This will be discussed in the next paragraph.

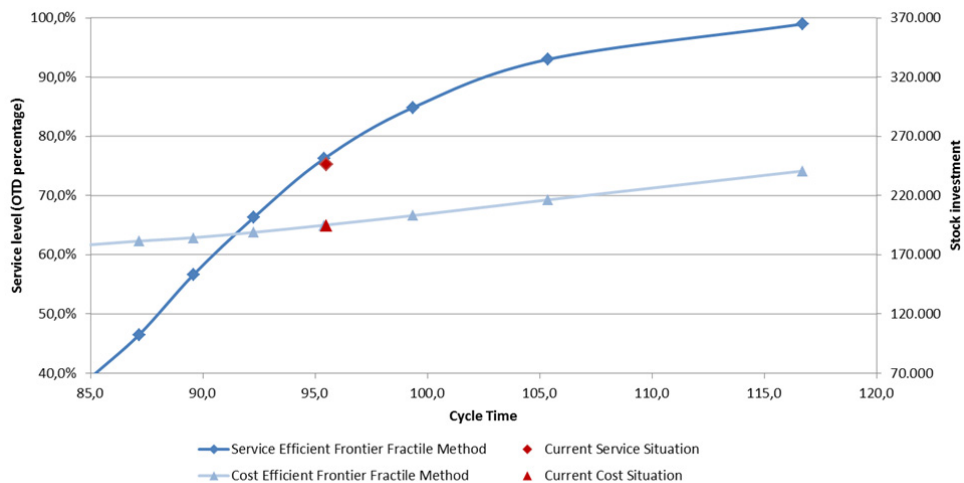


Figure 26: Current planned lead time settings Philips U-Arc compared with Fractile method

5.3.5. Towards improved planned lead time settings

Before we analyze alternative methods to determine planned lead times, we first provide an alternative expression for the expected total stock investments (costs) in the system.

$$C(PL) = \mathbb{E}\left[\sum_{i=1}^4 h_i \tau_i + H_0 \tau_0 + \sum_{i=1}^4 h_i (W_i + E_i) + h_0 E_0\right] \quad [5.20]$$

The first two parts in this alternative expression are independent from the planned lead times, and we therefore omit them in our stock investment evaluation of alternative methods below. The remaining part of the expression can be regarded as stock investments due to waiting times / earliness.

In Table 5 we present the results of our analysis for three alternative methods to determine the planned lead times. We use the current situation as the benchmark: the cycle time (i.e. longest cumulative planned lead time) and cost under this situation are normalized at 100%.

Critical Chain. This method is based on a conceptual approach introduced by Goldratt (1997). He claimed that the safety buffer in project networks with uncertain activity durations (note the similarity with our planned lead time model) should be positioned at the end of the project. We set the planned lead times of the components equal to their average lead time, and set the planned lead time of the final stage equal to 0. Then we modify this planned lead time at the final stage until the current service level of 75,3% is met (in order to account for a small deviation between the model-based service level of 75,3% and the real service level of 75,1%, we use the model-based service level for the comparisons).

Critical Chain Extreme. Taking the Critical Chain concept to the extreme, we also consider the alternative method in which all planned lead times are set to 0. Then the planned lead time of the final stage is increased until the current service level of 75,3% is met.

Newsvendor heuristic. In their paper, Atan et al. (2015) provide an iterative heuristic procedure to determine planned lead times in an order-driven assembly system. The heuristic is based on the decomposition of the assembly system into serial systems and a conjecture related to generalized newsvendor equations. In Appendix H we provide some more information about this heuristic.

Table 5: Performance of alternative methods in the current scenario

Method	Current Scenario				
	OTD	Cycle time		Stock investment	
Current	75,3%	95,5	100,0%	37.900	100,0%
Critical Chain	75,4%	94	98,4%	37.350	98,5%
Critical Chain Extreme	75,3%	90,6	94,9%	39.830	105,1%
Newsvendor heuristic	75,3%	93,6	98,0%	37.130	98,0%

Based on these results, we derive that the current planned lead times aren't performing bad compared to the alternatives. The Critical Chain concept results in a small improvement in terms of both a cycle time reduction and stock investment reduction. Taking the Critical Chain concept to the extreme results in a further reduction of the cycle time, although the stock investments increase with about 5%. The Newsvendor heuristic, finally, result in a decrease of 2% of both the cycle time and stock investments.

In order to investigate the sensitivity of these results, we analyze the performance of the alternatives for three other scenarios in the next paragraph.

5.3.6. Sensitivity analysis

Compared to most other main customer systems produced by VDL ETG, the Philips U-Arc module has two distinct characteristics. First of all, the rather low service level of about 75% is considered as reasonable due to the concept of consignment stock, which does not only protect against demand

uncertainty, but to lead time uncertainty as well. Since the consignment stock is not used for most other main customer systems, we also consider the scenario in which the target service level is set to 90%. Secondly, about 50% of the total cost price of the Philips U-Arc is added during the final production stage, whereas the added value during the final assembly window of the ASML NXT3 system for example is between 5-10%. We therefore also consider an alternative scenario in which the added value of during final module production is 10%. A third alternative scenario results from combining alternative Scenario 1 and 2, i.e. a high service level and limited added value during the final stage. We report our findings in Table 6, Table 7 and Table 8 below. Since the planned lead times for these alternative scenarios are not known under the current method, we use the Fractile method as the benchmark.

Table 6: Performance of alternative methods under alternative Scenario 1

Alternative Scenario 1: higher service level					
Method	OTD	Cycle time		Stock investment	
Fractile	90,0%	103,9	100,0%	55.320	100,0%
Critical Chain	90,0%	100,7	96,9%	54.170	97,9%
Critical Chain Extreme	89,9%	97,5	93,8%	57.160	103,3%
Newsvendor heuristic	90,0%	100,7	96,9%	53.050	95,9%

We find that the results for alternative Scenario 1 are quite similar to the results for the current scenario, with a slightly bigger improvement effect of all alternative methods compared to the Fractile method. The stock investment reduction benefit of the Newsvendor heuristic gets more substantial as the added value during the final stage is limited. Moreover, also the cycle time reduction benefit of the Newsvendor heuristic slightly increases as the added value during the final stage is limited (cf. Figure 42 and Figure 43 in Appendix H). If we consider alternative Scenario 3, which best represents the situation of most main customer systems, we see that a cycle time reduction of 4.3% can be obtained, associated with a stock investment reduction of 11.2%

Table 7: Performance of alternative methods under alternative Scenario 2

Alternative Scenario 2: lower added value final stage					
Method	OTD	Cycle time		Stock investment	
Fractile	75,3%	95,5	100,0%	28.650	100,0%
Critical Chain	75,4%	94	98,4%	26.710	93,2%
Critical Chain Extreme	75,3%	90,6	94,9%	28.300	98,8%
Newsvendor heuristic	75,3%	92,6	97,0%	26.180	91,4%

Table 8: Performance of alternative methods under alternative Scenario 3

Alternative Scenario 3: higher service level and lower added value final stage					
Method	OTD	Cycle time		Stock investment	
Fractile	89,9%	103,9	100,0%	39.975	100,0%
Critical Chain	90,0%	100,7	96,9%	35.910	89,8%
Critical Chain Extreme	89,9%	97,5	93,8%	37.780	94,5%
Newsvendor heuristic	90,0%	99,4	95,7%	35.510	88,8%

Compared with the Fractile method, the Critical Chain concept performs quite well for all alternative scenarios, whereas the extreme variant performs well mainly for the final two alternative scenarios. If we compare both Critical Chain concepts, we see that the main win of the basic Critical Chain concept is in the reduction of the stock investments, whereas the main win of the extreme variant is in the reduction of the cycle time.

The general insight from these experiments is that a substantial part of the system safety buffer should be positioned at the final stage. This is in line with the research of Goldratt (1997) and in line with

findings for multi-echelon inventory systems that the majority of the slack should be positioned at the most downstream stage (De Kok & Fransoo, 2003). However, one should be careful with simply applying an extreme version of the Critical Chain concept. This method will lead to the biggest reduction of the cycle time, but also implies that a major part of the cost reduction potential is lost.

Clearly, additional research is required to obtain more comprehensive insights about setting planned lead times in assembly systems with stochastic lead times. We further discuss this aspect during our discussion about options for further research in Chapter 7 and 8. Still, the above exploratory analysis revealed some valuable insights, which we further elaborate on in the next chapter.

5.4. Conclusions and insights

In this chapter we focused on the design of quantitative models which support understanding and analysis of buffer settings in order-driven assembly systems with stochastic customer due dates. We extensively modeled and analyzed buffering against two important classes of uncertainty in real-life complex supply chains: demand uncertainty and lead time uncertainty. We explicitly decoupled these classes of uncertainty, following our introductory discussion in Section 5.1.

First of all, by taking an alternative perspective on demand uncertainty faced under order-driven control, we formulated a stochastic single-item single-echelon inventory system which captures demand uncertainty at the MPS level. The model provides an explanation for the very high service levels which are obtained by VDL ETG while there is no (or very little) finished stock: there is a buffer in the form of hidden inventory in the work in progress. By analyzing the MPS item from a two echelon perspective, we showed that there is a kind of natural decoupling between the final assembly window and upstream production. In addition, sensitivity analysis revealed that a reduction of the target service level to 95% can be associated with a reduction in the required inventory buffer size of about 25%. Still, this remains a rather strategic discussion.

In order to investigate buffering against lead time uncertainty, we formulated and validated a stochastic planned lead time model, which has been implemented in a discrete event simulation tool. Our analysis for the Philips U-Arc revealed that for this MPS item, the current planned lead time settings are similar to the Fractile method used by ASML. Apparently, planned lead times are selected such that an on time performance of about 85% at individual stages is obtained. We analyzed three alternative methods for determining planned lead times. In combination with some sensitivity analysis, we showed that a rather 'simple' Critical Chain concept can result in a reduction of both the cycle time and stock investments, while meeting the current service level. A more sophisticated Newsvendor heuristic can result in additional improvements, up to 4% cycle time reduction and about 11% cost reduction in case of high target service levels and limited added value in the final assembly stage. The general finding is that the majority of the buffer against stochastic lead times in the system should be positioned at the final stage. This implies that, contrary to general believe at VDL ETG, not meeting due dates in upstream production stages does not necessarily deteriorate the overall system performance.

Design for improvement

"Continuous improvement is better than delayed perfection" -Mark Twain-

In the first and major part of the design phase (see previous chapter), we focused on the design of quantitative models to support understanding and analysis of buffer management in the stochastic assemble to order supply chain. The models and analysis increased the understanding of important stochastic processes in relation to buffering, and revealed valuable insights about improvement directions. In this chapter we continue with the second part of our design phase, as we elaborate on the design directions and specific options for improving buffer management and operational control at VDL ETG.

In Section 6.1 we discuss the directions for improvement of buffering and operational control under demand uncertainty. In Section 6.2 we formulate options for improving control and buffer management under lead time uncertainty. We provide a brief discussion on the necessity of suitable performance metrics to support decision making and control in Section 6.3. Finally in Section 6.4 we briefly generalize our findings as we elaborate on how other companies can benefit from our research.

6.1. Improved buffer management and control under demand uncertainty

In Section 5.2 we designed a quantitative model which captures demand uncertainty and rescheduling at the MPS level. By considering a MPS item as a single item with an integral planned lead time, we showed that we can model the supply chain of VDL ETG as a stochastic single-item single-echelon inventory system. More specifically, we showed that the current order-driven control with uncertain due dates can be analyzed as forecast-driven control with demand uncertainty. The hidden inventory concept provides the missing link between the obtained high service level and final inventory which is currently absent or very small. Below we discuss two main options for improvement as a result of our analysis of demand uncertainty.

Visualization of the hidden inventory buffer to reduce nervousness

Based on our analysis and quantitative model, we argue that much system nervousness and inefficiency can be taken away by explicitly following initial production plans. Our analysis revealed that the hidden inventory buffers result from customer orders (or forecasts) which exceed real deliveries (delaying orders) and scheduled receipts which are rescheduled to match demand. Since the added value during the final assembly window is rather limited (e.g. about 5-10% of the cost price for the ASML NXT3 system, of which about 20-25% is labor driven instead of material driven), the cost efficiency of updating production plans is marginal. Moreover, the risk of holding inventory is hedged by customer orders (or committed forecasts). Following initial production plans will visualize the hidden inventory buffer (with limited additional costs) and will reduce the nervousness at the MPS level, thereby reducing inefficiency and reducing nervousness which is propagated through the system. In addition, it has the potential to ease planning, since there will be less rescheduling and less haziness about the real 'size' of the work in progress to which resources have to be allocated to finish it.

We believe that the biggest benefit thus comes from the alignment of plans with execution, i.e. by (largely) following initial production plans at the MPS level, much system nervousness can be reduced and the inventory buffer can be explicitly managed, while meeting the current high service level. Since our single-echelon model simply explains the relation between the inventory buffer and service level, there is no direct option for improvement. Underlying our modeling and analysis is the MTS perspective to analyze buffering against demand uncertainty. More detailed modeling, i.e. multi-echelon inventory structures, might create an option for improvement via smarter positioning of safety stocks (against demand uncertainty) in the supply chain. Upstream positioning of the buffer, however, will increase the complexity of integral control as this will intervene with lead time uncertainty. Moreover, from previous research we know that in multi-echelon inventory systems the majority of the slack should be positioned at the most downstream stage (De Kok & Fransoo, 2003).

Based on the above discussions and insights, we suggest to start a pilot test for a MPS item. More practically, by (more) strictly following initial production plans at the MPS level, the currently hidden inventory buffer will be visualized. Our Stochastic Inventory System Tool supports decision making at the MPS level by providing a reference level for the buffer size which should be in place to protect against demand uncertainty in order to obtain a target service level. The pilot test then should reveal the size and the evolution of the final inventory buffer. Moreover, it will reveal the extent to which nervousness is reduced in the entire supply chain.

Exploration of the effect of lower target service levels

Considering the high-tech B2B environment in which VDL ETG operates, one might argue about the necessity of target service levels which are about 99%. In addition, we hypothesize that the capacity of human planners enables an increase of a target (theoretical) service level of 95% with a few percent. In order to investigate the effect of lower target service levels, we performed some sensitivity analyses. These revealed that a reduction of the target service level to 95% can be associated with a reduction in the required buffer size of about 25%. Our Stochastic Inventory System Tool therefore can also be used to support decision making regarding the investments in inventory buffers for various service levels. In addition, the tool can help to explore the impact of the move rate (average demand) on the required inventory buffer.

6.2. Improved buffer management and control under lead time uncertainty

Analysis of ERP data revealed that lead times at VDL ETG are currently 'uncontrolled'. There are issues with lead time monitoring, planned lead times are stochastic and lead time uncertainty is currently not explicitly managed. Due to different lead time related data issues, we selected a MPS consignment stock item (Philips U-Arc) for the modeling and analysis of the planned lead time problem. A stochastic model has been formulated and empirically validated with historical data.

Via discrete event simulation we analyzed three alternative methods to determine planned lead times. The simulations showed that an efficiency increase via reductions in both the cycle time and stock investments can be obtained by determining the planned lead times via rather easy Critical Chain concepts. Moreover, a more sophisticated Newsvendor heuristic can result in further efficiency gains. Although these insights are obtained based on the analysis for only a single real life case, they already reveal that planned lead time settings are an important and promising option to buffer against lead time uncertainty in the supply chain of VDL ETG.

Investigate the planned lead time model for more systems

Based on our analysis of the planned lead time model, we recommend to further investigate the improvement potential of planned lead times within VDL ETG. Our planned lead time model and complementary tool can be used to acquire a better understanding of the performance impact of current planned lead time settings. Moreover, it will allow for quantifying the improvement potential of alternative methods for setting buffer norms in the form of planned lead times (safety times).

Our Planned Lead Times Simulation Tool can be used to explore the service and cost effect of different planned lead times for a basic two-echelon structure. It will be relatively easy to extend the tool to more comprehensive assembly structures, which will allow for a more detailed analysis. We explicitly recommend to further explore the promising Newsvendor heuristic, since this looks to be a very effective and efficient method to set buffer norms against lead time uncertainties.

Decouple lead time uncertainty from demand uncertainty

For our modeling and analysis of buffer management in the order-driven assembly system, we explicitly decoupled between lead time uncertainty and demand uncertainty (cf. Section 5.1). We argue that explicitly visualizing and 'managing' the final inventory buffer (see Section 6.1) in combination with explicit use of planned lead times, operationalizes the decoupling within VDL ETG. More specifically, it thereby becomes possible to explicitly monitor and manage lead time uncertainty, since demand uncertainty (rescheduling) will intervene with production order due dates (and performance measures) to a much smaller extent.

6.3. Explicit control and feedback loops

During the past couple of years, issues and uncertainties related to material flows in the supply chain of VDL ETG (CLIP suppliers, own CLIP performance of deliveries, costs, inventory investments, etc.) have been made visible. Via special Program Managers, there now is explicit management of these issues and feedback loops are created. Based on our quantitative and qualitative analysis throughout the entire research project, we believe that it is time for the next improvement phase: creating a better understanding of information related uncertainties (demand uncertainty, rescheduling, etc.) and planning concepts (planned lead times, inventory buffers). People are aware of related issues, but only improved understanding and insights will enable VDL ETG to manage them, improve them and to create feedback loops. This allows VDL ETG to become pro-active instead of re-active.

An important prerequisite for pro-active management and operational control (under uncertainties) is the use of suitable performance metrics. In Chapter 4 we argued about the unsuitability of the current CLIP and RLIP measures to support and evaluate decision making. Moreover, different data-related issues limit the use of performance metrics to evaluate operational control, e.g. lead times of production orders at Systems are not properly monitored due to the focus on only customer CLIP measures. For our quantitative modeling and analysis, we therefore calculated alternative performance scores which are suitable for evaluation and decision support, e.g. the weekly demand fill rate and the on-time delivery performance of production orders. Hence we recommend to put in place new performance metrics, and more importantly, explicitly monitor them in order to allow for feedback loops. A basic starting point is the use of OTD-based measures for individual production orders in the assembly stage, which is currently lacking. Moreover, the current CLIP scores still can be used to measure delivery reliability towards customers, but this indicator should not solely guide operational decision making and control.

Besides the lack of explicit control and feedback loops with regard to operational decision making and control, we briefly point to the design of another improvement direction for performance measurement. Up until the start of our research project, the different types of stock related capital investments (see Chapter 2) were not monitored consistently across different control reports. Through multiple iterations with the manager of Integral Planning (Langenhuysen, Manager Production Office), we therefore designed and developed a new Stock Investment Performance Report structure consisting of three main reports (see Appendix I). These new reports are already used within the company since April 2015. We therefore recommend to keep using these reports in order to increase the understanding and awareness about stock investments and risks among people involved with the planning and control of customer chains. Moreover, the reports can be improved based on experiences and ideas from people using them.

6.4. Generalizability of design and research findings

Finally in this section we briefly discuss how other companies can benefit from our findings, especially from the models which have been designed and analyzed in the previous chapter.

Firstly, our model with hidden inventory allows for analyzing buffering in order-driven supply chain systems with stochastic customer due dates based on a make-to-stock system with demand uncertainty. The model therefore can be use by other order-driven manufacturing companies which operate in dynamic (B2B) environments in which customer orders do provide certainty about the customer buy, but not about the real moment of buy. In case a customer item is produced via an assembly structure, integral planned lead times (can) allow for abstracting from detailed assembly structures and lead time uncertainties. Our model (and analysis) can be used to acquire a better understanding of the service and inventory effect of order due date uncertainty and scheduling decisions at the MPS level. Furthermore, it supports decision making regarding required inventory buffers for various service levels, different move rates and different degrees of order due date volatility.

Secondly, the general lead time model which has been formulated in Section 5.3 can be used by other companies for evaluating planned lead time settings in order-driven assembly systems. Once companies can explain the service level (and stock investments) under existing planned lead time settings, they can start thinking of improving the settings. Our analysis revealed that basic Critical Chain concepts can provide a valuable starting point to reduce both cycle times and stock investments via smarter positioning of buffer time (actually more towards to end of the assembly system). Moreover, the Newsvendor heuristic which has been empirically tested in our research can be used by companies for a system-wide optimization of their planned lead time settings.

Together, the stochastic inventory model and the stochastic planned lead time model provide a powerful concept for understanding two complex classes of uncertainties in order-driven assembly systems: due date uncertainty and lead time uncertainty. Companies can use the stochastic inventory model to support and explore the determination of important inventory buffers under due date uncertainty, and methods based on the Critical Chain concepts or a more sophisticated Newsvendor heuristic can be used to determine important time buffers under lead time uncertainty. Both aspects are important for efficient and effective buffer management and control in what we can regard as 'make to order-driven stock' supply chains.

Finally, note that our discussions on the role and position of the CODP in real-life complex supply chains and our discussion on the 'need' for decoupling demand uncertainty from lead time uncertainty for robust operations planning, might provide a valuable starting point for discussions about improved buffer management and control for other companies as well.

Conclusions

"The more I learn, the more I realize I don't know" -Albert Einstein-

We conclude the business focused part ("regulative cycle") of our research study by answering the research questions and providing recommendations for further research within VDL ETG.

7.1. Research questions

In the introduction of this thesis, we stated that companies in ATO environments face many different uncertainties, but it is unclear how to control operations and determine buffers in order to improve the supply chain efficiency and control. As a case study, VDL ETG has been used to study this problem. After a comprehensive explorative problem analysis and the development of a roadmap (Kamps & Arts, 2014), we formulated the following main research question:

How should VDL ETG manage buffers and control operations in its dynamic ATO/MTO environment, such that the supply chain efficiency and controllability is improved?

The focus of this research question is on the operations planning and control activities at the Goods Flow Control level (Integral Planning at VDL ETG). We now address this overarching question in an integral way by answering our research sub questions.

1. What are key strategic, tactical and operational features in the supply chain of VDL ETG?

In order to gain understanding of important aspects to take into account for improving operational control and buffer management in the design phase of our research, in Chapter 2 we analyzed key strategic, tactical and operational features in the as-is situation at VDL ETG.

We identified flexibility and responsiveness as two important, related, strategic features. Two related tactical features are capital investment risk and customer commitment. Planning stability and nervousness have been discussed as two important operational features. We concluded our discussion of this research question by formulating the main planning and control objectives: meeting high customer service levels (above 95%) while keeping the inventory and work in progress investments as low as possible. In addition, we identified reduction of rescheduling workload as a third objective.

2. What are the different types of uncertainty and their magnitude in the supply chain of VDL ETG?

In the first half of Chapter 3 we constructed a framework (see Figure 9) of the key types of uncertainties observed in VDL ETG's supply chain. The general classes of uncertainty are: supply, manufacturing process and demand uncertainty. Quantitative analysis revealed that for the supply and manufacturing process uncertainty, it is mainly the lead time uncertainty type which is the most comprehensive, rather than the yield uncertainty type. For demand uncertainty, we identified two related types: demand due date uncertainty and forecast uncertainty. Demand due date uncertainty at VDL ETG has been investigated extensively by Kamps (2015), therefore in this study we mainly focused on forecast

uncertainty: we showed that forecasts and orders provided by customers are volatile and imply quantitative uncertainty about future period demand.

Next to the above types of uncertainty which are faced (at the Goods Flow Control level) by VDL ETG, we extended our discussion with some analysis of other types of uncertainty which are actually propagated through the supply chain by VDL ETG itself: delivery uncertainty sent towards customers, internal production order due date uncertainty, and purchasing order due date uncertainty sent towards external suppliers.

Our desk research as well as interviews revealed that there is a strong focus on material flow uncertainties and associated performance metrics at VDL ETG. In contrast, there is much less understanding and monitoring of information flow related uncertainties and underlying planning and control concepts.

3. How does VDL ETG currently deal with uncertainties in its supply chain and what can be learned from this?

In the second half of Chapter 3, we discussed the different options which are currently used by VDL ETG to buffer against uncertainties. Capacity buffering is mainly used via dynamic capacity planning at Parts, production planning at Systems is performed while assuming infinite capacity (static). Qualitative and quantitative analysis revealed the following main buffer options which are currently used: explicit item safety stock (about 7,5% of all active items), explicit item safety time (less than 0,5% of all active items), MPS planning with buffers, general buffer of one week between internal and external customer due dates, and consignment stock (for a few customer chains, e.g. Philips).

Different types of buffers are used at different moments and places. The application of buffers is mainly operationalized based on employees' experiences (from planners, factory engineers, etc.). There is a lack of explicit performance feedback loops and control with regard to uncertainties and methods used to buffer against it. This makes it hard to create a solid understanding of the existence and especially the impact of uncertainties, let alone of the 'optimal' buffer parameter settings.

4. How can operational decision making and control within VDL ETG's supply chain be improved?

In Chapter 4 we provided some conceptual discussions which were important for the development of appropriate models to support our design phase. These discussions provided insights about how operational decision making and control can be improved, or actually 'supported'. In the second part of our design phase (Chapter 6), we further elaborated on the design of directions for improvement. Amongst others, we discussed the development of appropriate control performance indicators which allow for feedback loops, a shared focus on production plans instead of disunity among people in terms of steering based on external demand dates or internal production plans, decoupling demand uncertainty from lead time uncertainty, and explicit buffer management. This final aspect has been analyzed extensively in Chapter 5 and is the main subject of the next sub question.

5. How should VDL ETG set norms for buffers in materials and time such that demand is met effectively (on time) and more efficiently (with less costs and nervousness)?

Based on exploratory analysis and alternative thinking discussed in Chapter 4, we formulated two main quantitative models in Chapter 5 to analyze buffer norm setting in relation to two important classes of uncertainty: demand uncertainty and lead time uncertainty.

In Section 5.2 we showed that a kind of hidden inventory buffer arises due to actual receipts at the MPS level which are generally closely matched with real customer demand, and real demand which is significantly lower than the forecasted/ordered demand (cf. Figure 17). So, the (hidden) inventory buffer basically can result from more strictly following initial production plans. In addition, our stochastic inventory model (and complementary tool) can be used as a reference to support the evaluation and size of the required inventory buffer under different levels of due date uncertainty, different move rates and different cycle times. Finally, we showed that a reduction of about 25% in the required inventory buffer can be obtained if target service levels are decreased to a level of 95%.

In Section 5.3 we analyzed safety time buffers to protect against lead time uncertainty. Via our planned lead time model (and complementary discrete event simulation tool), we investigated three alternative options to determine planned lead times. Compared with the current planned lead time settings (which are similar to using a Fractile method), we showed that 'easy' Critical Chain concepts can result in a reduction of both the cycle time and stock investment. A more sophisticated Newsvendor heuristic to set planned lead times can result in additional savings, up to 4% cost reduction while reducing the cycle time with about 11% (cf. Table 8). Although these insights are obtained based on the analysis for only a single real life case, they already reveal that planned lead time settings are an important and promising option to buffer against lead time uncertainty in an order-driven assembly system. We therefore recommend this 'problem' as an interesting option for further research in Section 7.2.

6. How can VDL ETG use and implement the new insights?

Based on the insights which we obtained during our research study and the associated tools which have been developed, we 'designed' recommendations and options for using them in Chapter 6. Amongst others, we suggested to use the new Stock Investment Performance Report structure; to start a pilot test for visualizing the hidden inventory buffer; and to investigate the planned lead time model and the heuristics for more customer items. We believe that our research is a great leap forward in terms of contributing to the important understanding of buffer management and operational control in the real-life complex supply chain of VDL ETG, and by indicating the potential of different improvement options. The next step is to operationalize and design detailed control and parametrization rules, for which our research should be regarded as a vital starting point.

In summary, our main business contributions are: the development of a roadmap for a series of supply chain improvement projects; the development of a new performance report structure for supply chain capital investments; the development of a model (and associated tool) which explains the service performance of a MPS item under volatile demand given the inventory buffer size, and which supports the determination of the inventory buffer size given a target service level; the development of a model (and associated tool) which allows for exploring alternative planned lead time settings and their effect on the on time delivery performance and stock investments; the design of directions for improving buffer management and operational control.

7.2. Recommendations for further research within VDL ETG

Next to the recommendations for using the insights and tooling as discussed in Section 7.1, we make the following recommendations for (general) further research within VDL ETG.

Detailed production unit control at Parts

As discussed several times in this report, we took an integral planning perspective for analyzing and modeling uncertainties and buffer methods. This implies that we considered uncertainties at the

detailed production unit level (e.g. uncertain lead times of items produced by Parts) as endogenous to the problem of determining buffer norms. For example, during our analysis of planned lead times, we assumed a given uncertainty of item lead times. Additional gains can be realized if these uncertainties are reduced. Especially within Parts, detailed production unit control is very challenging, due to the interactions of items and limited resources. In addition, the problem of planned lead times can be further explored.

Operational coordination of work order release

The main focus of our research was on the analysis of buffer management for protection against demand and lead time uncertainty. We also shed light on how our insights can improve operational control at VDL ETG. Although we did use some alternative concepts to model and analyze uncertainties and buffer management, the general findings and insights were discussed by considering their application under the current control practices. We believe that the supply chain efficiency and control can be further improved by further investigating the problem of how to operationally coordinate the timing and quantity of work order releases. More practically, we showed that the current MRP-based control poses multiple problems, so an investigation of more constrained based work order release concepts (e.g. SBS policies (De Kok & Fransoo, 2003)) can enable additional improvements. Moreover, qualitative and quantitative analysis revealed the improvement potential of smarter planned lead time settings, so we recommended to include this problem in this direction of further research.

Supply chain design and responsiveness

Considering the cause and effect diagram (see Figure 28) discussed in Chapter 1, we note that our research mainly focused on the 'problems' of high inventory and WIP investments, and the high rescheduling workload (nervousness). The fourth problem, i.e. low supply chain responsiveness, has been addressed only indirectly. We discussed the role of supply chain responsiveness and flexibility from a planning and control perspective in Section 2.1. For our quantitative modeling and analysis of tactical buffer management and operational control, we considered the required responsiveness as 'given', reflected by the current customer service levels and lead times. In the volatile environment of VDL ETG, high responsiveness can be an important competitive advantage. We therefore consider it as an promising option for further research, which can be regarded as a 'design' or 'strategic' oriented problem in the planning hierarchy (see Figure 6). Many interesting considerations emerge when designing flexibility in a system (Bertrand, 2003), e.g. alternative production strategies to achieve high customization while maintaining 'quick' deliveries (Meredith, Akinc, Zwartelé & Arts, 2015). In addition, the concept of consignment stock can be investigated as a design option to buffer against demand and lead time uncertainty for other major customer systems next to the products for which consignment stock is currently used.

Finally, we cannot stress enough the integral nature of the planning and control problems in the supply chain of VDL ETG. This thesis provides insights and tools to 'solve' and improve a part of the problems, but we underline the importance of keeping the entire picture in mind. The improvement of the supply chain via series of (thesis) projects therefore is a good way to address the various challenges. Next to the above comprehensive research directions, we therefore refer to the other projects as listed in the roadmap (see Figure 30) for other promising options for further research at VDL ETG.

Reflection

"All models are wrong, but some are useful" -W. Edwards Deming -

In this chapter we complete the reflective cycle (Figure 1) by reflecting on our case study at VDL ETG and improving our design knowledge. In addition, we provide future research directions.

8.1. Design knowledge

Below we discuss the most interesting observations from the case study and we summarize our main scientific contributions.

Explanation of service in a single-item single-echelon stochastic inventory model based on the average inventory and average order size

In Chapter 5 we investigated the validity of our hypothesis that the service in a single-item single-echelon stochastic inventory system can be 'explained' by the average inventory in combination with the average order size as system outcomes, and that this service is relatively insensitive to the operational control rules/parameters under certain circumstances. Based on formal mathematical analysis of the inventory system behavior, we formulated expressions for the estimated control parameters implicitly used under different control rules.

Empirical analysis for three real life examples revealed the validity of our hypothesis, at least in the high-tech environment of VDL ETG characterized by high service levels, long lead times and low volumes. This implies that it is mainly a system's average inventory in combination with the average order size which 'drives' service performance, rather than the detailed control parameters and concepts.

For case studies in real life supply chains, an analysis of the average inventory in combination with the average order size thus can reveal valuable insights about the system performance.

'Hidden inventory' under MTO control with order due date uncertainty

One of the most striking observations in our case study is that MTO control at the MPS level with uncertain customer due dates can be analyzed as MTS control with hidden inventory buffers. Driven by the 'inexplicable' phenomenon of high service levels which are obtained under volatile demand without (or only very little) final stock, we introduced the concept of hidden inventory.

This hidden inventory arises due to cumulative actual receipts at the MPS level which differ from the cumulative scheduled receipts (order driven), as a result of order-driven control, i.e. rescheduling actual receipts to match with customer orders, which are stochastic in terms of their due date. The hidden inventory can be considered as a kind of inventory which is hidden/kept in the work in progress. This inventory is spread in the pipeline in such a way that there is enough hidden inventory which can quickly enough be converted in real stock in order to cope with the stochastic demand from customer side, thereby obtaining a certain service level.

A distinction between the forecast-driven part and order-driven part thus does not really exist in the real life complex supply chain of VDL ETG. Traditionally, buffer management in the forecast-driven part of a supply chain system is analyzed under the assumption of deterministic lead times (De Kok & Fransoo, 2003). Buffer management in the order-driven part is typically analyzed under the assumption of deterministic customer order due dates (Axsäter, 2005). In the dynamic and volatile environment of VDL ETG, these explicit distinctions vanish: production is basically order-driven, but the uncertainty of order due dates creates uncertainty which can be analyzed as demand uncertainty in forecast-driven inventory models. The case study at VDL ETG illustrates that we can regard real-life order-driven supply chains in dynamic environments as a kind of stochastic 'make to order-driven stock' systems.

For case studies in real life supply chains, the hidden inventory thus provides a powerful concept which allows for evaluating and understanding human decision making at the order-driven MPS level, from the perspective of a stochastic inventory system. Moreover, we showed that it can be used to explore the required inventory buffer size to protect against demand (due date) uncertainty for different target customer service levels and demand move rates.

Safety time buffering under stochastic lead times

In the second part of Chapter 5, we analyzed safety time buffering under lead time uncertainty. We formulated a two-echelon assembly model based on a real-life example within VDL ETG. Analysis of historical data for this example showed that the current planned lead time settings are similar to using a Fractile method, a method which is used by ASML too. Based on a discrete event simulation, we analyzed alternative methods to set planned lead times. The analysis revealed that efficiency and effectiveness gains can be obtained in terms of both lower stock investments and lower cycle times. A comprehensive heuristic results in significant improvements (about 4% cycle time reduction and 11% cost reduction under high service levels and low added value during the final stage), but rather 'simple' Critical Chain based concepts can already result in important improvements too. The general insights we obtained from our analysis is that the majority of the buffer against lead time uncertainty should be positioned at the end.

For case studies in real life supply chains, the concept of the Critical Chain thus might be a valuable first option to investigate the improvement potential of smarter safety stock buffering. In addition, one should realize that not meeting due dates in upstream production stages should not necessarily be detrimental for the overall system performance in the real-life supply chain. One should thus be careful with immediately rescheduling capacity and priorities in case it looks like planned due dates within the supply chain are not met.

In summary, our main 'scientific' contributions are: the introduction and validation of the hypothesis about the service explanatory power of the average inventory and order size in a general inventory system; the introduction and empirical validation of 'hidden inventory' as a new mathematical concept which allows for the analysis of buffering under demand due date uncertainty in order-driven systems as buffering under forecast uncertainty in inventory systems; the formulation of a planned time model for a two-echelon assembly system along with the empirical validation for a real life example; an empirical analysis of two Critical Chain concepts and a Newsvendor based heuristic (Atan et al., 2015) as promising methods to set planned lead times under lead time uncertainty in an order-driven assembly system.

8.2. Future research directions

Based on our research and case study we identify promising areas for further academic research.

Modeling human planner behavior

In Chapter 5 we investigated the effect of lower target service levels on the required inventory buffer size to cope with demand uncertainty. We hypothesized that human planner capacity can enable an increase of a 'target' or 'model' service level of 95% with a few percentages. Stochastic operations models and concepts can provide important support for human decision making, but they probably never will totally substitute human planners. Quantitative analysis of human planning behavior can reveal valuable insights, which in turn can be used to further improve the models and concepts to support it.

Lot sizing under lead time uncertainty in order-driven control

Our analysis of setting planned lead times under lead time uncertainty was conducted for a real life customer module at VDL ETG which is produced to order, with lot sizes equal to the order quantity. One might think of examples in which production is order-driven, but lot sizes are used for one or more of the production stages. In this case, lead time uncertainty should be modeled differently. We hypothesize that our model discussed in Chapter 5 then provides a kind of lower bound on the service level, since stochastic lead times at the stage(s) with lot sizing do not affect earliness/tardiness in each order cycle.

Capacitated systems and planned lead times

For our quantitative analysis and modeling, we didn't consider limited capacity explicitly. We argued that if planned lead times are set correctly, we can assume that the capacity flexibility is such that the planned lead time is met with a high reliability. We thus consider lead times to be exogenous to the integral planning and control 'problem', implying that the system needs to take care of controlled lead times such that they are more or less fixed (cf. De Kok & Fransoo, 2003). Further research should reveal the relative effectiveness and efficiency of this concept in capacitated systems.

Divergent networks with lead time uncertainty

In Chapter 5 we formulated a planned lead time model for a two-echelon assembly structure, with four parallel stages preceding a single final stage. We analyzed the performance of several methods to set planned lead times under lead time uncertainty in such a system. One of these methods was a heuristic developed by Atan et al. (2015), which is based on decomposing the assembly system into mutually dependent serial systems. Future research should reveal if the approach underlying the heuristic can be used to find 'optimal' planned lead times in general networks. Other heuristics for the planned lead time problem in general networks might be developed as well.

Hybrid push-pull concepts

In Section 7.2 we briefly mentioned the improvement potential of a more constraint based planning within VDL ETG. More specifically, the top-down MRP-based material coordination lacks constraints which take account of material availability in upstream stages. It is a push-concept which therefore results in many rescheduling activities. On the other hand, pull-driven material coordination (e.g. SBS policies (De Kok & Fransoo, 2003)), allows for incorporating operational constraints for order releases. Our quantitative analysis revealed that we can model the push-driven control at the MPS level as pull-driven control under demand uncertainty. We therefore can think of a promising option for the design of comprehensive hybrid push-pull concepts, in which intelligent use of early (uncertain) demand information is incorporated as well as the use of more operational constraints for order releases.

Control process flow descriptions

A.1. Swimming lane diagram

In this section we show the so called 'swimming lane diagram' which outlines the main planning and control processes discussed in Section 1.2, along with their time dependencies.

Note that the diagram shows the regular decisions which are taken, including a special part which represents the optional occurrence of rescheduling activities. In this diagram, we focus on the decision functions which are important for the control of information and material in the supply chain, i.e. we focus on planning, control and release decisions. Execution processes (e.g. component manufacturing or assembling activities) are therefore excluded. Control starts by the order acceptance decision function performed by an order manager (contact with customer) and ends at the moment the order manager releases the order for shipping, i.e. the process flow ends again at the point of contact with the customer.

All the processes in Figure 27 actually consist of one or more detailed decision functions, each having their own input, control and output variable(s), along with associated control mechanisms. A detailed overview of each of the decision functions is provided in Section A.2.

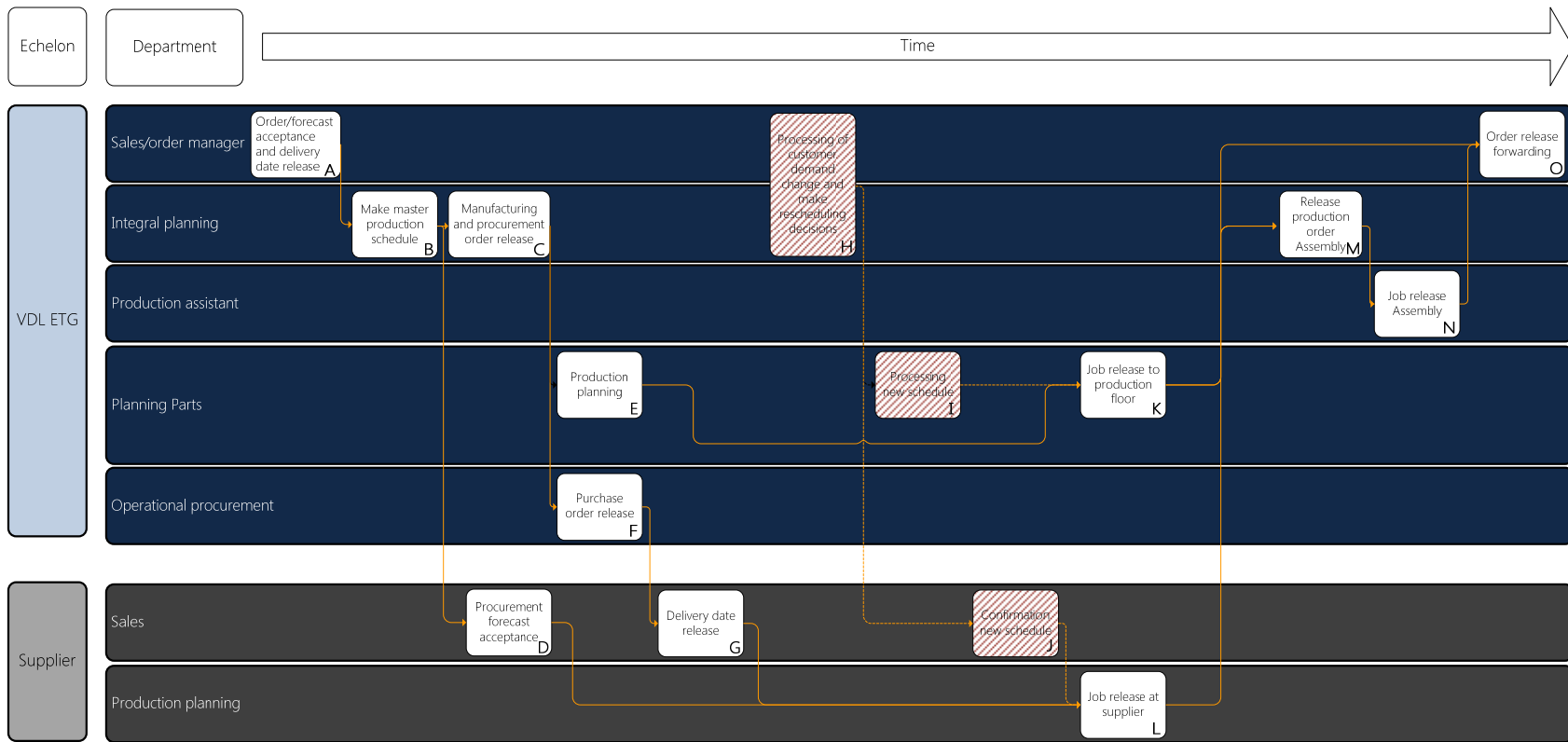
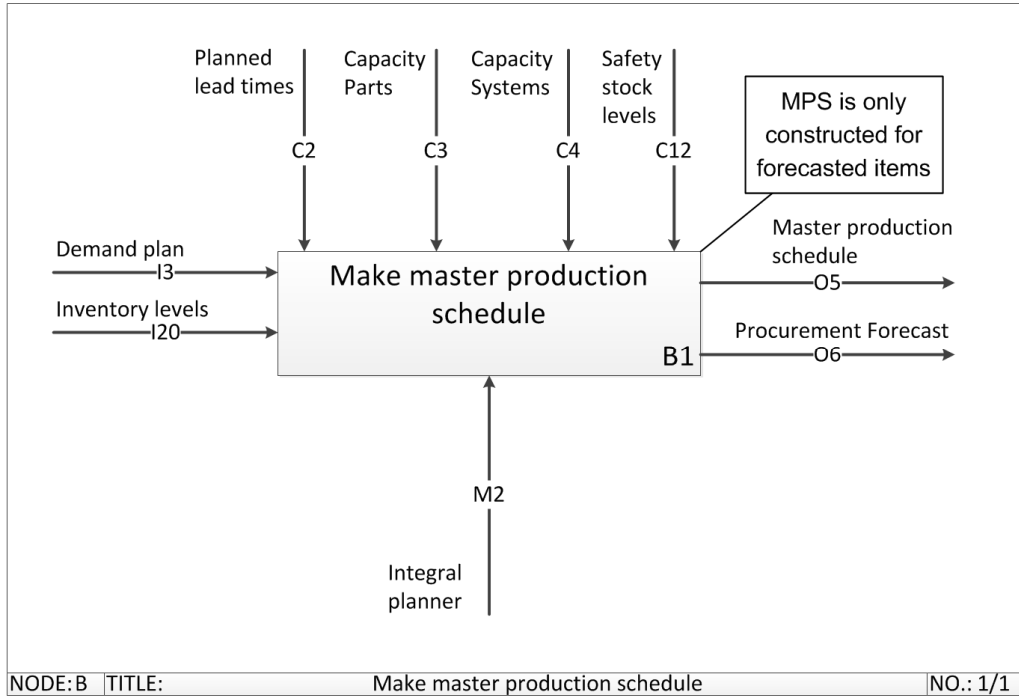
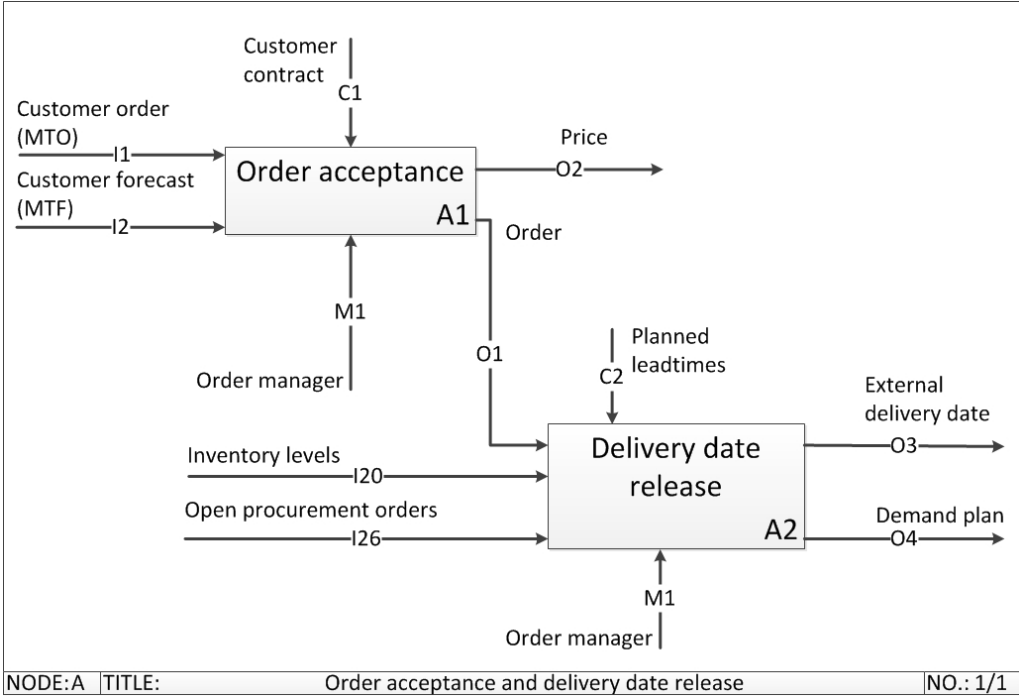
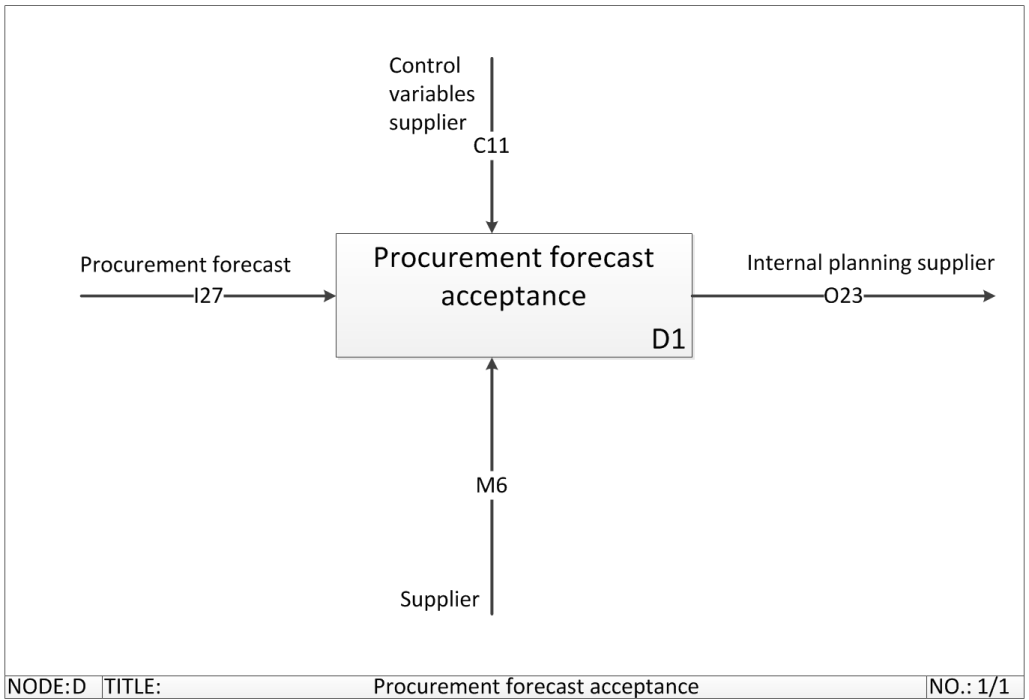
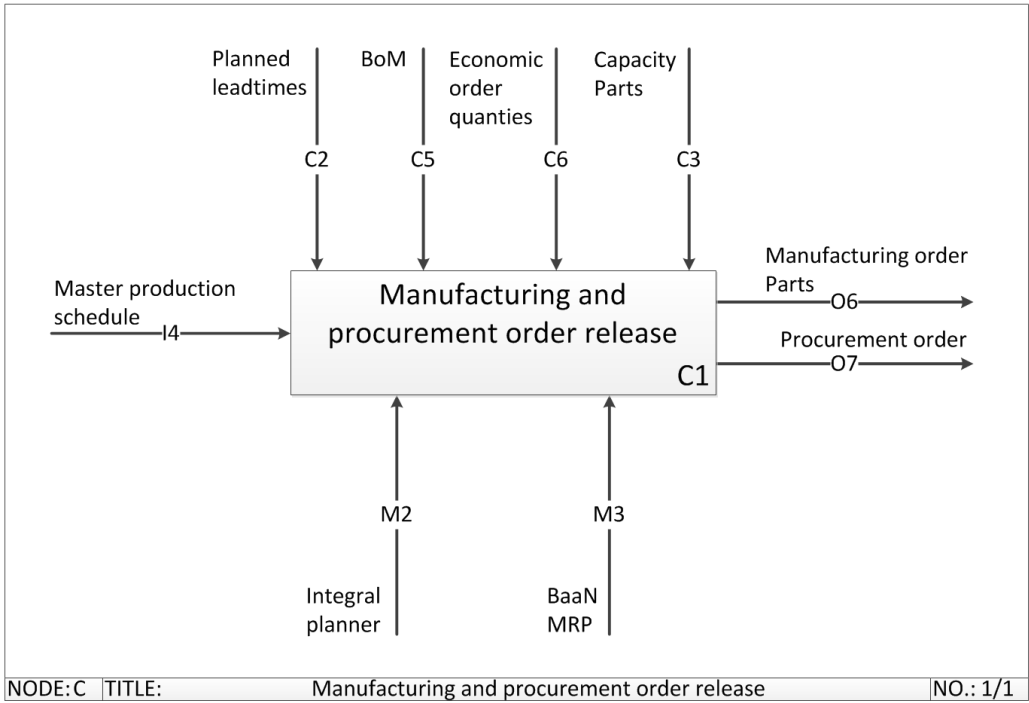


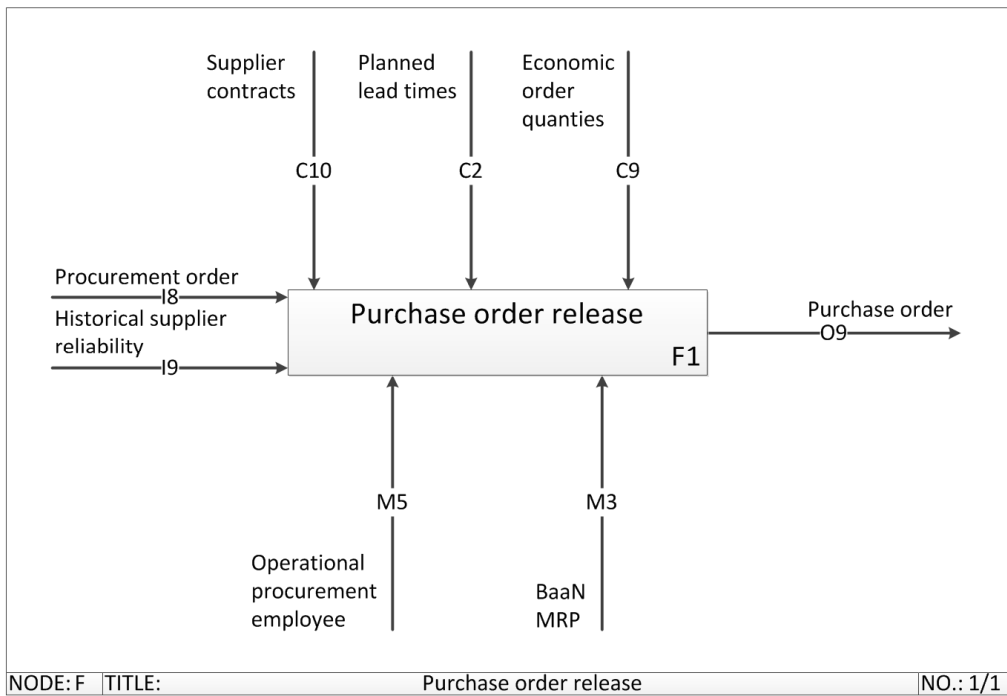
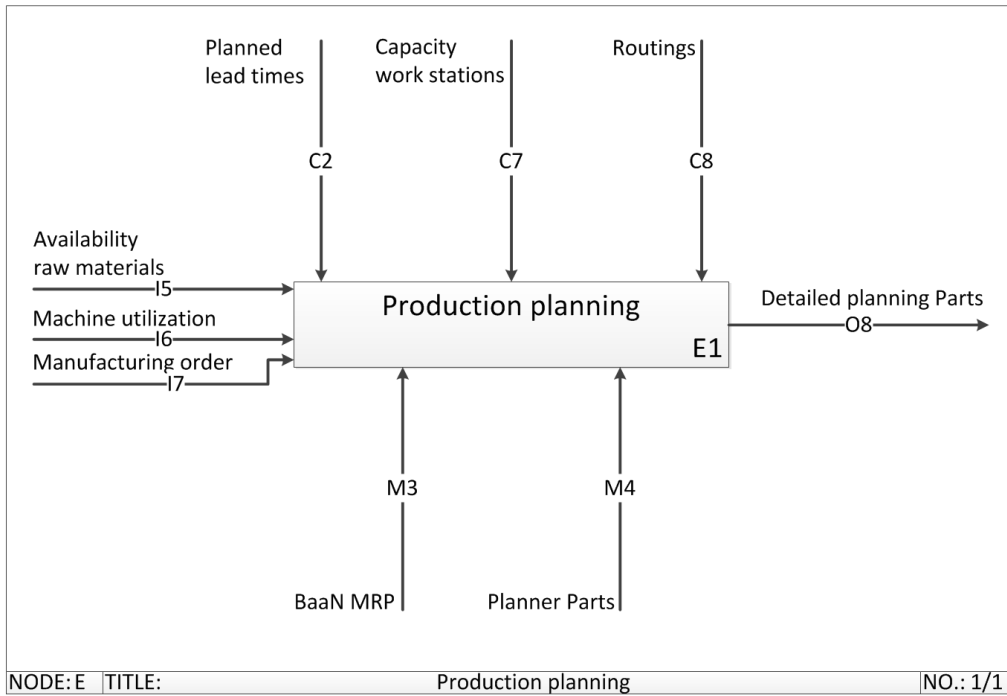
Figure 27: Swimming lane diagram of operational supply chain control decisions

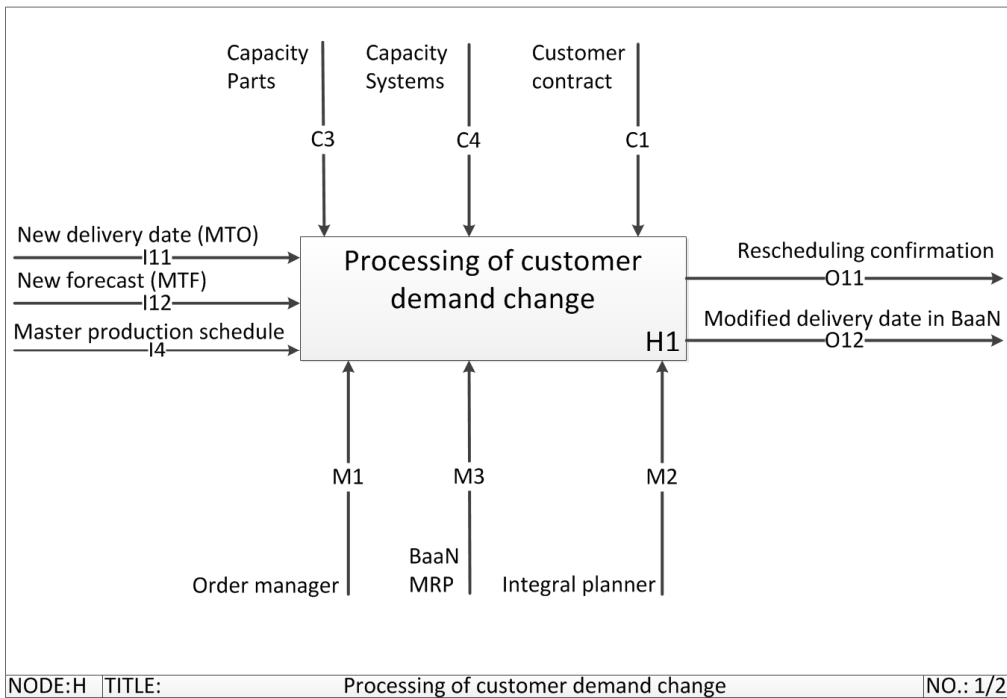
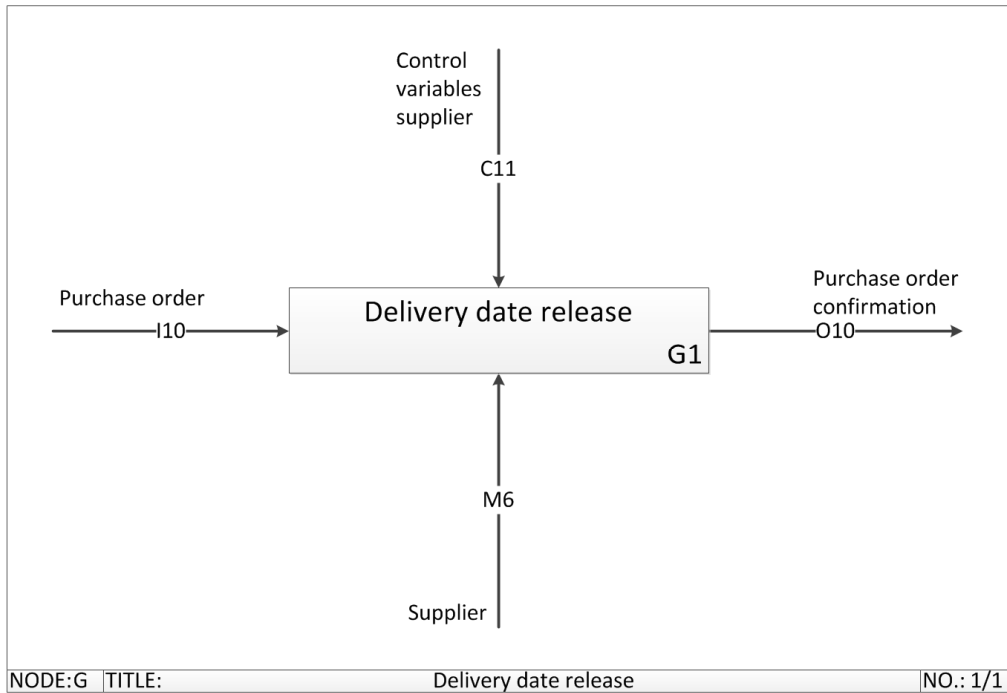
A.2. IDEF0 process descriptions

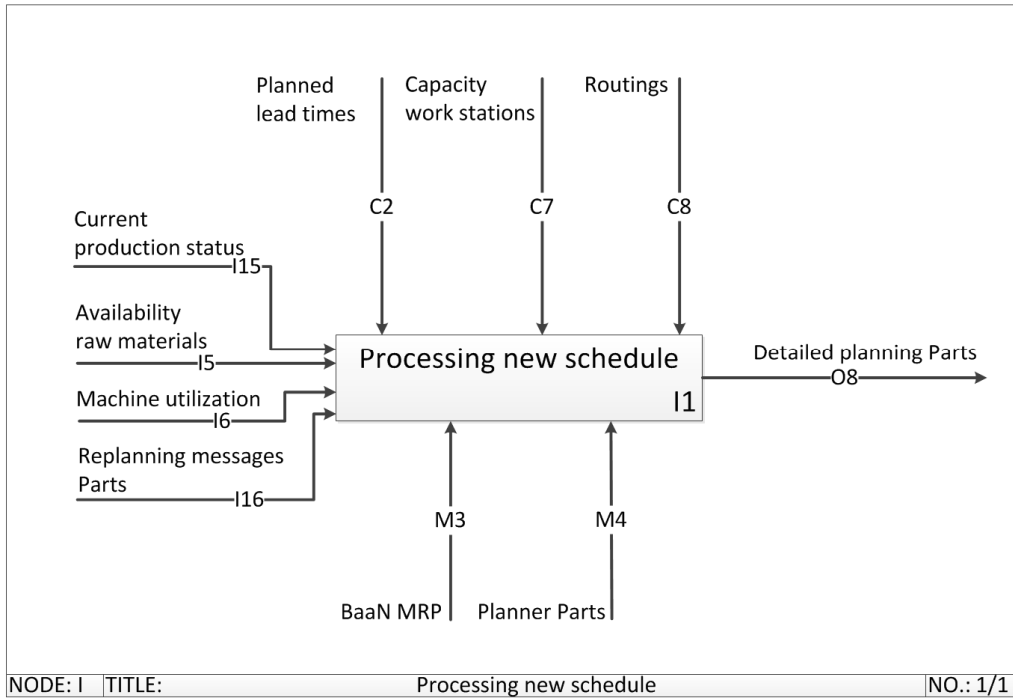
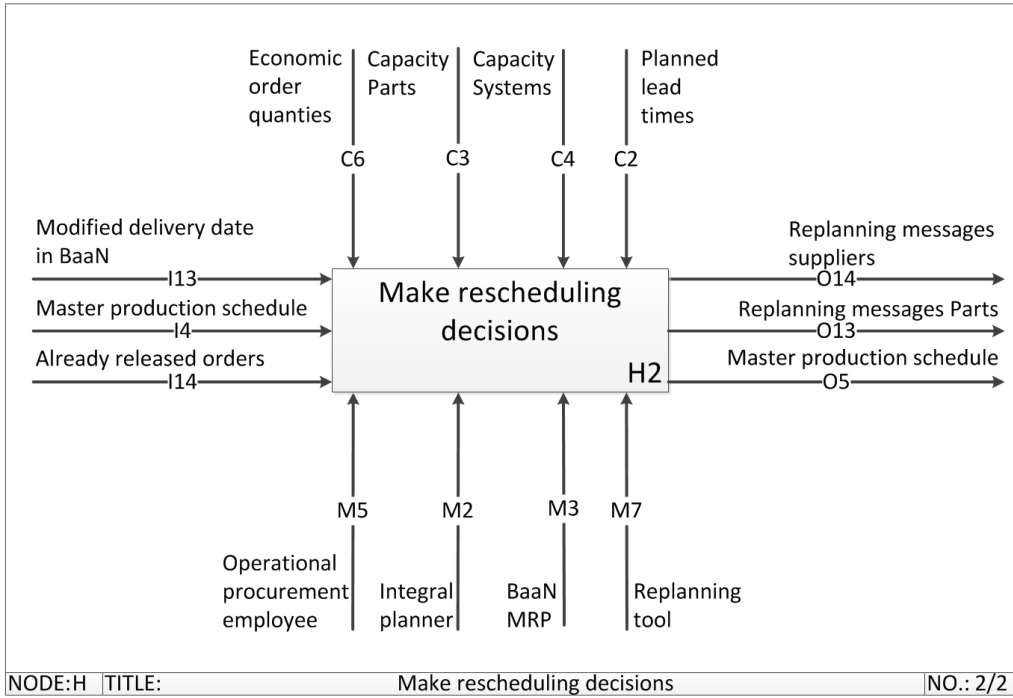
For each of the processes in Figure 27 introduced in the previous section, we show the details of the associated decision functions using the IDEF0 notation. Note that at the end of this appendix, we provide a list with all input, control and output variables used, along with the mechanisms.

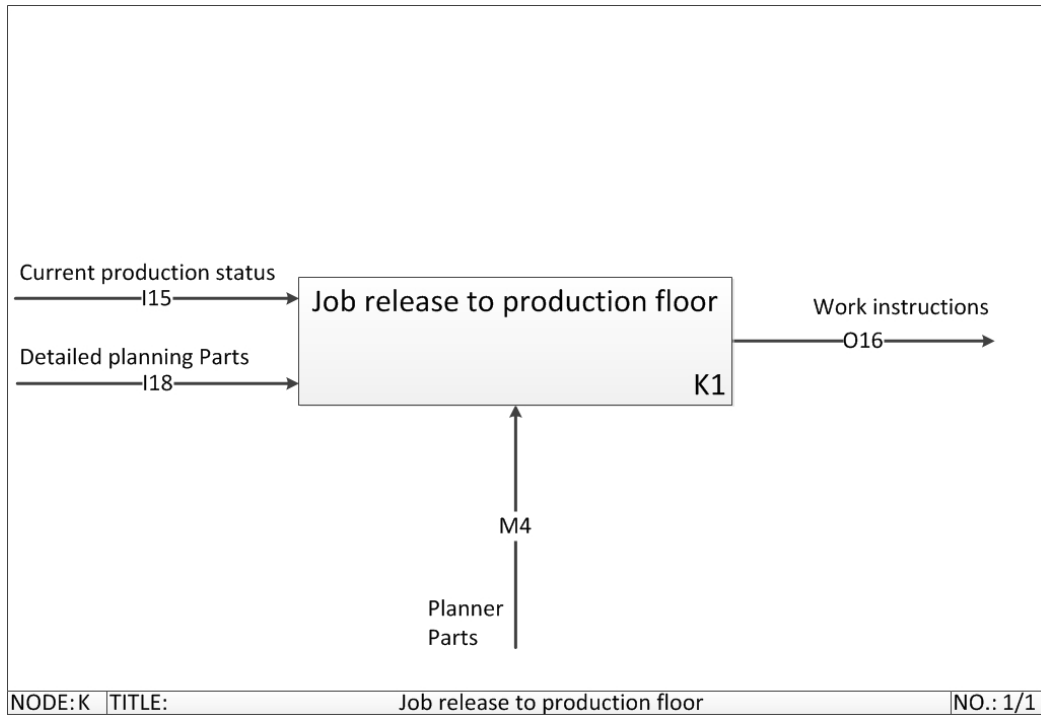
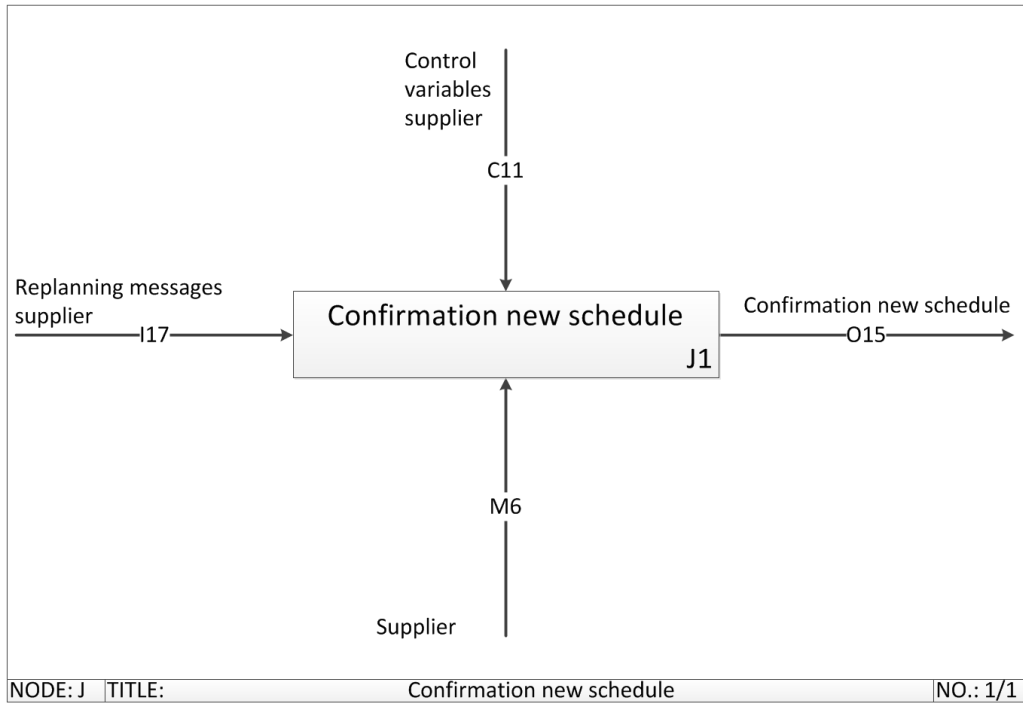


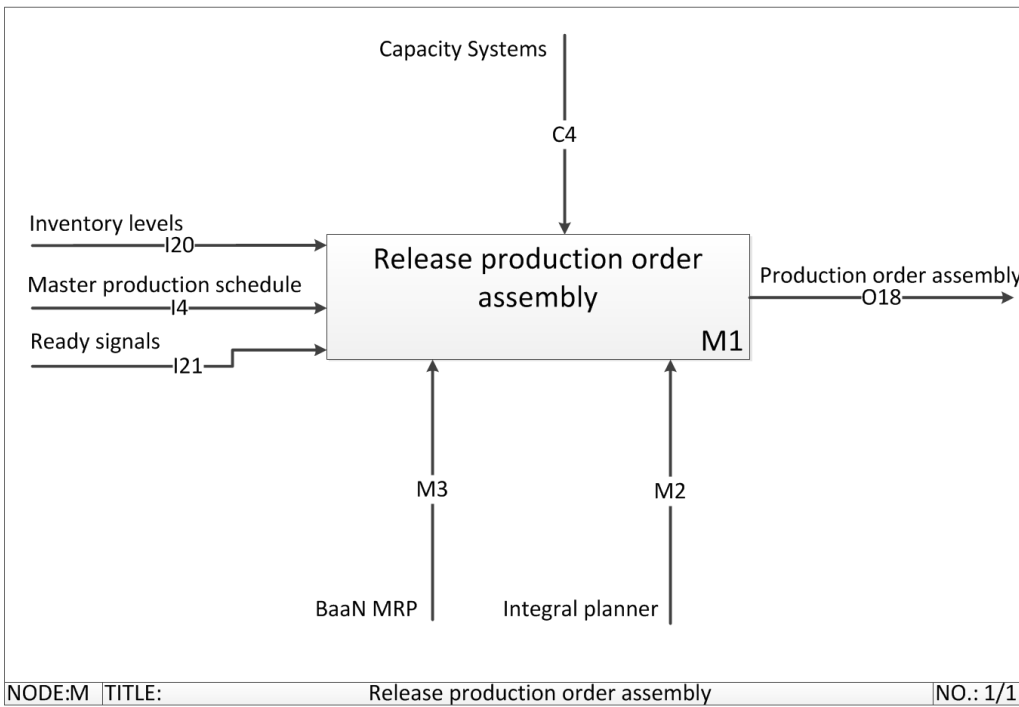
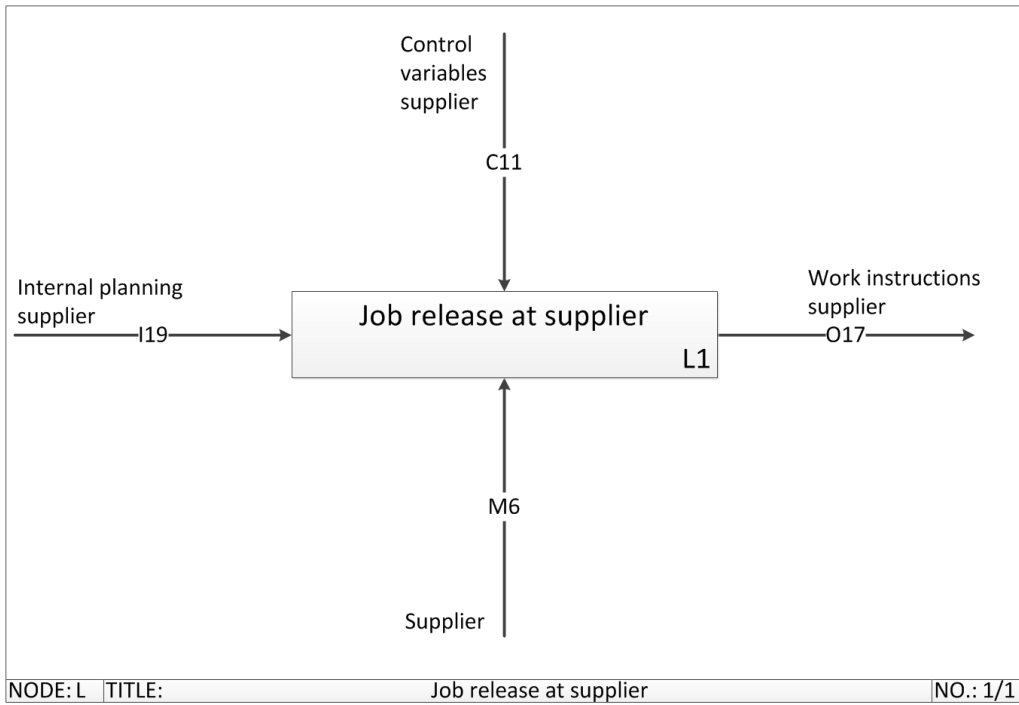


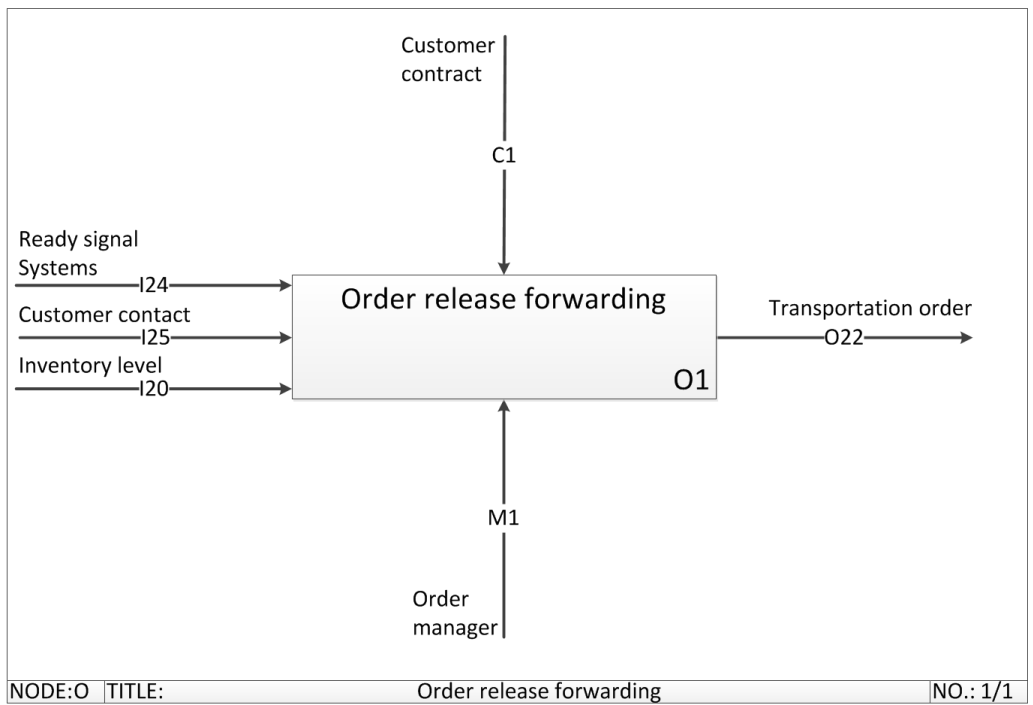
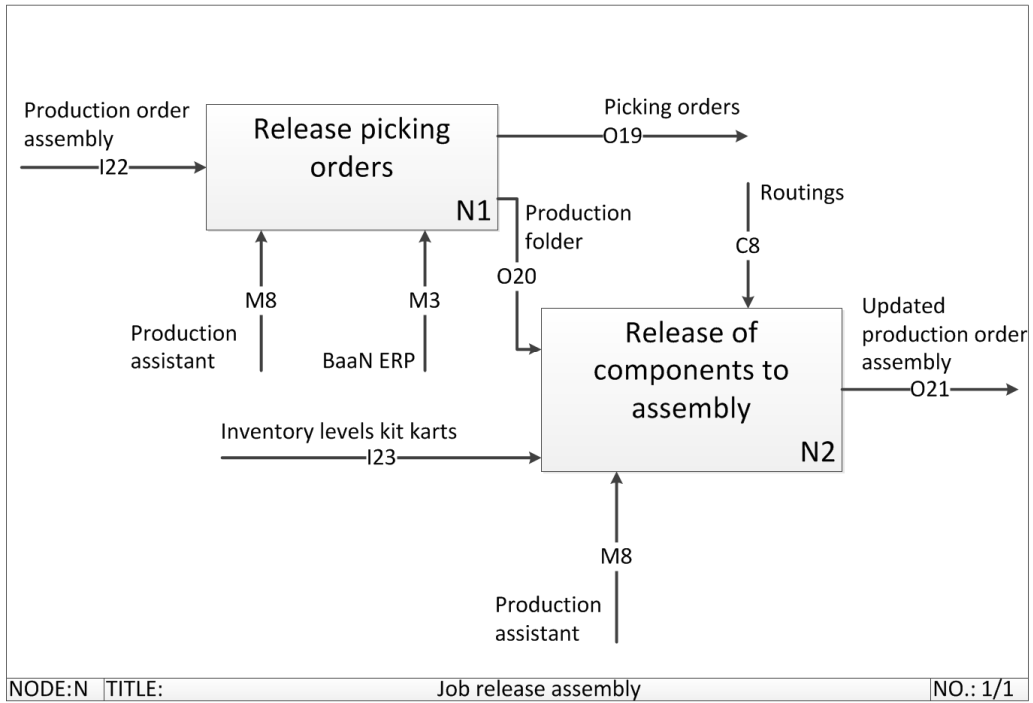












A.3. Variables and mechanisms

Nr.	Input variable
I1	Customer order (MTO)
I2	Customer forecast (ATO)
I3	Demand plan
I4	Master production schedule
I5	Availability raw materials
I6	Machine utilization
I7	Manufacturing order
I8	Procurement order
I9	Historical supplier reliability
I10	Purchase order
I11	New delivery date (MTO)
I12	New forecast (ATO)
I13	Modified delivery date in BaaN
I14	Already released orders
I15	Current production status
I16	Replanning messages Parts
I17	Replanning messages suppliers
I18	Detailed planning Parts
I19	Internal planning supplier
I20	Inventory levels
I21	Ready signals
I22	Production order assembly
I23	Inventory levels kit karts
I24	Ready signal Systems
I25	Customer contact
I26	Open procurement orders
I27	Procurement forecast

Nr.	Mechanism
M1	Order manager
M2	Integral planner
M3	BaaN MRP
M4	Planner Parts
M5	Operational procurement employee
M6	Supplier
M7	Replanning tool
M8	Production assistant

Nr.	Output variable
O1	Order
O2	Price
O3	External delivery date
O4	Demand plan
O5	Master production schedule
O6	Manufacturing order Parts
O7	Procurement order
O8	Detailed planning Parts
O9	Purchase order
O10	Purchase order confirmation
O11	Rescheduling confirmation
O12	Modified delivery date in BaaN
O13	Replanning messages Parts
O14	Replanning messages suppliers
O15	Confirmation new schedule
O16	Work instructions
O17	Work instructions supplier
O18	Production order assembly
O19	Picking orders
O20	Production folder
O21	Updated production order assembly
O22	Transportation order
O23	Internal planning supplier

Nr.	Control variable
C1	Customer contract
C2	Planned lead time
C3	Capacity Parts
C4	Capacity Systems
C5	Bill of materials (BoM)
C6	Economic order quantities
C7	Capacity work stations
C8	Routings
C9	Economic order quantities
C10	Supplier contracts
C11	Control variables supplier
C12	Safety stock level

Roadmap sections

B.1. Cause and effect diagram

Figure 28 shows the cause and effect diagram which has been discussed in Section 1.3.2.

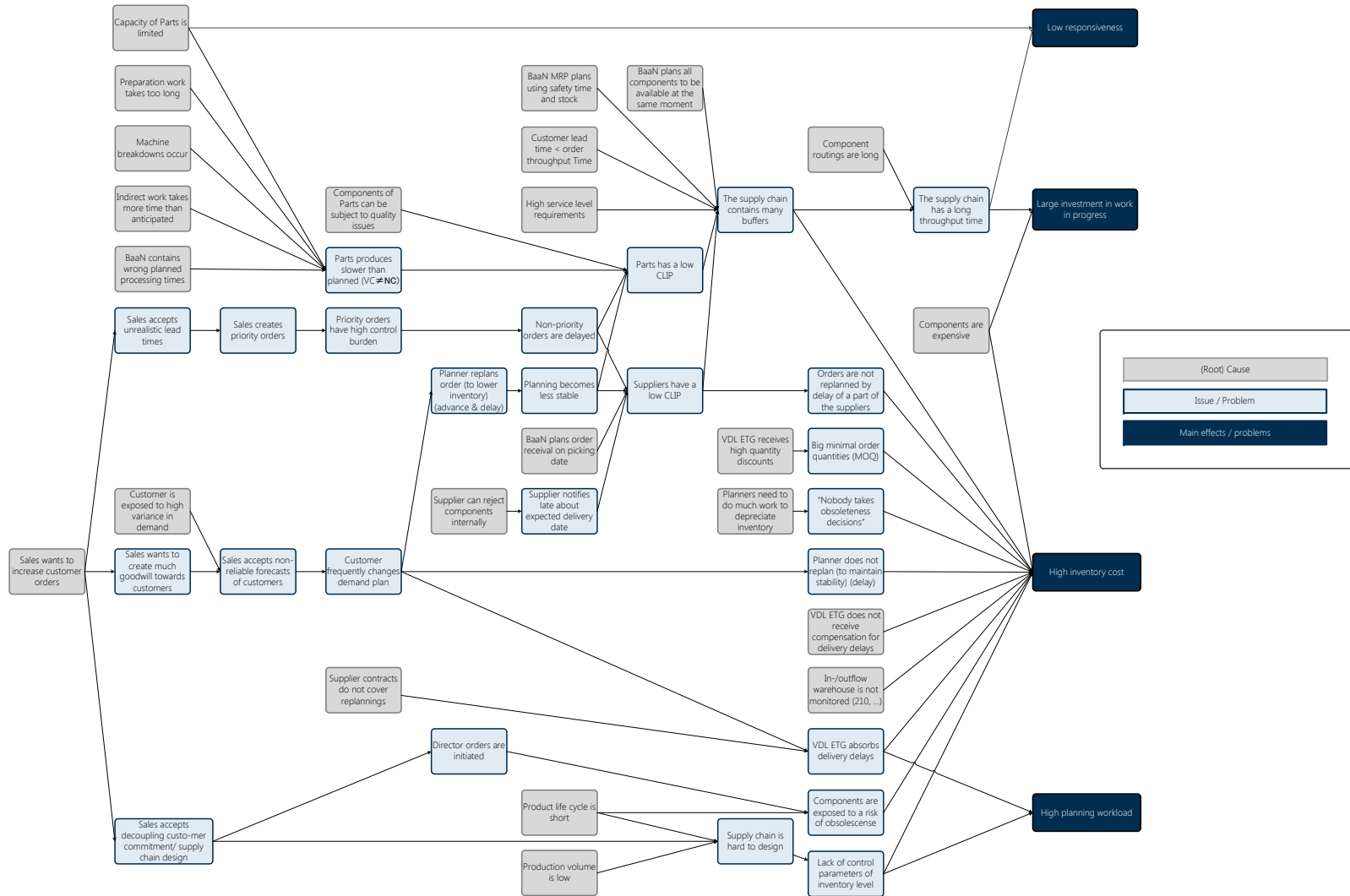


Figure 28: Cause and effect diagram

B.2. Projects and dependencies

Based on the cause and effect diagram introduced in the previous section and the quantitative problem validation (cf. Kamps & Arts, 2014), we constructed an overview of different types of projects and their rough dependencies (Figure 29).

We classified the different projects based on the focus of their problem: does the problem relate to either strategic, tactical or operational decision making processes? In addition, we included the basic dependency relations between them, indicating which project(s) preferably should be executed before the start of another project. Note that all problems are actually somehow related to each other and iterations might be needed, but the basic and logical sequence is represented in the figure. A detailed description of each of the projects is provided in Section B.3.

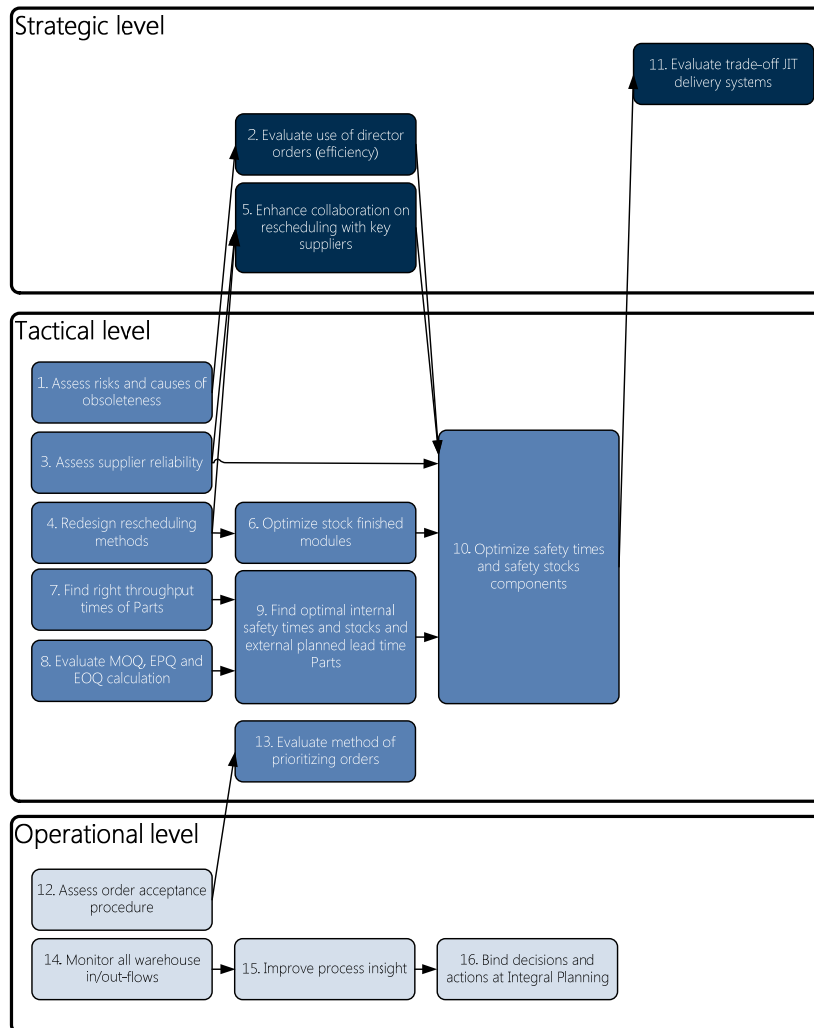


Figure 29: Rough project dependencies

B.3. Project descriptions

In this section we provide a brief general description of each of the 'projects' which have been outlined in Figure 29 in the previous section.

1. Assess risks and causes of obsolescence

The process of decision making about obsolescence was mentioned as "much paperwork". Discovering both the causes of the obsolescence and the process could contribute to a reduction of obsolescence and the workload of dealing with obsolete products.

2. Evaluate use of management orders (efficiency)

When there is no customer commitment for an order (yet); a management order can be released to reduce lead time or produce an EOQ. This is however risky as it is uncertain whether and when demand will arrive. This project should focus on the inventory created by management orders and the associated cost.

3. Assess supplier reliability

Many suppliers do not deliver on time or deliver too early. In both cases, this is inefficient. Studying the costs of low supplier performance and designing a framework to give (operational) procurement tools to manage their suppliers, could enhance supplier discipline, providing a more lean supply chain. A difference between NPI and R4V should be made.

4. Redesign rescheduling methods

The costs of rescheduling (or not rescheduling) upon a demand change are unclear. Furthermore, rescheduling currently happens based upon gut feeling and rules of thumb. More insight in optimal rescheduling could reduce lead times, decrease inventory levels and lead to more consistent communication towards both customers and suppliers. Main question would be: what is the cost of rescheduling; and when should one reschedule?

5. Enhance collaboration on rescheduling with key suppliers

Currently, VDL ETG absorbs rescheduling as customers demand flexibility and suppliers do not provide it. This gap between flexibility offered to customers and flexibility agreed with suppliers should be investigated and addressed. When a group of suppliers can enhance collaboration with VDL ETG in a way that they provide flexibility, inventory levels can be reduced. A possibly interesting concept related to this issue is the concept of Logistics Forecast Agreements (LFA), which can be used to reduce the planning workload and instability.

6. Optimize stock finished modules

Via the use of real options, one could estimate in which cases it is beneficial to create a real option by increasing inventory levels of critical-path components to reduce throughput time. It then is important to have a good estimate of the additional sales value that can be obtained by responding quicker.

7. Find right throughput times of Parts

The parameter values used to schedule work within this job-shop environment are old and might not be right anymore; this especially holds for the waiting times. Finding the right parameter values and optimizing the planning process could contribute to a higher throughput, lower work in progress and a higher fill rate. This could also include the splitting of jobs and flattening the capacity utilization.

8. Evaluate MOQ, EPQ and EOQ calculation

As employees indicate that minimal order quantities (MOQs) are rather high, and this results in high inventory, it seems valuable to evaluate the MOQ calculations.

9. Find optimal internal safety times and stocks and external planned lead time Parts

When project 7 is completed, optimal internal safety times and stocks can be calculated and external lead times can be determined.

10. Optimize safety times and safety stocks components

Via the use of management orders, 'safety stock' is created to decrease throughput time. It is however not yet clear when these orders are optimal and what optimal order sizes would be. On the other hand, when out-of-stock occurs, inventory costs also rise due to work-in-progress problems. In achieving an optimal inventory level, there is a balancing between high holding costs and high out-of-stock costs. Manufacturing yield; supply uncertainty and demand uncertainty should be incorporated.

11. Evaluate trade-off JIT delivery systems

Currently, assembly nearly always starts when all components are arrived, while not all components are needed in the first sprint. When planning takes into account the moments on which components actually are required, inventory levels could be reduced, but more picking might be needed. BaaN can accommodate such a way-of-working, but it is rarely used at this moment. Effects of and requirements for successful application of a JIT principle should be investigated.

12. Assess order acceptance procedure

Orders are not always accepted for realistic deadlines, this can be due to an attempt to increase orders and subsequently sales. It could both lead to unrealistic expectations as well as high pressure for the supply chain.

13. Evaluate method of prioritizing orders

Sometimes priority orders are released; these have a rather high work load. Evaluation of the process of release and the subsequent planning processes could reveal the costs of a priority order and better methods to accept priority orders.

14. Monitor all warehouse in/outflows

For some warehouses, like the clean rooms, not all in- and outflows of materials are monitored. Therefore the inventory levels are unclear. Increase of monitoring could lead to more insight in the inventory positions within VDL ETG.

15. Improve process insight

For many parties, it is not clear what the status is of the manufacturing process, and what causes of delays are. Furthermore, the ERP system is not used in the way that it is designed for. Several by-passes are built to make the work of some people easier, but this complicates the analysis of and insight in the system. More insight could reduce workload of people and increase process stability.

16. Bind decisions and actions at Integral Planning

Many actions of planners have to be done manually and one by one. This could lead to errors and subsequently to higher cost. It would be valuable if related decisions of planners are made in one action. This could be realized by a decoupling between the moment of confirming the outgoing order and the moment of release towards procurement and Parts.

B.4. Roadmap

We prioritized the projects introduced in the previous sections in order to schedule them in time, based on their priority in combination with the general dependency relations. The projects have been prioritized based upon their expected impact (cost savings, inventory reduction, performance improvement, etc.) and required effort (time, resources, supervision of project, etc.). As some projects do not provide implementable results, they are grouped. Jeroen Zwiep, Jasper Weterings (both supply chain innovation engineers), Hilde Botden (supply chain engineer) and John Langenhuysen (manager of Production Office) have ranked the projects. Next to these three rankings, we made an assessment from a student's viewpoint (Kamps & Arts, 2014).

Based on these ranked and grouped projects, and the rough dependencies between the individual projects as discussed above, a roadmap which outlines the planning of the different projects in time has been constructed. This roadmap (Figure 30) shows the planned order of execution, along with the departments at which the projects probably will be performed. Overall, the roadmap covers the important projects which address the key issues, and eventually should result in an improvement of the control and efficiency of VDL ETG's supply chain.

Finally, note that the projects with a yellow dotted line are tentative, these projects are not planned yet. They are listed for the sake of completeness right after the first evaluation moment, but their final planning and way of execution still has to be determined.

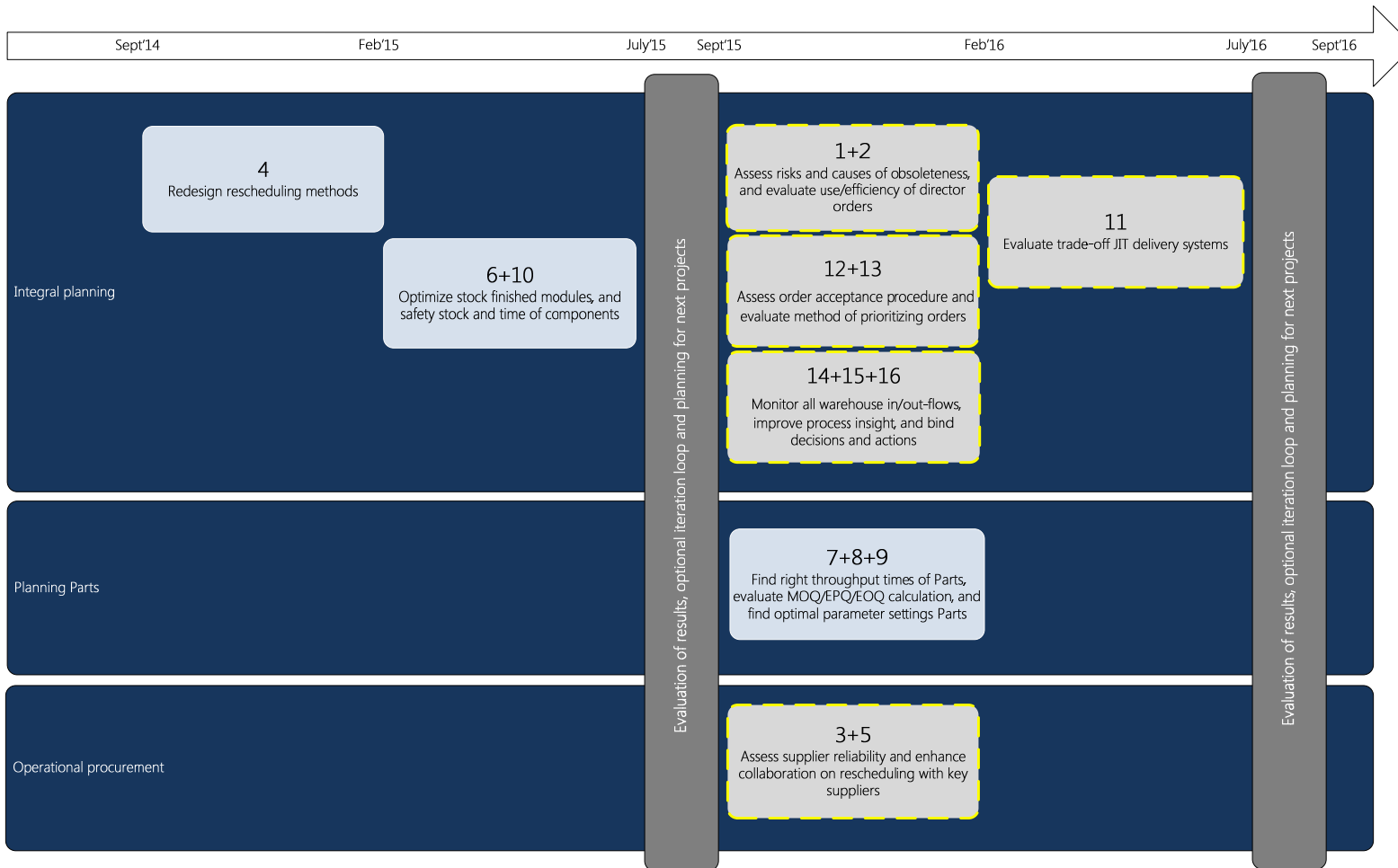


Figure 30: Roadmap towards improvement of supply chain efficiency and control

Integrating the supply chain uncertainties

This appendix extends our discussion of uncertainties in the supply chain of VDL ETG, by providing the results of our analysis of three types of uncertainties which are 'created' by VDL ETG itself: purchase order due date uncertainty 'sent' to suppliers, internal production order due date uncertainty, and delivery uncertainty 'sent' to customers.

Adding these types to the framework (Figure 9) introduced in Chapter 3, results in the extended framework shown in Figure 31 below.

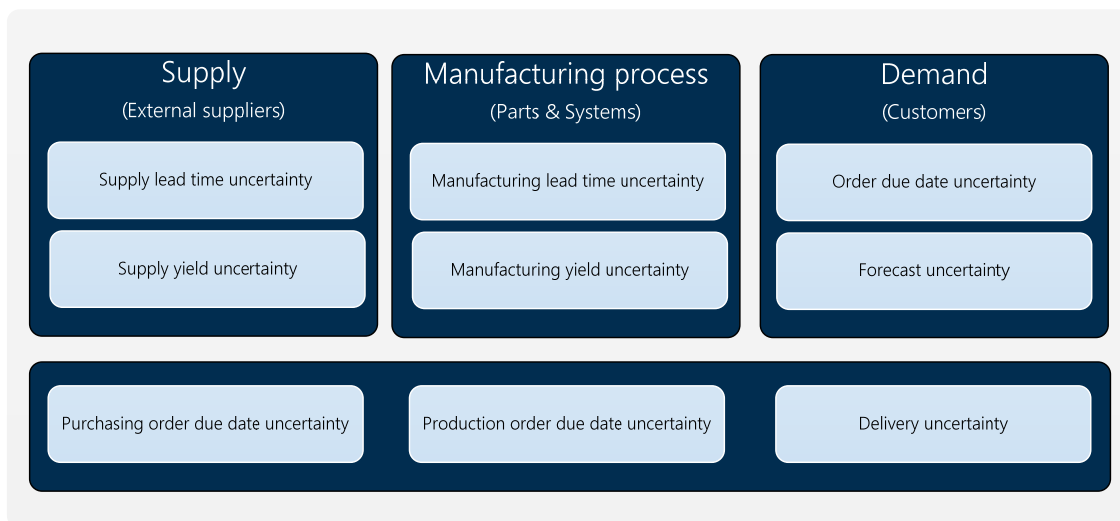


Figure 31: Extended framework of uncertainties in the supply chain of VDL ETG

In the final section of this appendix, we provide an integral view on all uncertainties which have been discussed (neglecting quantity uncertainty), by positioning them in the supply chain control structure of VDL ETG (cf. Figure 4). Note that due to confidentiality, the vertical axis is hidden in all figures.

C.1. Purchase order due date uncertainty sent towards suppliers

Similar to the analysis of the customer due date uncertainty faced by VDL ETG (Section 3.4.1), we analyzed the purchase order due date uncertainty sent towards external suppliers, i.e. the demand due date uncertainty which is observed by VDL ETG's suppliers. For this analysis, we used ERP-based historical data. We excluded non production related purchasing order lines (e.g. services and transportation). Since only data from rescheduled planned deliveries in November and December 2014 are available, we compared these rescheduled order lines with all purchasing order lines in November and December. The results are shown in Figure 32, which reveals that VDL ETG typically sends its suppliers more advancements than delays. Planners try to avoid unnecessary nervousness by not immediately sending purchase order delays if a customer delays demand, although delays are sent to suppliers in case of ramp-downs. In case of customer order advancements, purchase orders are advanced too if this is necessary to meet customer service levels (Nas, 2015b).

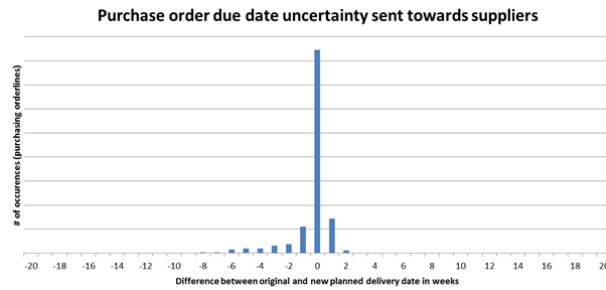


Figure 32: Purchase order due date uncertainty

C.2. Internal production order due date uncertainty

Not only do planned due date changes occur regarding the purchasing orders sent towards external suppliers, internal production order due dates do face uncertainty too. In other words, the planned due date of a production order can be changed (possibly multiple times). Ideally, we would like to retrieve the uncertainty as ‘created’ by integral planning and control procedures, i.e. production order due date changes sent as a result of replanning. Within VDL ETG, however, only data with all rescheduled production order due dates are available, which also includes rescheduling due to production delays. If a certain production operation is delayed, the due date of the production order is often delayed too.

Data analysis, however, still provides an indication of the existence of this type of uncertainty and nervousness. For this analysis, we used ERP-based historical data, filtered on new delivery dates between 01-01-2014 and 28-02-2015. This eventually resulted in 5217 rescheduled production order lines at Parts (cf. total number of 18176 production order lines of which the lead times have been analyzed) and 1274 rescheduled production order lines at Systems (cf. total number of 13154 production order lines of which the lead times have been analyzed). The deviations between the old and new planned due dates in weeks are shown in Figure 33. Note that due to the data availability issues, these figures thus only show the rescheduled production order lines.

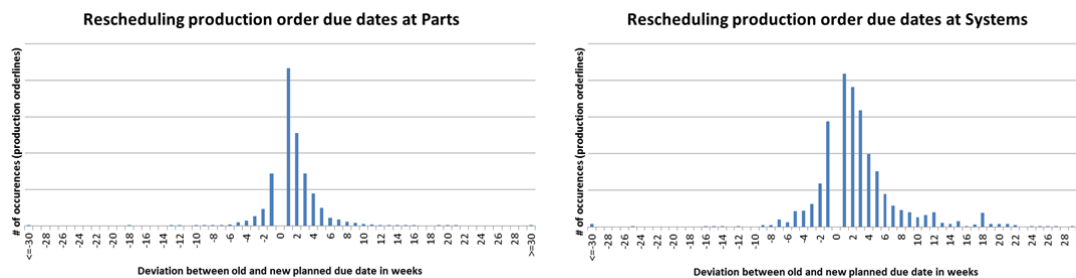


Figure 33: Internal production order due date uncertainty Parts and Systems

Again, we mention the lack of an explicit distinction between the different ‘drivers’ for a re-planning. In his thesis, Van den Broek (2013) already mentioned this lack within VDL ETG and he identified different drivers of rescheduling, e.g. customer due date rescheduling, material shortage and production delay. Such a differentiation would definitely facilitate and improve the analyses of planning and control procedures. For now, our analysis identifies the extent to which rescheduling is present. Based on experiences from the planners (Nas, 2015b), we note that for Parts, advancements are typically the result of rescheduling by integral planners, whereas delays are typically the result of rescheduling by Parts planners (during operation). For Systems, integral planners are mainly responsible for both advancements and delays.

C.3. Customer delivery uncertainty

Similar to our analysis of the external supply uncertainty (Section 3.2), we performed an analysis of VDL ETG's reliability as a supplier to its customers, i.e. customer delivery uncertainty. For this analysis, we used ERP-based historical data, filtered on customer orders which are fulfilled by Systems (deliveries directly by Parts or RS&S are excluded) during the period of 2014 – feb 2015, which resulted in 4984 customer order lines.

The delivery time uncertainty based on CLIP information (delivery date in comparison to confirmed planned delivery date) is shown on the left-hand side in Figure 34. The figure shows that the delivery performance in terms of the CLIP score is very high (considering on time or one day earlier delivery as a CLIP hit, about 93% delivery performance). The average deviation is -0,2 days with an associated standard deviation of 15,7 days. In addition, the performance in terms of the order quantity is very high as well, with a perfect delivered quantity for 99% of the customer order lines (average deviation is -0,06 units, standard deviation is 2,4 units).

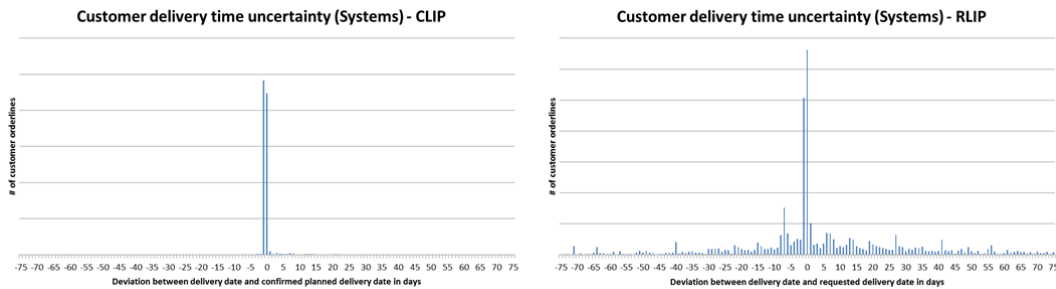


Figure 34: Customer delivery uncertainty based on CLIP and RLIP scores

This delivery performance, however, is largely influenced by the degree to which the customer is able/willing to offer flexibility in terms of modifying the requested delivery date, e.g. a customer can accept a delivery date delay if VDL ETG indicates that it will deliver a certain item a week later than the original requested delivery date. Since the CLIP analysis therefore only provides limited insight about the operating performance from a pure supply chain planning and control perspective, we also analyze the uncertainty based on RLIP information. This score focuses on the difference between the delivery date and the original requested delivery date by the customer. The results on the right-hand side in Figure 34 show a higher delivery time uncertainty as well as quantity uncertainty which is propagated downstream the supply chain towards the customers.

The RLIP delivery performance is about 26%. The average date deviation is -9,7 days, standard deviation equals 116,6 days. If we consider quantity uncertainty, we derive that for 96,7% of the order lines, the delivered quantity was equal to the requested quantity. The average deviation was -0,13 units, with an associated standard deviation of 2,7 units.

We thus identify a very large gap between the RLIP and CLIP scores. In other words, there is a large gap between the 'capability' and 'reliability' of VDL ETG's supply chain planning and control. This stresses the importance to consider suitable performance metrics for our quantitative modeling and analysis in the design phase.

C.4. Framing the uncertainties in VDL ETG's supply chain control structure

We now frame the different types of uncertainties which have been discussed above in the supply chain control structure of VDL ETG, see Figure 35. Note that we do not (aim to) make any claims regarding formal causalities between these types of uncertainties. With the picture below we rather aim to provide a more integrated perspective on the different types of uncertainties, by positioning them in the supply chain control structure and indicating likely relations between them.

We make a clear distinction between the information flow and related uncertainties (in orange, x-axis in weeks) on the one hand, and the material flow and related uncertainties (in blue, x-axis in days) on the other hand. Note that we do not include quantity uncertainties in the figure, we only focus on (lead) time uncertainties.

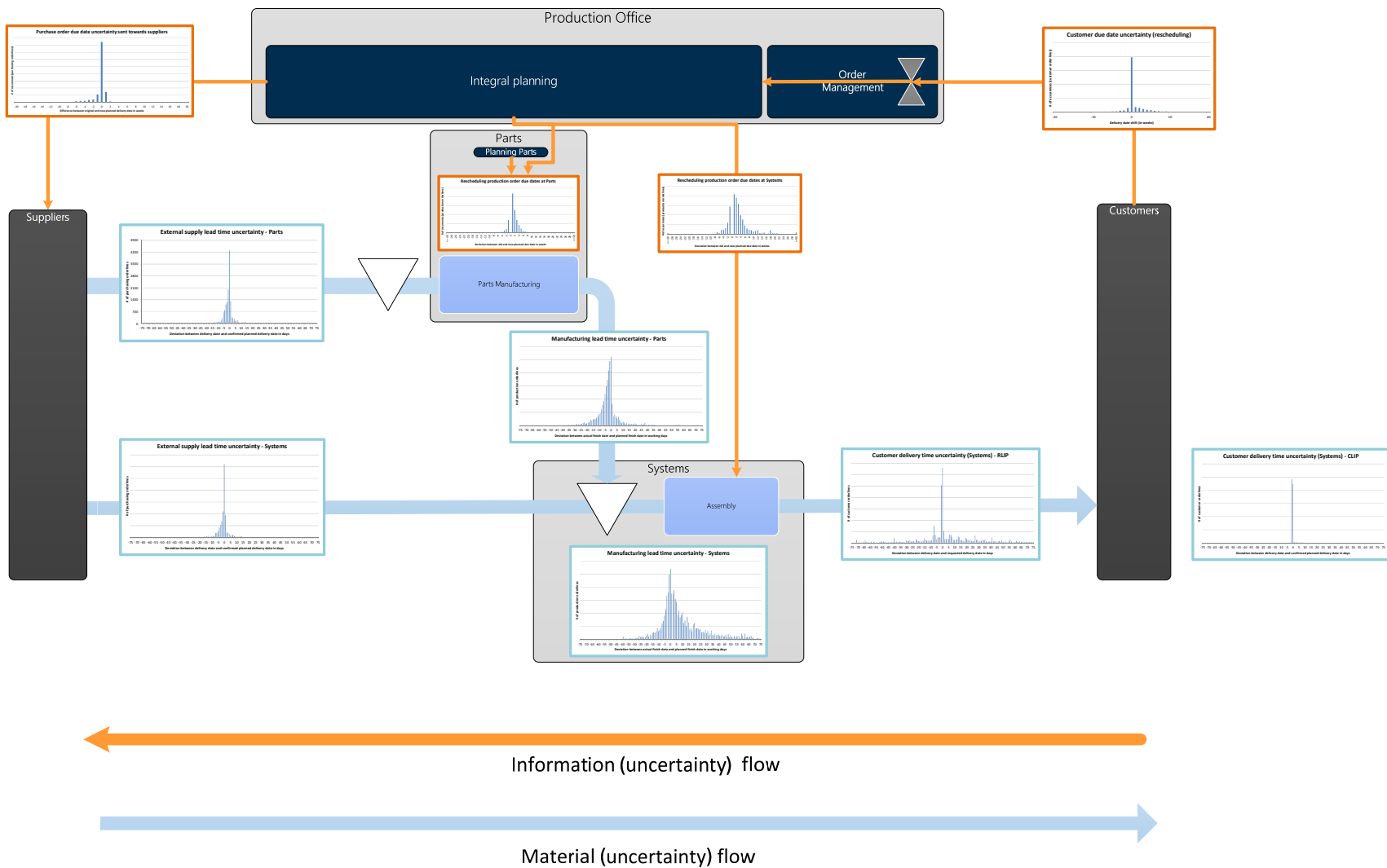


Figure 35: Towards an integral perspective on supply chain uncertainties

MPS demand and production analysis

D.1. MPS forecast uncertainty in relation to production planning

In this section we show the results of our quantitative analysis of forecast uncertainty in relation to production planning for the ASML NXT3 system and the FEI Project Assy (cf. Figure 17 in Chapter 4). Due to confidentiality, the vertical axes are hidden.

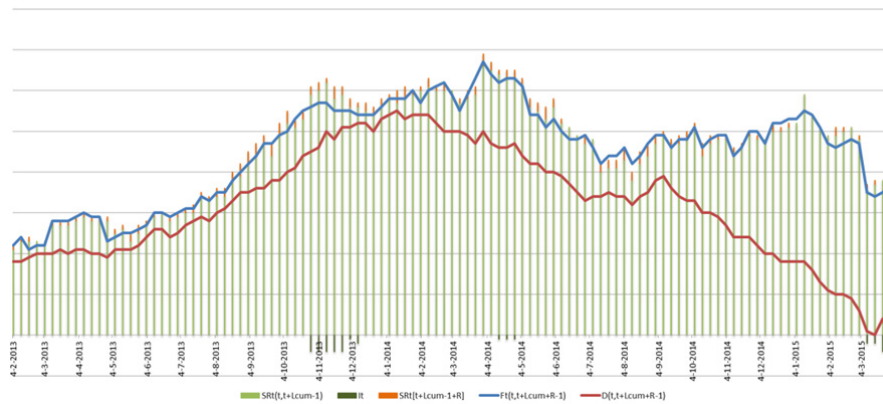


Figure 36: Cumulative demand uncertainty ASML NXT3 system

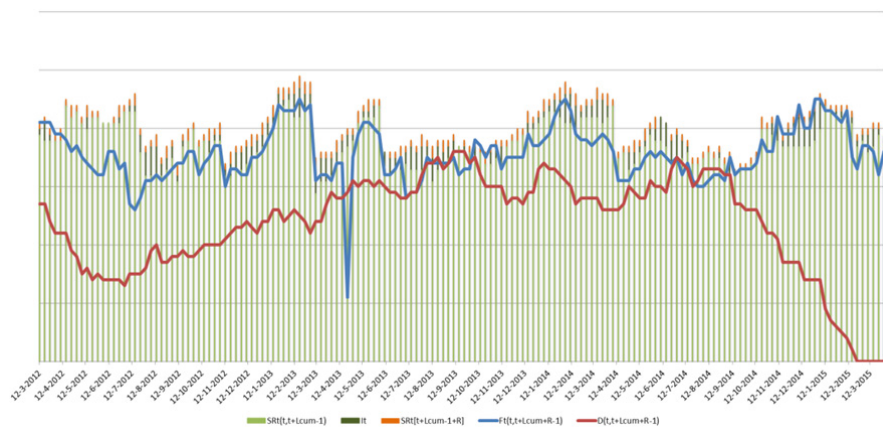


Figure 37: Cumulative demand uncertainty FEI Projector Assy

D.2. MPS demand and production nervousness

This section provides detailed results supporting our discussion in Section 4.2.

Visualization

In order to visualize the comparisons in Section 4.2, we show a part of the analysis for the ASML XT4 system (integral leadtime of 17 weeks) in Figure 38 and Figure 39. The review date positioned on the vertical axis, the period date on the horizontal axis. A red cell indicates an increase in the quantity (forecast or scheduled receipt), a yellow cell indicates a decrease in the quantity. The black borders indicate the lead time of 17 weeks. Changes above these cells with black borders imply a change outside the lead time, changes below imply a change within the lead time. Finally note that due to the inclusion of both backlog demand and scheduled receipts in the review week just before each period, we observe an increase in both the forecasts and scheduled receipts for nearly all cells on the lowest diagonal line.

These figure show the smoothing effect of MPS planning, i.e. the production plan as represented by the scheduled receipts is more stable than the demand plan as represented by the customer forecasts. Moreover, especially within the lead time this dampening effect can be observed. Outside the lead time there seems to be no dampening effect. It actually seems like the production plan outside the lead time (planned receipts instead of scheduled receipts) is more volatile than the demand plan.

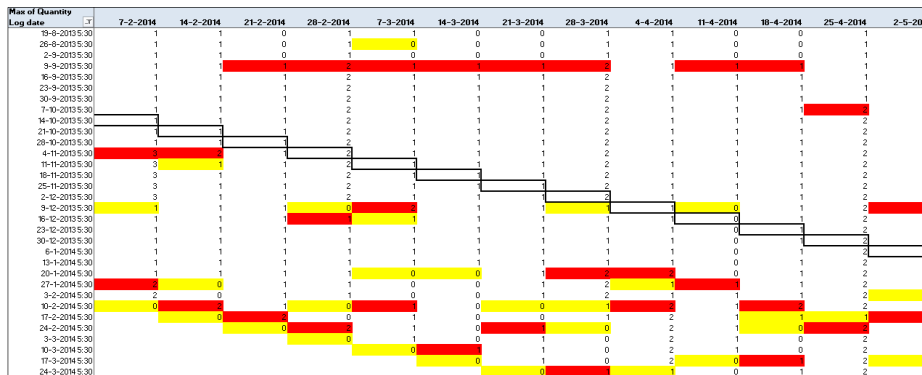


Figure 38: Example visual analysis forecast revisions ASML XT4 system (lead time = 17 weeks)

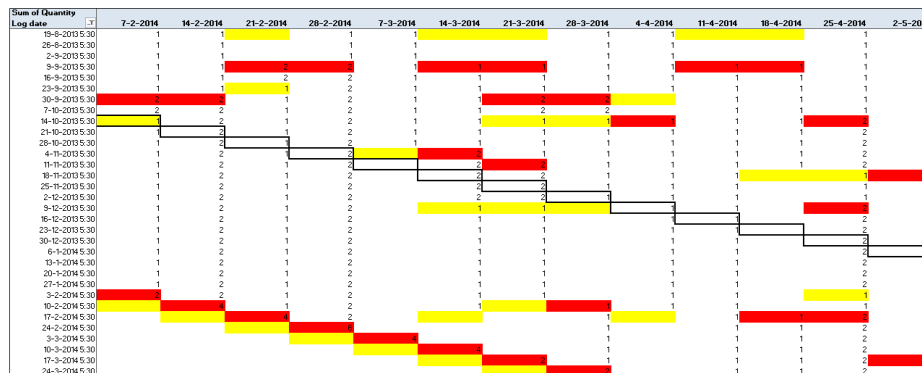


Figure 39: Example visual analysis production revisions ASML XT4 system (lead time = 17 weeks)

Quantification

The detailed results of our quantitative analysis of demand and production nervousness at the MPS level are reported in the tables below (cf. our discussion in Section 4.2).

Table 9: ASML XT4 system (lead time = 17 weeks, data from March 2012 till March 2015)

ASML XT4 system							
All	Total # of revisions	Decrease		Increase		Average decrease size	Average increase size
Forecasts	899	415	46,2%	484	53,8%	-1,2	1,2
Production	716	326	45,5%	390	54,5%	-1,1	1,2
	79,6%	78,6%		80,6%			
Outside lead time	Total # of revisions	Decrease		Increase		Average decrease size	Average increase size
Forecasts	448	176	39,3%	272	60,7%	-1	1,3
Production	483	192	39,8%	291	60,2%	-1,1	1,2
	107,8%	109,1%		107,0%			
Within lead time	Total # of revisions	Decrease		Increase		Average decrease size	Average increase size
Forecasts	451	239	53,0%	212	47,0%	-1,3	1,2
Production	233	134	57,5%	99	42,5%	-1,1	1,1
	51,7%	56,1%		46,7%			

Table 10: ASML NXT3 system (lead time = 27 weeks, data from February 2013 till March 2015)

ASML NXT3 system							
All	Total # of revisions	Decrease		Increase		Average decrease size	Average increase size
Forecasts	677	277	40,9%	400	59,1%	-1,2	1,2
Production	463	178	38,4%	285	61,6%	-1,1	1,2
	68,4%	64,3%		71,3%			
Outside lead time	Total # of revisions	Decrease		Increase		Average decrease size	Average increase size
Forecasts	214	56	26,2%	158	73,8%	-1,2	1,2
Production	232	63	27,2%	169	72,8%	-1,2	1,2
	108,4%	112,5%		107,0%			
Within lead time	Total # of revisions	Decrease		Increase		Average decrease size	Average increase size
Forecasts	463	221	47,7%	242	52,3%	-1,2	1,2
Production	231	115	49,8%	116	50,2%	-1	1
	49,9%	52,0%		47,9%			

Table 11: FEI Projector Assy (lead time = 28 weeks, data from March 2012 till March 2015)

FEI Projector Assy							
All	Total # of revisions	Decrease		Increase		Average decrease size	Average increase size
Forecasts	744	343	46,1%	401	53,9%	-1,5	1,5
Production	362	146	40,3%	216	59,7%	-1	1,1
	48,7%	42,6%		53,9%			
Outside lead time	Total # of revisions	Decrease		Increase		Average decrease size	Average increase size
Forecasts	347	126	36,3%	221	63,7%	-1,5	1,5
Production	194	47	24,2%	147	75,8%	-1	1,2
	55,9%	37,3%		66,5%			
Within lead time	Total # of revisions	Decrease		Increase		Average decrease size	Average increase size
Forecasts	397	217	54,7%	180	45,3%	-1,4	1,4
Production	168	99	58,9%	69	41,1%	-1	1
	42,3%	45,6%		38,3%			

Single-item single-echelon inventory model

The variables and expression in this appendix are adapted from De Kok (2010).

E.1. Definitions

$X(t) :=$ net stock at time t

$X(t^-) :=$ net stock just before time $t \rightarrow X(t^-) = \lim_{t \rightarrow t^-} X(t)$

$Y(t) :=$ inventory position at time t

$D :=$ demand per period

$D(t_1, t_2] :=$ demand during the interval $(t_1, t_2]$ with $(t_1, t_2] = \{x | t_1 < x \leq t_2\}$

$s :=$ reorder point

$Q :=$ order quantity

$S :=$ order up to level

$\tau_i :=$ i^{th} replenishment order moment after time $t = 0$ ($i = 1, 2, \dots$)

$\tau_0 := 0$, time at origin at which the first replenishment order is placed

$L_i :=$ delivery time of the replenishment order placed at time $t = \tau_i$ ($i = 0, 1, \dots$)

$SS :=$ expected net stock immediately before the arrival of a replenishment order (safety stock)

$B(t_1, t_2] :=$ demand backordered in $(t_1, t_2]$

$U_i =$ undershoot at time $t = \tau_i$

$U_i^R =$ undershoot in periodic review model at time $t = \tau_i$

$x^+ := \max(0, x)$

$P\{\dots\} :=$ Probability $\{\dots\}$

$E[\dots] :=$ Expectation $[\dots]$

$\sigma^2[\dots] :=$ Variance $[\dots]$

$P_1 :=$ probability of not being out of stock just before a replenishment order arrives (ready rate)

$P_2 :=$ long run fraction of total demand, which is being delivered from stock on hand (fill rate)

E.2. Assumptions

- (i) Subsequent orders cannot overtake each other, i.e. an order placed later cannot arrive earlier
- (ii) All demand which cannot be met immediately from stock is backordered
- (iii) The stochastic demand is stationary

E.3. Performance expressions

The derivation of probability density functions and performance expressions is based on the analysis of the inventory system during two order cycles. The analysis starts at a moment in time at which the first replenishment order is being placed, which is considered as the time origin: time 0. Other moments in time which are used for the analysis are:

$L_0 :=$ the delivery time of the order placed at time 0

$\tau_1 :=$ the moment the second replenishment order is placed

$\tau_1 + L_1 :=$ the moment the second replenishment order is delivered

General Equations

$$P_1 = P\{X((\tau_1 + L_1)^-) \geq 0\}$$

$$P_2 = 1 - \frac{E[B(L_0, \tau_1 + L_1)]}{E[D(L_0, \tau_1 + L_1)]}$$

$$B(L_0, \tau_1 + L_1) = (-X((\tau_1 + L_1)^-))^+ - (-X(L_0))^+$$

$$D(L_0, \tau_1 + L_1) = X(L_0) - X((\tau_1 + L_1)^-)$$

$$E[X] = \frac{1}{2} (E[X(L_0)] + E[X((\tau_1 + L_1)^-)])$$

$$SS = E[X((\tau_1 + L_1)^-)]$$

The expressions for $X(L_0)$ and $X((\tau_1 + L_1)^-)$ depend on the replenishment logic used and will be described below as general as possible, while using only assumption (i) and (ii).

$$X(L_0) = Y(0) - D(0, L_0]$$

$$X((\tau_1 + L_1)^-) = X(L_0) - D(L_0, \tau_1 + L_1]$$

$$= Y(0) - D(0, L_0] - D(L_0, \tau_1 + L_1]$$

$$= Y(0) - D(0, \tau_1 + L_1]$$

$$= Y(0) - D(0, \tau_1] - D(\tau_1, \tau_1 + L_1]$$

$$= Y(0) - (Y(0) - Y(\tau_1^-)) - D(\tau_1, \tau_1 + L_1]$$

$$= Y(\tau_1^-) - D(\tau_1, \tau_1 + L_1]$$

(s,Q)

$$X(L_0) = s + Q - U_0 - D(0, L_0]$$

$$X((\tau_1 + L_1)^-) = s - U_1 - D(\tau_1, \tau_1 + L_1]$$

(R,s,Q)

$$X(L_0) = s + Q - U_0^R - D(0, L_0]$$

$$X((\tau_1 + L_1)^-) = s - U_1^R - D(\tau_1, \tau_1 + L_1]$$

(s,S)

$$X(L_0) = S - D(0, L_0]$$

$$X((\tau_1 + L_1)^-) = s - U_1 - D(\tau_1, \tau_1 + L_1]$$

(R,s,S)

$$X(L_0) = S - D(0, L_0]$$

$$X((\tau_1 + L_1)^-) = s - U_1^R - D(\tau_1, \tau_1 + L_1]$$

From the equations above we derive two 'translation' mechanisms. First of all, if we consider the (.,s,Q) and (.,.,S) systems, we see that the expressions for $X((\tau + L)^-)$ are equal and that the expressions for $X(L)$ are actually similar too, with $S = s + Q - U$ (or $S = s + Q - U^R$ in the case of periodic review). This implies that the expected safety stock (SS), the expected inventory ($E[X]$), the expected $P1$ service level and finally the expected $P2$ service level are equal.

On the other hand, there is a 'translation' of continuous review models and period review models via the expected undershoot. In the case of period review models, of course, the undershoot would be expected to be higher. This is reflected in the expression for the expectation we will use later on.

We first drop the indices under the assumption of stationary demand and undershoot distributions. Then:

(s,Q)

$$X(L) = s + Q - U - D(0, L]$$

$$X((\tau + L)^-) = s - U - D(0, L]$$

$$E[X] = s + \frac{Q}{2} - E[U] - E[D(0, L)]$$

$$P2 = 1 - \frac{(D(0,L)+U-s)^+ - (D(0,L)+U-s-Q)^+}{Q}$$

(R,s,Q)

$$X(L) = s + Q - U^R - D(0, L]$$

$$X((\tau + L)^-) = s - U^R - D(0, L]$$

$$E[X] = s + \frac{Q}{2} - E[U^R] - E[D(0, L)]$$

$$P2 = 1 - \frac{(D(0,L)+U^R-s)^+ - (D(0,L)+U^R-s-Q)^+}{Q}$$

(s,S)

$$X(L) = S - D(0, L]$$

$$X((\tau + L)^-) = s - U - D(0, L]$$

$$E[X] = \frac{1}{2}S + \frac{1}{2}s - \frac{1}{2}E[U] - E[D(0, L)]$$

$$P2 = 1 - \frac{(D(0,L)+U-s)^+ - (D(0,L)-s)^+}{s-s+U}$$

(R,s,S)

$$X(L) = S - D(0, L]$$

$$X((\tau + L)^-) = s - U^R - D(0, L]$$

$$E[X] = \frac{1}{2}S + \frac{1}{2}s - \frac{1}{2}E[U^R] - E[D(0, L)]$$

$$P2 = 1 - \frac{(D(0,L)+U^R-s)^+ - (D(0,L)-s)^+}{s-s+U^R}$$

Based on the formulas and analyses discussed above, we hypothesize that the service level which is obtained is primarily explained by the average inventory in combination with the average order size, and that this service is relatively insensitive of the specific control policy which is used. More specifically, given the external parameters and the average inventory in combination with the average order size, we can approximate the 'implicitly used' input parameters under each control rule.

We define:

μ_D := average demand per period

σ_D^2 := standard deviation of demand per period

μ_L := average lead time (in number of periods)

\bar{X} := the average inventory as a system outcome

\bar{Q} := the average order size as a system outcome

Then we calculate the demand during the lead time and we approximate the undershoot via:

$$E[D(0, L)] = \mu_D * \mu_L$$

$$E[U] = \frac{\sigma_D^2 + \mu_D^2}{2\mu_D}$$

$$E[U^R] = \frac{\sigma_D^2 + \bar{Q} * \mu_D}{2\mu_D}$$

Mathematical rewriting using the variables and expressions discussed above results in the following approximations of the control parameters for each of the policies as follows:

(s,Q)

$$Q = \bar{Q}$$

$$s = \bar{X} + \mu_D * \mu_L + \frac{\sigma_D^2 + \mu_D^2}{2\mu_D} - \frac{\bar{Q}}{2}$$

(R,s,Q)

$$R = \frac{\bar{Q}}{\mu_D}$$

$$Q = \bar{Q}$$

$$s = \bar{X} + \mu_D * \mu_L + \frac{\sigma_D^2 + \bar{Q} * \mu_D}{2\mu_D} - \frac{\bar{Q}}{2}$$

(s,S)

$$S - s = \bar{Q} - \frac{\sigma_D^2 + \mu_D^2}{2\mu_D}$$

$$s = \bar{X} + \mu_D * \mu_L + \frac{\sigma_D^2 + \mu_D^2}{2\mu_D} - \frac{\bar{Q}}{2}$$

(R,s,S)

$$R = \frac{\bar{Q}}{\mu_D}$$

$$S - s = \bar{Q} - \frac{\sigma_D^2 + \bar{Q} * \mu_D}{2\mu_D}$$

$$s = \bar{X} + \mu_D * \mu_L + \frac{\sigma_D^2 + \bar{Q} * \mu_D}{2\mu_D} - \frac{\bar{Q}}{2}$$

E.5. Influence of lead time

In order to illustrate the negligible effect of the lead time on the difference between the service (fill rate) under continuous and period review, we illustrate the analysis for an artificial case with $\mu_D = 2$, $\sigma_D^2 = 1$, $\sigma_L^2 = 0$, $E[X] = 5$, $E[Q] = 5$, in Figure 40 below. Note that for this case, the difference between the service under continuous and period review is moderately high (cf. Figure 20).

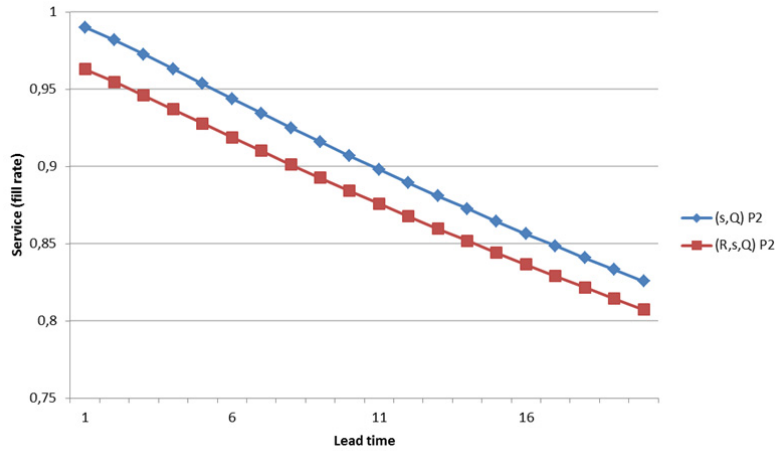


Figure 40: Illustration of lead time sensitivity analysis for the artificial case

Analysis via our Stochastic Inventory System tool revealed that, compared with the effect of the average inventory and order size in relation to the average demand, the effect of the lead time on the service gap is negligible.

Base-stock vs. MRP-control at the MPS level

In this appendix we proof that base-stock control at the MPS level can be regarded as an equivalent of MRP control at the MPS level, under no lot sizing restrictions. Adapted from De Kok (2001).

Variables

L_i := *planned (integral)lead time of MPS item i*

$F_i(t, t + s)$:= *forecasted demand for MPS item i in period t + s, made at the start of period t*

$r_i(t)$:= *quantity of MPS item i released at the start of period t*

ss_i := *safety stock for MPS item i*

We assume not lot size restrictions, i.e. we assume no MOQ and a lot size multiple quantity of 1.

Base-stock policy (Statistical Inventory Control) - Pull

Inventory position of item i at start of period t:

$$Y_i(t) = I_i(t) + \sum_{s=1}^{L_i} r_i(t - s) \quad [E.1]$$

Quantity of item i released at start of period t:

$$r_i(t) = \max[0, S_i(t) - Y_i(t)] = \max[0, S_i(t) - I_i(t) + \sum_{k=1}^{L_i} r_i(t - k)] \quad [E.2]$$

MRP policy - Push

The Time-Phased Orderpoint logic of the MRP logic leads to release quantities for MPS item i at the start of period t which equals:

$$r_i(t) = \max[0, \sum_{k=0}^{L_i+R} F_i(t, t + k) + ss_i - I_i(t) - \sum_{k=1}^{L_i} r_i(t - k)] \quad [E.3]$$

Equivalence between MRP policy and base-stock policy

From equations [E.1] and [E.3] it easily follows that:

an MRP policy for the MPS item is equivalent to a base-stock policy with:

$$S_i(t) = \sum_{k=0}^{L_i+R} F_i(t, t+k) + ss_i \quad [E.4]$$

So a base-stock policy with a time-dependent base-stock level is equal to a MRP policy. It then uses forecasted demand when calculating the release quantities, and thereby thus becomes a push system.

Planned Lead Times Simulation Tool

This appendix provides some additional information on the Planned Lead Times Simulation Tool, which implements the planned lead time model discussed in Section 5.3.

G.1. Structure

The simulation tool, built in Microsoft Excel, actually consists of three main sheets.

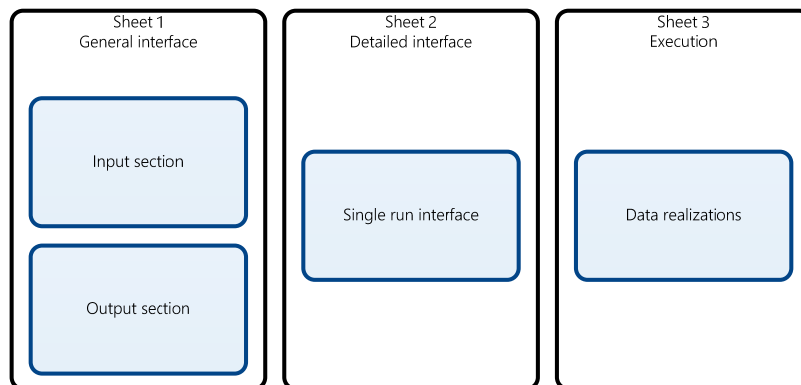


Figure 41: Structure of Planned Lead Times Simulation Tool

In the first sheet, there is an input section, which requires the following information about each of the items/stages in the two-echelon assembly structure:

- Average of stochastic lead time
- Standard deviation of stochastic lead time
- Planned lead time
- Added value (cost) per item

Concerning the planned lead time values, one basically needs to provide the planned lead time per item. There is, however, also an option to provide a value in a special cell for the Fractile method. More specifically, if one provides a percentage value in this cell for the Fractile method, the tool automatically determines the planned lead time for each stage accordingly.

In addition, the user needs to define the number of simulation runs. Note that one simulation run includes 500 realizations, i.e. 500 production cycles.

The output section in Sheet 1 provides the key performance measures:

- the service level in terms of the OTD percentage
- the cycle time
- the average stock investments due to waiting times / earliness
- the average total stock investments including WIP investments (cf. expression [5.20])

Sheet 2 provides a more detailed interface, by showing detailed simulation outcomes per item / stage. Note that this sheet provides the results of one simulation run. More specifically, it shows for each individual stage:

- the average earliness
- the average tardiness
- the average waiting time due to other stages
- the average WIP investment
- the average investment due to waiting time and earliness
- and the OTD performance of each individual stage

In Sheet 3, the detailed data realizations are reported. For each of the 500 production cycles, the realizations of the lead times are listed (see next paragraph). Based on these realizations, the relevant variables for the costs and service expressions (cf. Section 5.3) are calculated.

G.2. Assumptions

In addition to the assumptions discussed in Section 5.3.3 (a.o. infinite supply of raw material, holding back final assembly in case all component stages are finished on time), we use one additional assumption for the generation of data realizations in our simulation tool (Sheet 3): lead times are stationary and Normally distributed. This assumption allows for instantaneous lead time realizations for a single run via Excel, but more importantly, turned out to be a fair representation of reality in terms of the empirical validity of the simulation-based system performance outcome (see Section 5.3.4).

Newsvendor heuristic

In this appendix we provide some background information on the Newsvendor heuristic (Atan et al., 2015), which has been analyzed in Section 5.3 as a promising method to determine planned lead times in an order-driven assembly system.

H.1. Solution approach

The heuristic was developed with the intention of solving the planned lead time problem at ASML, which is actually very similar to the problem of determining planned lead times at VDL ETG (see Section 5.3). In their article, Atan et al. (2015) study an assembly system that consists of a number of parallel multi-stage process feeding a multi-stage final assembly process. The authors developed an iterative heuristic procedure for determining planned lead times that relies on a conjecture related to generalized Newsvendor functions. Although we do not aim to provide all mathematical details behind the heuristic, note that the authors rely on two-moment mixed Erlang fits to approximate the distributions of the sum of waiting times, tardiness and throughput times (cf. expressions [5.11] - [5.16]). By comparing numerical results of their heuristic with the results from a numerical optimization method (Davidon-Fletcher-Powell), the authors conclude that the heuristic performs well with a percentage cost error of 1.33%.

Note that the heuristic is based on the minimization of the sum of waiting/earliness costs and penalty costs (cf. our costs expressions [5.19] and [5.20] which include no penalty costs). The authors exploit the relationship between the Newsvendor fractile and the on-time delivery probability to estimate penalty costs associated with late deliveries of a system.

H.2. Efficient frontiers

In order to illustrate the improved performance of the Newsvendor heuristic over the Fractile method (used by ASML and also similar to the planned lead time settings at VDL ETG), we compare the efficient frontier of both methods for the Philips U-Arc case (see Section 5.3).

More specifically, we draw two efficient frontiers: one cost efficient frontier (Figure 42) and one cycle time efficient frontier (Figure 43), for varying service levels. Figure 42 shows that the Newsvendor heuristic does not only successfully 'optimize' the total relevant costs (sum of penalty costs and waiting costs) compared to the Fractile method, the waiting costs separately are lower under the Newsvendor heuristic too. Finally note that Figure 43 confirms our findings as discussed in Section 5.3: the Newsvendor heuristic allows for a reduction of the cycle time compared to the Fractile method, with slightly higher gains for higher target service levels.

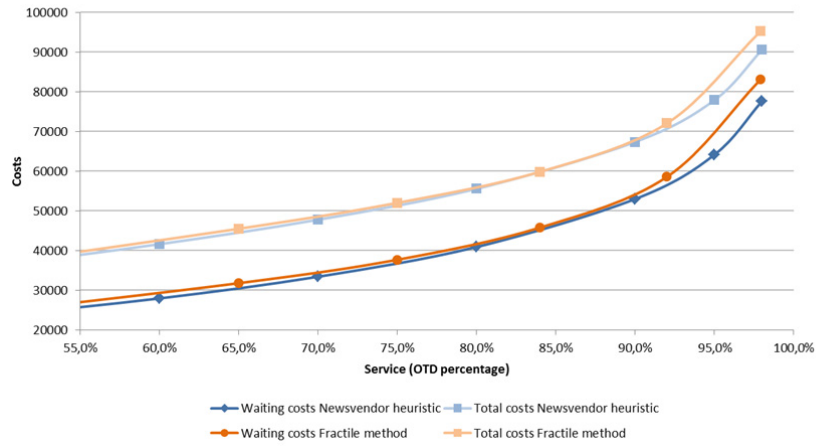


Figure 42: Cost efficient frontiers of the Newsvendor heuristic and Fractile method

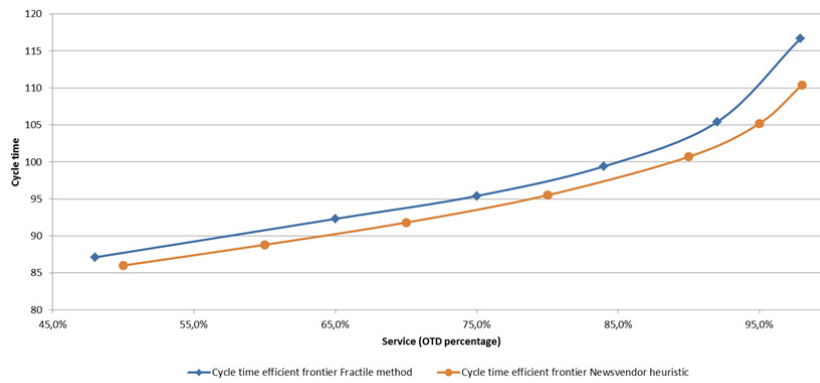


Figure 43: Cycle time efficient frontiers of the Newsvendor heuristic and Fractile method

Stock Investment Performance Report

I.1. Performance report structure

Figure 44 below shows the new Stock Investment Performance Report structure which has been designed during this research project (see Section 6.3). The new structure actually consists of a triple of reports, which we briefly elaborate on in the next sections.

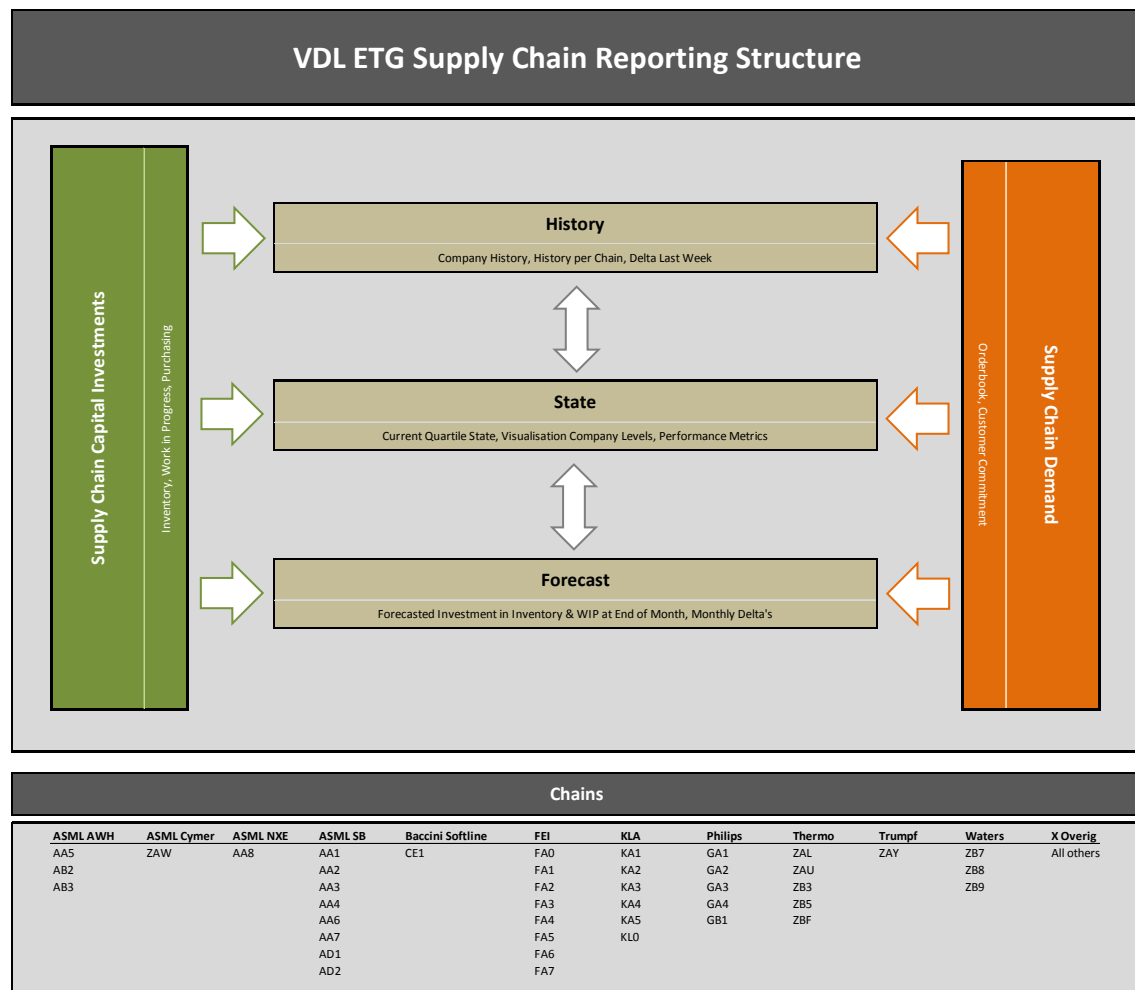


Figure 44: New Stock Investment Performance Report structure

I.2. History report

The history report (weekly focus) actually consists of two main parts: a part in which historical information for the company VDL ETG (Eindhoven) is reported, and a part in which the historical information per 'chain' is reported. A representation of the general part is provided below. This report shows the (weekly) evolution of investments in inventory, work in progress and purchasing. Moreover, it contains deltas in terms of the comparison of this week's investments with the investments of the previous week. Note that due to confidentiality, some numbers, lines and axis are hidden.

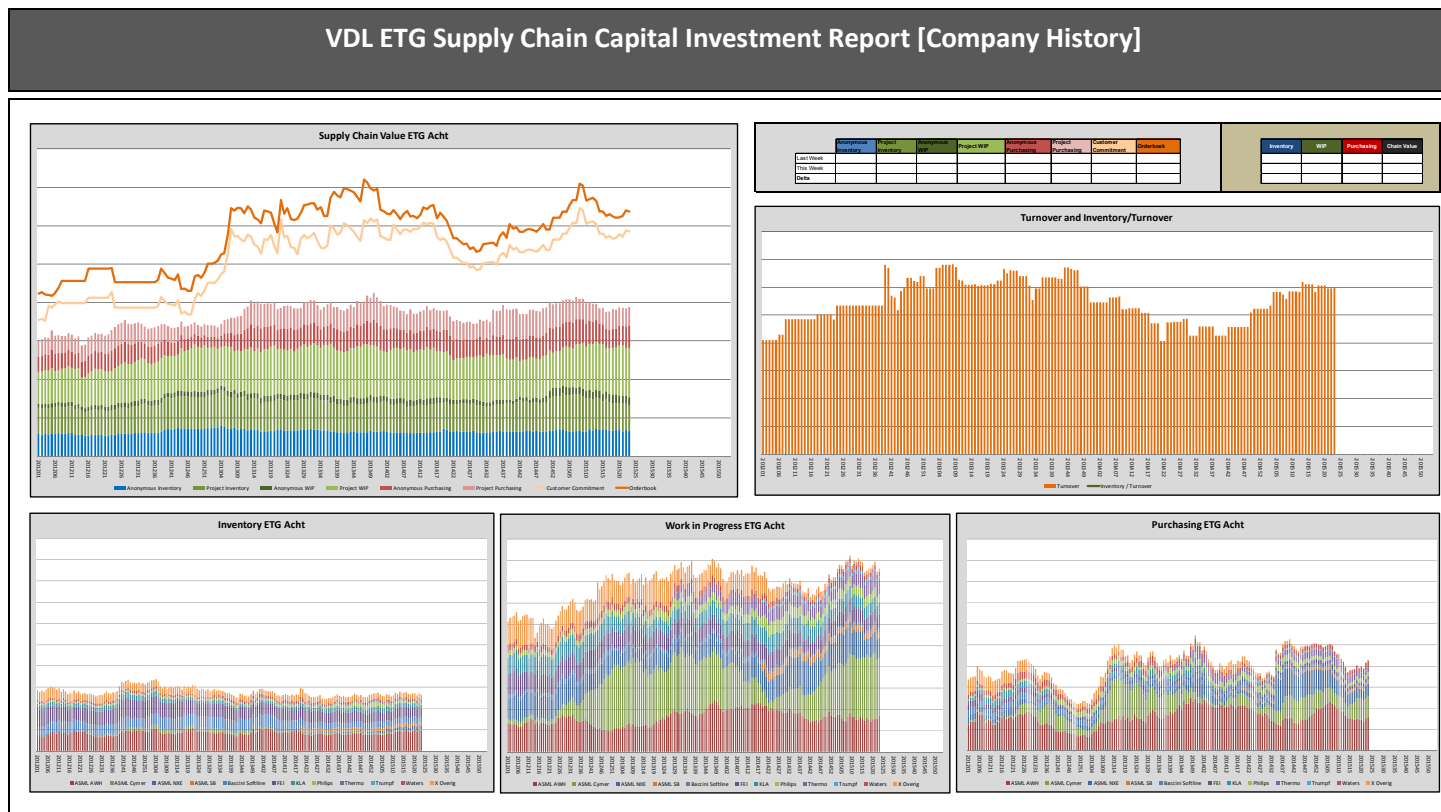


Figure 45: Adapted representation of the general part of the history report

I.3. State report

A simplified version of the state report is shown in the figure below. The state report shows the current investments (automatically updated each night) in inventory, work in progress and purchasing, both order-driven as well as forecast-driven. Note that due to confidentiality, numbers and axis are hidden.

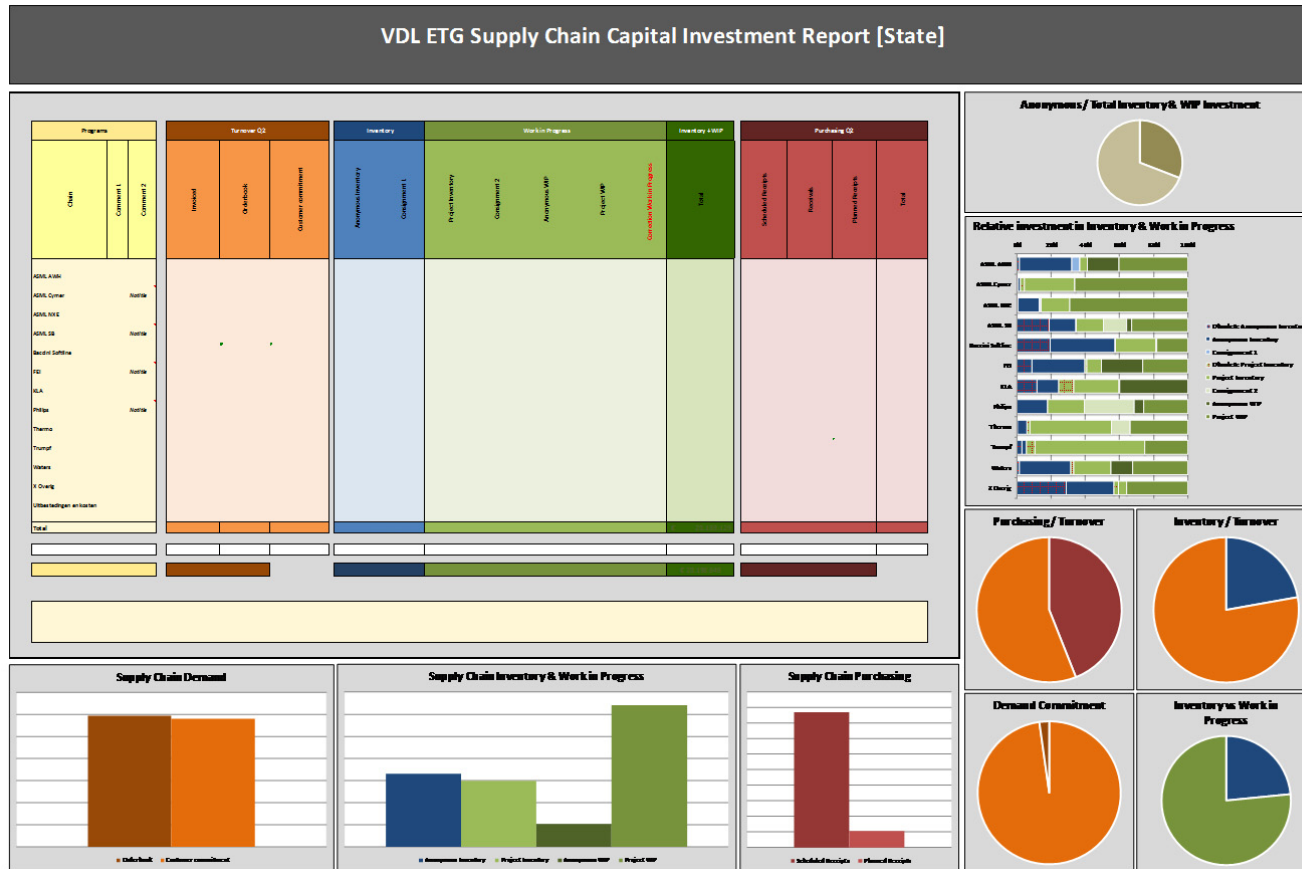


Figure 46: Adapted representation of the state report

I.4. Forecast report

The figure below shows the structure of the forecast report (monthly focus). Note that this report automatically forecasts the investments in the inventory and work in progress for the end of the next month, based on information about the current state (see previous section). Moreover, it provides deltas with regard to differences between different months. Due to confidentiality, numbers are hidden.

VDL ETG Supply Chain Capital Investment Report [Forecast]																		
Programs			Month		State	Month	Forecast 31-5-2015			30-4-2015			31-3-2015			Delta Previous Two Months		
Chain	Comment 1	Comment 2	Orderbook	Value Factor	Total Inventory & Wip	Total Purchasing	Total Inventory & Wip	Delta with Last Month	Inventory	Work in Progress	Total Inventory & Wip	Inventory	Work in Progress	Total Inventory & Wip	Inventory	Work in Progress	Total Inventory & Wip	
ASML AWH																		
ASML Cymer	Notitie																	
ASML NXE																		
ASML SB	Notitie																	
Baccini Softline																		
FEI	Notitie																	
KLA																		
Philips	Notitie																	
Thermo																		
Trumpf																		
Waters																		
X Overig																		
Total																		
							Delta Current State											

Figure 47: Adapted representation of the forecast report

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