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The Impact of Late Plan Changes on Production Planning
An Empirical Study in the Semiconductor Industry

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The Impact of Late Plan Changes on Production Planning

An Empirical Study in the Semiconductor Industry

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Abstract

Objective: The present study investigates how timing plan changes, late in the process, impact production planning. **Methods:** A greedy algorithm has been developed that is stylized according to the production planning procedures within a company in the semiconductor industry. The algorithm operates based on a weekly rolling horizon. Each week, the algorithm plans jobs from the Master Production Schedule (MPS) at the end of the horizon; generates demand, supply, and process uncertainty; and reschedules the planning according to the uncertainty. We collected MPS data for 287 jobs and we estimated uncertainty levels based on quantitative and qualitative data between Q3 2016 and Q2 2021. We simulate the greedy algorithm between Q3 2019 and Q2 2021 with varying levels of uncertainty to measure Key Performance Indicators (KPIs), such as schedule stability, on-time delivery, and production output. **Results:** Increases in uncertainty levels negatively impact the KPIs. The individual types of uncertainty impact the performance of the model differently. There is an interplay between the individual types of uncertainty as the impact of holistic uncertainty is different than the sum of its parts. **Conclusion:** Uncertainty becomes increasingly troublesome the more it is present in production planning and yields significant amounts of schedule instability. Rescheduling for uncertainty bears a significant cost that must not be excluded from scheduling decisions, especially if production planning is done manually.

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List of Abbreviations

BOM Bill of Material

CRD Customer Requested Delivery

CRN Common Random Numbers

CRP Capacity Requirements Planning

DUV Deep Ultraviolet

EF EUV Factory

EUV Extreme Ultraviolet

FCFS first-come-first-served

FIFO First In First Out

FTE Full-time Equivalent

IL Illuminator

IRD Independent Requirement Date

JIT Just in Time

KPI Key Performance Indicator

KPIs Key Performance Indicators

LE Lens

MB Module Build

MF MetroFrame

MPS Master Production Schedule

MRP Material Requirements Planning

MTO Make-to-Order

PP PrePack

RCCP Rough-Cut Capacity Planning

SI System Integration

SP System Performance

SSE Sum Squared Error

TF TwinScan Factory

VMI Vendor Managed Inventory

WBS Work Breakdown Structure

WIP Work-in-Progress

WOPA Weekly Operational Planning Alignment

WS WaferStage

Chapter 1

Introduction

Over the last decades, much effort has been directed towards optimizing production processes and planning. Unfortunately, there are many forms of uncertainty that impact the production within organizations. Uncertainty that impacts the production processes can originate from different sources. For example, external sources such as demand uncertainty and supply delays or internal sources, such as operator absence or machine breakdown. As a consequence of uncertainty, it might be necessary to revise previously generated production schedules. These revisions are often referred to as plan changes. By allowing frequent plan changes to schedules to account for uncertainty, companies experience what is called schedule nervousness or schedule instability. In the current manufacturing environment, where markets are becoming increasingly volatile, and where globalization of demand and supply leads to long and uncertain lead times, changes to production schedules have become the norm in many companies (Pujawan & Smart, 2012). Frequent plan changes to a production schedule can be especially disruptive in multi-level production systems that use Material Requirements Planning (MRP) logic for their production planning. In MRP systems, changes to the Master Production Schedule (MPS) subsequently result in changes in lower levels of the product's sub-structure (e.g. sub-assemblies, components, and materials). While plan changes in production schedules can reflect increased responsiveness to uncertainty, they also lead to negative impacts, such as less effective operations (Blackburn et al., 1986), loss in planning confidence (De Kok & Inderfurth, 1997), higher inventory and production costs (Xie et al., 2003), resource idleness, a higher WIP inventory (Herroelen & Leus, 2005), ineffective relationships with suppliers (Sahin et al., 2008), high costs associated with production changeovers (Pujawan & Smart, 2012), less productivity, loss of morale of the employees on the work floor and in the planning department, and a worse on-time delivery performance (Atadeniz & Sridharan, 2020).

Due to the large impact that uncertainty has on production processes, it has gained much traction in the literature. The conclusions about the effectiveness of rescheduling in the literature tend to differ between the MPS and MRP planning, shop floor scheduling, and supply chain scheduling sub-streams (Hozak & Hill, 2009). This can be explained by the different sets of assumptions made between the sub-streams. In practice, production processes and planning are complex and do not fit seamlessly within the mathematical and simulation models present in the literature. Therefore, we present an empirical study that transcends the boundaries of the different sub-streams in the literature which addresses rescheduling. Moreover, while rescheduling has always been very much a practical problem, few empirical studies are presented in the literature (Pujawan & Smart, 2012). The negative impact of schedule instability on supply chain performance is widely recognized in different industries though. It has been reported as a major concern in a survey of 116 executives in the airline industry (Law, 2011), 230 executives in various manufacturing industries (Pujawan & Smart, 2012), and 180 executives in consumer electronics and electronic components manufacturers (Law & Gunasekaran, 2010). This gave rise to the notion that, in order to optimize production processes, uncertainty must be considered when designing and operating these processes. ASML, a manufacturer of lithography machines for the semiconductor industry, also recognizes the impact of schedule instability on its production planning. This research aims to provide empirical insights for both the literature and industry into how uncertainty impacts production planning. Furthermore, most current literature tries to give remedies for single types of uncertainty in the form of scheduling policies and methods. In practice however, multiple sources of uncertainty can impact production planning and processes. To this end, we take a holistic approach to uncertainty by studying how multiple sources of uncertainty impact production planning. By doing so, we help in the provision of a cause-and-effect structure of uncertainty in the semiconductor industry. A clear cause-and-effect structure can help organizations gain a better understanding of the impact of their plan changes (Koh et al., 2002). In order to guide this study, we define a set of research questions. The answers to these questions will give more insights into the impact of (late) plan changes. The main research question reads:

How do timing plan changes inside the frozen horizon impact production planning?

To answer the main research question, we draw the following sub-research questions:

1 *What types of uncertainty cause these changes?*

2.1 *How does uncertainty impact the schedule instability?*

2.2 *How does uncertainty impact the on-time delivery performance?*

2.3 *How does uncertainty impact the production output?*

3 *How do the results vary for the different types of uncertainty that cause these changes?*

4 *What is the difference in impact between preponing orders and postponing orders?*

5 *Is there a relation between the timing of a timing plan change inside the frozen horizon and its impact?*

Schedule instability can result both from changes in the timing and quantity of planned and open orders (Steele, 1975). The demand in the semiconductor industry is higher than the production capacity. In a make to order context, this yields long pipelines with orders waiting to be processed (i.e. little uncertainty in the quantity of planned and open orders). Therefore, we limit our analysis to changes in the timing of orders (i.e. timing plan changes). Finally, since plan changes become more problematic the closer they occur to the execution date of orders, we only study plan changes that occur late in the production planning process. In order to prevent these troublesome late changes, many organizations use a frozen horizon in which no further changes to schedules should be made. While research assumes that these frozen horizons are strictly adhered to, in practice this is unlikely (Pujawan & Smart, 2012). This is also the case for the production planning department of ASML.

To answer the research questions, we use an empirical research design that mainly uses quantitative data, but also some qualitative data where quantitative data lacks. We develop a greedy scheduling algorithm that is stylized according to the production planning procedures present at ASML's TwinScan Factory (TF). The algorithm greedily finds the first possible order start in time against a set of constraints. The algorithm includes both a scheduling and rescheduling step. The scheduling step adds new input from the MPS to the end of the frozen horizon due to the rolling of the horizon. The rescheduling step accounts for the different types of uncertainty, that are generated by the algorithm, by rescheduling the production schedule generated by the scheduling step. In order to derive insights from the algorithm, we simulate the model over a period of two years, between Q3 2019 and Q2 2021. This is the longest period that is representative of the current market conditions in the semiconductor industry and the current way of working within the production planning department of ASML's TF. Furthermore, the necessary data from different sources is available in this interval. To arrive at results for the proposed schedule instability, on-time delivery, and production output Key Performance Indicators (KPIs), we run the simulation 20 times per reported result. Each simulation run plans the machine orders (n = 272) over the analysis horizon (n = 105 weeks) with different uncertainty seeds. Every week, the greedy algorithm generates demand, supply, and process uncertainty. This uncertainty is estimated from data within ASML. In order to assess the impact of plan changes, we manipulate the level of uncertainty between low, medium, and high levels. Here, the medium level is the estimated uncertainty based on uncertainty data from previous years at ASML. Furthermore, we manipulate the presence of different types of uncertainty in the analysis of the model to provide a holistic overview of how uncertainty impacts the production planning.

The remainder of this report will be structured as follows. Chapter 3 will provide a theoretical background that summarizes the findings in the current literature on rescheduling under uncertainty. Chapter 4 describes the methodology used to study the research questions. This chapter contains four sections. Firstly, a model description is given (Section 4.1). Secondly, Section 4.2 reports how the data is collected. Thirdly, a model verification step is outlined in Section 4.3. Fourthly, Section 4.4 describes how the analysis of the model is executed. Chapter 5 reports on the results that stem from the analysis. And finally, Chapter 6 provides a discussion and conclusion that answers the research questions and provides managerial insights, limitations, and future research directions.

Chapter 2

Problem Definition

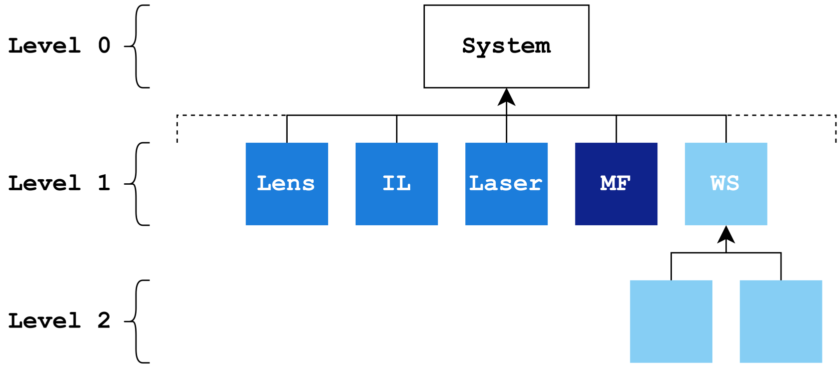
2.1 Empirical Context

This research is conducted within ASML. ASML is one of the world's leading manufacturers of chip-making equipment in the semiconductor industry, founded in 1984. The hardware, software and services that ASML provides to its customers allows them to mass produce patterns on silicon through lithography. ASML's lithography machines perform an essential step in the manufacturing process of integrated circuits, otherwise known as microchips. ASML has over 60 locations in 16 countries and is headquartered in Veldhoven, The Netherlands. There are over 32,000 ASML employees worldwide (in Full-time Equivalent (FTE)), from which the headquarter comprises over half.

ASML assembles its final machines in two factories in Veldhoven: the TF and the EUV Factory (EF). In the former, machines with Deep Ultraviolet (DUV) technology are being assembled. In the latter, machines are assembled with new, groundbreaking Extreme Ultraviolet (EUV). This research will focus on the TF. Generally speaking, ASML has a multi-level assembly process: each machine (level 0) consists of multiple modules (level 1), of which some consist of submodules (level 2) (Figure 2.1).

Figure 2.1

Part of ASML's Multi-level Production Process in the TwinScan Factory

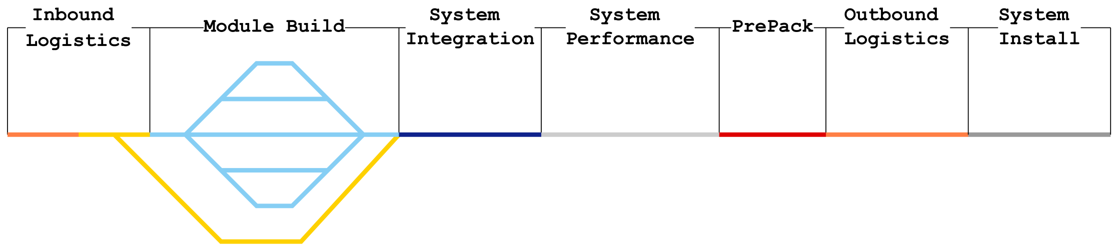


Note. IL = Illuminator, MF = MetroFrame, WS = WaferStage

A general overview of the manufacturing process in the TF within ASML is given in Figure 2.2. Here the modules are assembled in the Module Build (MB) step, the final machine is assembled in the System Integration (SI) step, the machine is tested in the System Performance (SP) step, and prepared for transport (i.e. disassembled) in the PrePack (PP) step. After the machine is packed, it is flown to the customer and installed at their location. At ASML, the assembly of the modules and machines takes place at fixed locations (i.e. a project shop manufacturing process). The modules are assembled in so-called work centers. All resources come to these work centers until the module is finished. The SI, SP and PP steps are performed in cabins. The same principle holds as for the work centers: all resources come to the cabin until the SI, SP and PP steps are finished. The SI and PP can basically be seen as reverse steps. At the SI the machine gets assembled, and at the PP the machine gets partly disassembled in a reversed manner. Furthermore, the planning of these two steps is combined, as both use the same resources (operators, cabin, tooling, etc.). The SP step on the other hand, is different in nature and uses different resources. Therefore, we will use the abbreviation SI&PP to denote the combined SI and PP steps in the remainder of this report. Furthermore, we will use the term SYSTEM to refer to the combined SI, SP and PP steps.

Figure 2.2

Manufacturing Process TwinScan Factory ASML

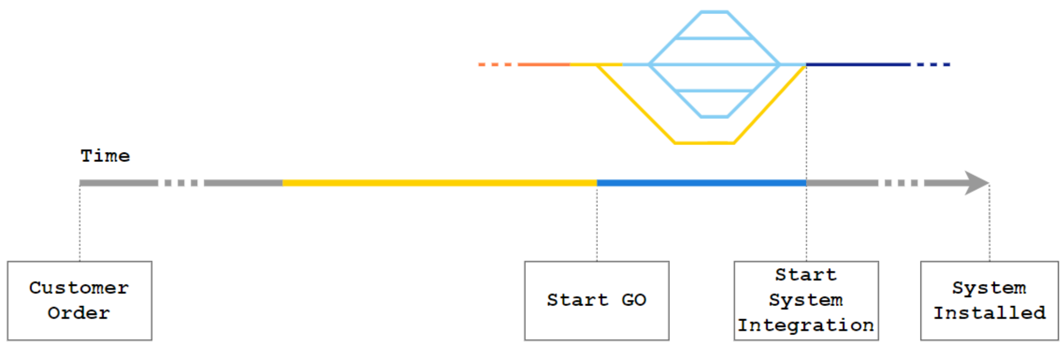


According to ASML's policy, customer is king. To serve the needs of their customers, ASML's TF offers two machine types (XT and NXT), each having multiple versions, with multiple different configurations and options. Nearly all modules that ASML assembles, require the chosen customer preferences in order to be finalized. Therefore, the modules can generally be seen as Make-to-Order (MTO) products. The submodules are mostly stocked based on the Kanban principle. Due to high demand for the machines of ASML, customers must place an order well in advance of the agreed upon delivery date. To put this into perspective, all the machines that ASML will assemble in the TF in 2022 had already been sold before the start of 2022. Between the placement date of the order and some weeks prior to the start of the assembly of the machine, a lot can change. Especially in the high-tech industry, which drives on technological breakthroughs. This ever developing market is exemplified by Moore's law, which states: *"The number of transistors incorporated in a chip will approximately double every 24 months."* (Intel, n.d.). Hence, a formal agreement between ASML and the customer is negotiated a few weeks prior to the start of the assembly. This agreement contains information about the final configuration and the delivery date of the machine. Production orders for SI can be opened if a *Start GO* is received. A Start GO includes three items: (1) a formal agreement, (2) material availability according to the formal agreement and (3) capacity and resource availability in the TF, which is denoted by a production start- and output date. This output date is called the Independent Requirement Date (IRD). The IRD is the date on which the TF promises to have the machine ready for shipment.

The opening of the production orders for SI marks the transition of the *yellow horizon* to the *blue horizon*. The yellow horizon lies between ten and four weeks prior to the start of the SI and the blue horizon between four and zero weeks. In the yellow horizon the Start GO is prepared. This is done by planning the allocation between supply (item 2 and 3 of Start GO) and demand (item 1 of Start GO), and by looking ahead to the progress of the opened orders in the blue horizon and Work-in-Progress (WIP). The blue horizon, also dubbed the frozen horizon, lasts until the start of the SI. During this interval, no further changes to the formal agreement (item 1 of Start GO) should be made to prevent troublesome rescheduling of material (item 2 of Start GO), capacity, and resources (item 3 of Start GO). Figure 2.3 gives a general overview of the timeline between the placement of a customer order and the delivery of the machine, including the yellow- and blue horizon (denoted in their respective colors). Part of the manufacturing process is roughly plotted above the timeline of Figure 2.3 to denote their interrelation.

Figure 2.3

Timeline Customer Order



The following paragraph will zoom in on the production planning activities in the timeline of a customer order. Each four weeks, MPS is updated and sent to the production planning departments. All the production planning departments in the TF (MB, long term SYSTEM, short term SYSTEM and configuration SYSTEM) work off this MPS according to a weekly drumbeat. Each week, the production planning departments update the planning for the part of the manufacturing process that they are responsible for. The production planning sequence generally follows a chronological order. From the MPS, the long term SYSTEM planners take note of the machines that are nearing the blue horizon. At ASML, the start date of the SI (level 0 of the multi-level production process) is the date used for production planning. These dates have to be planned inside their respective MPS week. For example, before week 36 starts, the long term SYSTEM planners take note of the MPS planned starts for week 39. Let us say that order numbers 2029, 2030, 2031 and 2032 have to be started in week 39. After Start GO's are given for the planned orders, the long term SYSTEM planners start to open the production orders for these machines. This is done by planning them four weeks ahead in the blue horizon according to material, capacity, and personnel constraints. The opened production orders are planned to start on a specific day during the aforementioned week (e.g. order number 2029 is planned to start on Monday in week 39, order number 2030 on Tuesday, etc.). If a start GO is not finalized when an order nears the blue horizon, the order halts before the blue interval, which can result in lead time delay. After the SI start has been planned in the blue horizon, the MB planners start opening the production orders for the assembly of the modules against material, capacity and personnel constraints. Currently, due to unexpected high demand, they use the planned SI start as due date for the modules that they plan. In the near future, the aim is to plan both the SI starts and MB starts on the MPS. The start of the SI coincides with the end of the blue horizon (Figure 2.3). Once an open production order of a machine nears the start of the SI, the production order is updated by the short term SYSTEM planners. They do so against more up-to-date material, capacity and personnel constraints. The short term SYSTEM planners work in the same planning document as the long term SYSTEM planners. Because the short term SYSTEM planners are planning on an operational level, they update their planning on a daily basis. This extra short term planning step is required to account for uncertainties that can occur inside the blue horizon. During the entirety of this production planning process, the configuration SYSTEM planners update the planning for any changes that occur in the configuration of machines. In short, the tactical level MPS transforms in an operational level MRP during the blue horizon.

2.2 Problem Context

The problem that ASML faces is late plan changes in the production planning procedure of the TF, as described in Section 2.1. These plan changes can be described and classified by the timing of the occurrence of the changes due to uncertainty, and the possible causes and effects of the changes within the company.

2.2.1 Timing of Plan Changes

Unfortunately, the production planning procedure as described in section 2.1, does not always hold for ASML. The semiconductor industry, in which both ASML and its customers operate, is fast changing by nature. This characteristic of the industry, combined with ASML's 'customer is king' policy, leads to uncertainty that affects the planning of the manufacturing process. This uncertainty can cause plan changes and can occur anywhere between the initial placement of a customer order and the final installation of the machine at the customer site (Figure 2.3).

In the phases before the Start GO is given (prior to the blue horizon), plan changes do not pose much of a problem, since customer orders are only planned in the MPS based on a Rough-Cut Capacity Planning (RCCP). Therefore, plan changes in these orders can easily be accounted for without affecting the lead time of machines.

However, changes that occur after the Start GO is given, do pose a serious problem. After the Start GO, the customer orders in the MPS are transformed into a MRP based on Capacity Requirements Planning (CRP). This happens during the blue- or frozen horizon. As the name suggests, scheduled orders should not be changed anymore in this time period. This can be explained by the fact that during this horizon the production orders for SI and MB are opened. Material, capacity and personnel are allocated to these opened production orders. Even worse, production orders for MB might be in the WIP already when a plan change for a machine in the blue horizon occurs. Therefore, plan changes that occur inside the blue horizon lead to serious investments of manhours by the involved departments and can ultimately lead to increases in lead time of the machine and other machines.

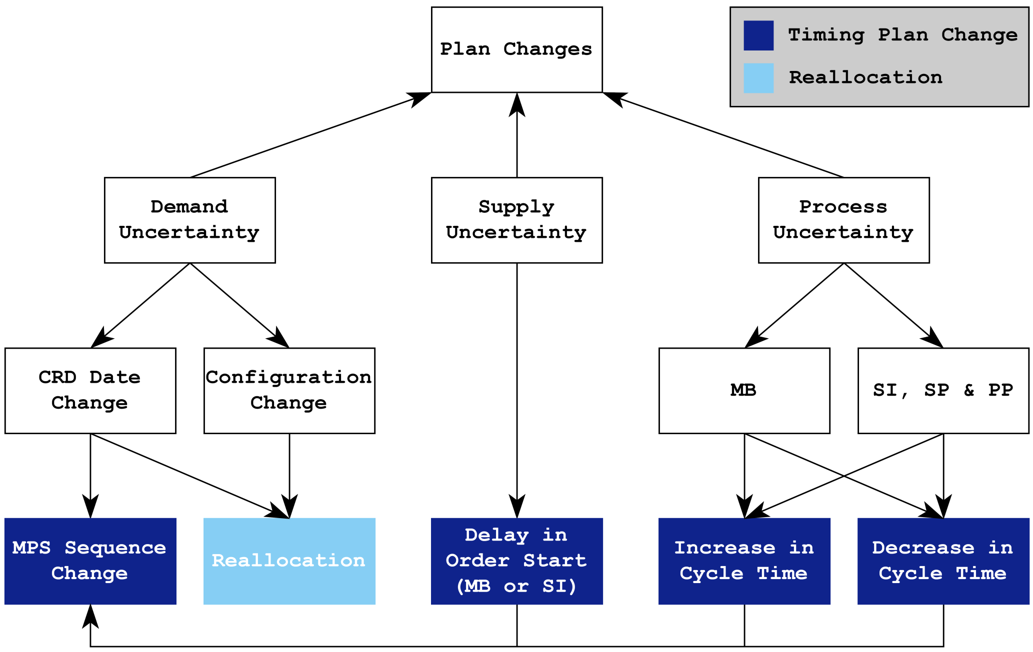
When the SI has started, no further changes to the planning of the machine can be made. The start of the SI marks the end of the machine planning and the start of the WIP of the machines. This does not take away from the fact that a machine in the WIP is also vulnerable to uncertainties. These uncertainties can result in deviations from the planned cycle times in the WIP, which in turn can cause plan changes in upcoming orders due to a chain reaction.

2.2.2 Plan Changes Defined

Plan changes that occur within a manufacturing process can have multiple causes. Koh et al. (2002) classified these causes into external supply, external demand, internal supply, and internal demand. When we apply this structure to ASML's context, we arrive at the following categorization: (1) demand uncertainty, (2) supply uncertainty and (3) process uncertainty. Note that these three categories roughly represent the contents of the Start GO. The plan changes that result from these uncertainties can be divided into changes in the timing of orders and changes in the configuration of orders. The timing plan changes can be caused by: (1) customer disagreement with the provided IRD of their order, (2) supply uncertainty, and (3) process uncertainty. Here, cause (1) is reflected by a customer changing its Customer Requested Delivery (CRD) date. The configuration plan changes can be caused by configuration changes requested by the customer (1). Figure 2.4 gives an overview of the classification of plan changes. In this classification, the *MPS Sequence Changes* are handled by the long term SYSTEM planners and the *Reallocations* by the configuration SYSTEM planners. The information on the remainder of the causes of timing plan changes (*Delay in Order Start*, *Increase in Cycle Time*, and *Decrease in Cycle Time*) are passed to the long term SYSTEM planning department as well, so that they can adapt the planning accordingly. The different types of plan changes and uncertainties are discussed in more detail in the next paragraphs.

Figure 2.4

Classification of Plan Changes



Note. *CRD = Customer Requested Delivery, MPS = Master Production Schedule, MB = Module Build, SI = System Integration, SP = System Performance, PP = Prepack.*

An ***MPS sequence change*** is defined as a change in the sequence of planned- or opened orders' start dates of the SI. A sequence change can occur anywhere between the placement of the initial customer order and the actual start of the SI (see Figure 2.3). A change in the start dates of SI in the sequence of planned orders does not affect the production planning much. These generally occur before the blue horizon. At this time, MB has not opened the orders for the modules of these machines yet, so the long term SYSTEM planners can switch them fairly freely according to capacity, resource, and CRD date constraints. These sequence changes do not have to be communicated explicitly to the MB planning, as they occur before the planning horizon of MB. Here, the only negative impact is on the manhours invested by the production planning departments. As discussed in section 2.2.1, sequence changes do have a significant negative impact on the manufacturing process when they occur after the Start GO (i.e. inside the blue horizon). Sequence changes after the start GO generally take place when MB has already opened (or even started) its orders. These sequence changes can have a negative impact on lead time for the order itself as for other orders. This holds for both the situation in which an order needs to be preponed (i.e. the planned start is moved closer to the actual date) and one in which it needs to be postponed (i.e. the planned start is moved further away from the actual date). This can be explained by the fact that the manufacturing process of the TF is capacity constrained (in terms of personnel and cabins). Due to this capacity bottleneck, a change in the timing of one order, always leads to a change in the timing of another order. If an order is preponed another order has to be postponed to adhere to the capacity constraints at any given time. Similarly, if an order is postponed, capacity is freed that allows another order to be preponed. When a requested sequence change occurs after the start GO, an investigation between MB and long term SYSTEM planning is required. In this investigation they check if the sequence change can occur according to all constraints, and subsequently perform a scenario analysis. When it appears that the requested sequence change cannot be executed due to time constraints at MB, the possibility of switching an already started module to another machine is investigated. When such a sequence change is implemented, lead times are further increased as the already started module needs to be rebuilt. The extra time this takes depends on the progress of the module and how much the current module configuration differs from the one it needs to become.

A ***reallocation*** is defined as a change in the sales document of the formal agreement. This entails both changes in the configuration plus options of the machine, and ownership of the sales document (i.e. the sales document changes customer). When the sales document changes ownership, the possibility of swapping the machines of two customers is investigated. Generally, these machines are of the same, or nearly the same, type and configuration. By swapping the ownership of orders, the production planners prevent changes in the production schedule. Reallocations can occur anywhere between the Start GO and the installation of the machine at the customer site (see Figure 2.3). Generally speaking, the later on a reallocation occurs in the production process, the bigger the impact on manhours and lead time (see Section 2.2.1). Think of it this way: a configuration change after the completion of the SI, during the testing phase of the machine, has a higher impact than a change in the configuration during the blue horizon, where MB might or might not have started assembling the modules.

Supply uncertainties are another cause of timing plan changes. These are generally only problematic when supplies arrive late. Most of the time, the department that is in charge of supplies notifies the production planning departments well in advance when supply delays are likely to occur. These supply delays can result in delays in order starts for both MB and SI. In more extreme cases of supply delay, it might be beneficial to investigate possible sequence changes. This can prevent later scheduled orders to be delayed as well or can prevent the idling of capacity.

Process uncertainty is the third category that causes timing plan changes. Process uncertainty can be divided into MB process uncertainty and SYSTEM (SI&PP, SP) process uncertainty (see Figure 2.2 for an overview of the manufacturing process). The former can impact the SI start date of an order, since the modules have to be finished before the SI can start. The latter can only impact SI start dates of subsequent orders, since these process uncertainties occur when the machine order has started already, i.e. the machine is in the WIP. In extreme cases of process uncertainty, MPS sequence changes can occur.

2.3 Problem Statement

The main problem that ASML wants to solve is plan changes that occur late in the planning process of the TF. Plan changes that occur in the yellow horizon, prior to the blue horizon, are not deemed as problematic, since their negative impact is minimal. The blue horizon (or frozen horizon) should be devoid of plan changes though. By adhering to the production planning in the blue horizon, a more stable manufacturing environment can be ensured. Nonetheless, frequent plan changes do occur within the blue horizon at ASML. These plan changes are deemed as problematic, since they significantly impact the manufacturing process in a negative way. Therefore, this research will focus on plan changes that occur within the blue horizon. At ASML the MPS is scheduled based on the start dates of the SI (level 0). During the blue horizon, this MPS is transformed into a MRP, that includes the modules (level 1). The submodules (level 2) are generally stocked according to the Kanban method and are thus not directly linked to a machine order. Therefore, to capture the problematic plan changes inside the TF, this research will focus on plan changes that occur on the machine level (level 0) inside the blue horizon. The MB planning (level 1), that is affected by these plan changes will be partly included in the research as well. For the sake of simplification, we will only include four of the modules (level 1) that ASML makes in Veldhoven for the process uncertainty of MB: the MetroFrame (MF), WaferStage (WS), Illuminator (IL), Lens (LE). Other modules on level one that ASML makes in Veldhoven will be assumed to not create process uncertainty. Modules that ASML makes on different locations in the world will be categorized under supply uncertainty. See Figure 2.1 for an overview of the multi-level production process.

As discussed in Section 2.2.2, plan changes within ASML can be caused by three types of uncertainty: demand, supply and process. Demand uncertainty can be divided in timing plan changes and configuration plan changes. Supply- and process uncertainty both result in timing plan changes (Figure 2.4). There is a high variety of configuration changes that a machine can undergo. These changes are handled partly by the configuration SYSTEM planners. During meetings with employees in this department, it has become clear that the configuration changes that are requested vary substantially in their characteristics. There are lots of different possible changes of the configuration, hardware, and software of the machine. Furthermore, reconfigurations can take place anywhere between the placement of a customer order and the installation at the customer site (Figure 2.3). While there are standardized procedures in place to address these reallocations, the impact that they have on several relevant key performance indicators (KPIs), such as number of assembly starts per period or on-time performance, is very differentiated and up to now not measured and included in the reallocation decision. Timing plan changes on the other hand, have less different characteristics as they can only result in planned orders being preponed, postponed or in a change in the sequence of planned orders. These changes are more tangible and historical data is easier to gather. This allows the timing plan changes to be modelled more easily. While process uncertainty in the WIP of the machines can cause delays or expeditions for upcoming orders in the MPS sequence, they generally do not result in problematic timing plan changes. Reason behind this is that the cycle times of the machines are fairly stable, and include buffer time. On the other hand, process uncertainty in the WIP of MB can result in problematic timing plan changes as the SI cannot start before the modules are finished. Finally, reallocations of the ownership of a machine due to customer requested changes, do not impact the scheduling inside the blue horizon. They only change which machine goes to which customer. The reasoning in this paragraph leads to the inclusion of: (1) sequence changes due to demand uncertainty, (2) timing plan changes due to supply delays, (3) timing plan changes due to process uncertainty at MB, in the scope of my research (Figure 3). The remaining plan changes are excluded: (1) configuration changes due to demand uncertainty, (2) reallocations due to CRD date changes, and (3) timing plan changes due to process uncertainty at SI&PP and SP (Figure 2.4). For ease of notification, the changes included in the scope will be referred to as 'timing plan changes' in the remainder of this report (previously, timing plan changes also included the changes due to process uncertainty at SI&PP and SP). Inside the TF, two types of machines are assembled: XT and NXT. XT machines are based on an older technique and are more volume-worthy and the assembly process is more streamlined and mature. NXT machines are also volume-worthy, but the assembly process is less routine. Therefore, the initial focus of this research will be on the XT machines. Currently, there are six different versions of regular XT machines that are being manufactured in the TF, each having their own cycle times for SI&PP and SP. All six versions will be included into the scope of this study.

The timing plan changes that occur inside the scope, as described by the paragraphs above, can have different impacts on the TF. Rescheduling of orders can result in extra work hours and less motivation for the production planning, and other involved departments. It can also result in other cost that would not have been incurred if no timing plan changes were present. Furthermore, it can have an impact on cycle- and lead times of orders. These are just a small subset of the possible impact categories of timing plan changes. For the sake of modelability and usefulness, this research will focus on on-time start performance, number of SI starts, and schedule stability as KPIs. Due to time constraints and the overall difficulty of measurement, impact categories like invested manhours in the replanning and the monetary cost of timing plan changes will be excluded from this research. However, by including a measure of schedule stability as a Key Performance Indicator (KPI), the invested manhours get partially addressed as well. This can be explained by the fact that the more stable a schedule is, the less plan changes occur and thus the less manhours have to be invested in rescheduling.

Chapter 3

Theoretical Background

It is widely known that manufacturing companies use production schedules to help plan their processes. Lots of research has been conducted to generate optimal schedules. In the real world however, optimal schedules rarely result in an optimal manufacturing process. This can be explained by the fact that the world is dynamic and stochastic. Therefore, the manufacturing companies that operate in it are subject to considerable uncertainties. These uncertainties often result in the inevitable revision of manufacturing schedules, which in turn results in rescheduling (i.e. plan changes). This led to the emergence of a literature stream that addresses production scheduling under uncertainty.

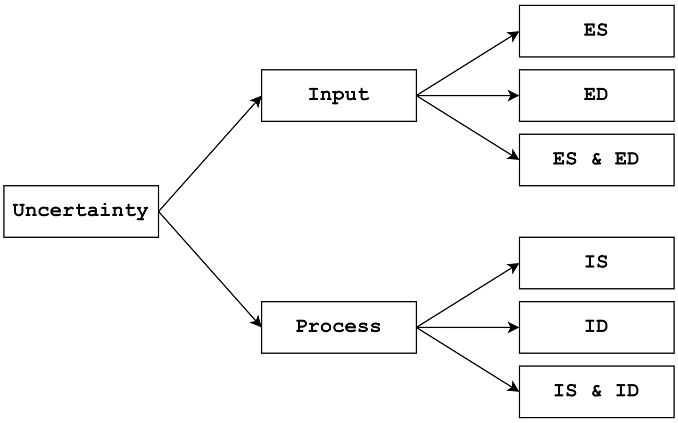
3.1 Sources of Uncertainty

Uncertainties, otherwise known as unexpected events, are the main cause of plan changes. Uncertainty in organizations and supply chains can originate from both ***operational*** factors and non-operational factors. In their book on disruption management, Yu and Qi (2004) state several ***non-operational*** factors: (1) Changes in the system environment. For example, snowstorms may affect transportation. (2) Unpredictable events. For example, terrorist attacks, union strikes, or the more recent COVID-19 pandemic. (3) New restrictions. For example, new government laws and regulations.

Uncertainty, that originates from ***operational*** factors is more widely present in the current literature. In their review of MRP systems under uncertainty, Koh et al. (2002) classified uncertainty into two main categories: input (as external supply or external demand) and process (as internal supply or internal demand). Figure 3.1 shows this categorization structure of uncertainty and Figure 3.2 shows the interrelationships between the uncertainties. Of course, any combination of input- and process uncertainty can exist as well.

Figure 3.1

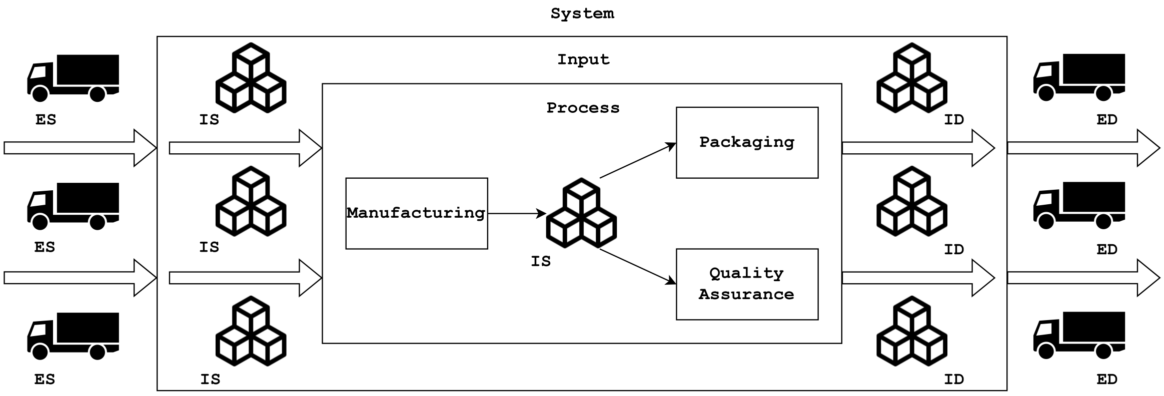
Uncertainty Categorization Structure



Note. Adapted from Koh et al., 2002, ES = External Supply, ED = External Demand, IS = Internal Supply, ID = Internal Demand.

Figure 3.2

Interrelationships between External and Internal Supply and Demand



Note. Adapted from Koh et al., 2002, ES = External Supply, ED = External Demand, IS = Internal Supply, ID = Internal Demand.

Uncertainty at ***external supply*** is mainly due to external suppliers that fail to deliver as promised (Atadeniz & Sridharan, 2020; Koh et al., 2002; Vieira et al., 2003). The ordered supplies can be both later than ordered or less than the ordered quantity. This can lead to unplanned changes in the periods that lie within the scheduling horizon of an organization. In more extreme cases, these supply uncertainties can even impact open orders, to which supplies have already been assigned. These supply uncertainties can propagate to higher levels in the manufacturing process and can cause costly adjustments and lead to indirect costs, such as losing the confidence of buyers (Atadeniz & Sridharan, 2020). Furthermore, the market price in a supply chain may change for (raw) materials, which also adds to external supply uncertainty (Yu & Qi, 2004). External supply uncertainty at ASML is represented by delays in external supply of suppliers. Here, suppliers can be both independent companies and ASML's own production facilities in different locations that supply to the headquarter in Veldhoven.

Uncertainty at ***External Demand*** can both be caused due to the uncertainty of future demand (Atadeniz & Sridharan, 2020; Blackburn et al., 1985) and inaccurate forecasts of future demand (Koh et al., 2002). In rolling schedules, the scheduling horizon is rolled forward and the forecasts of demand and the production schedule are updated with new information. If the actual demand is less than the forecast predicted, orders may be rescheduled to a later date. If actual demand is greater than the forecast predicted, an order might be rescheduled to an earlier date to account for the extra time needed to manufacture the products. Another type of uncertainty in external demand is the arrival of urgent-, rush-, or hot jobs (Vieira et al., 2003). Besides the uncertainty in the quantity and timing of demand, the content of demand might change as well. Hence, changes in the configuration of customer orders are a cause of uncertainty in external demand as well (Koh et al., 2002; Yu & Qi, 2004). At ASML, external demand uncertainty is present in the wishes of its customers, with regards to the configuration and timing of the delivery of the machines, which are already ordered. Because the demand for the machines is higher than the production capacity, uncertainty of future demand is hardly present in the coming couple of years.

Uncertainties that occur within the boundary of a company's system are grouped into the ***internal supply*** and ***internal demand*** categories by Koh et al. (2002) (Figure 3.1 and 3.2). Internal supply and demand uncertainty are interrelated and therefore discussed together in this research. For example, parts can arrive late from a previous step in the manufacturing process due to resource overload (Koh et al., 2002). The use of different lot-sizing rules can also affect internal supply capability between workstations. Whenever there is a deviation between the ordered lot size and the produced lot size, overages or shortages of products between workstations are created if safety stock is not available (Blackburn et al., 1985; Koh et al., 2002). Remaining sources of internal supply and demand uncertainty are given by Koh et al. (2002) and Vieira et al. (2003) capacity loading, interoperation move time, queue waiting time, process lead time, variability in set-up and run time, tooling unavailability, material unavailability, operator absence, machine breakdown, late supply, variability in resource supply, prematurely released orders, engineering changes, system uncertainty, lost work-in-progress (WIP), safety stock changes, quality variation in the production process, yield loss, scrap, changes in job priority, record errors and unplanned transactions. Yu and Qi (2004, p. 17) also state some of these uncertainties under their Changes in availability of resources and Uncertainties in system performance categories. Within the context of this research at ASML, internal demand and supply uncertainty is present in the process uncertainty of the different levels of the multi-level production process. Internal supply from ASML's warehouse to the work floor is assumed to be neglectable.

3.2 Impact of Plan Changes

3.2.1 Mixed Conclusions in the Scheduling Literature on Rescheduling

While there is a long-standing research base that addresses the advantages and disadvantages of frequent rescheduling within a manufacturing context, their conclusions are mixed. Hozak and Hill (2009) try to explain these mixed conclusions. To aid their explanation, they divided the literature stream on scheduling under uncertainty into three sub-streams: (1) internal planning, (2) shop floor scheduling, and (3) supply chain scheduling. Here, internal planning refers to the planning of techniques such as the MPS and the MRP (i.e., what to produce when in which quantities). The internal planning is used as input for the shop floor scheduling. Shop floor scheduling is typically concerned with assigning jobs to different machines on the shop floor. Both the internal planning and the shop floor scheduling sub-streams started to recognize the importance of adopting a supply chain view, instead of the traditional isolated company view. The supply chain sub-stream includes the papers that resulted from this shift and includes research in novel supply chain scheduling areas as well. Hozak and Hill (2009) explain the different modeling choices and assumptions that are made in the different sub-streams (Table

Table 3.1

Modeling Choices that may affect Conclusions about the Frequency of Rescheduling

Modeling choice	Supports more frequent (+) or less frequent (-) rescheduling
Not modeling all system nervousness and instability costs (e.g., not modeling high non-linear ordering costs)	+
Modeling demand, production, and distribution that may mask instability costs (e.g., assuming non-lumpy demand that requires production and distribution every period)	+
Not modeling instability costs related to 'human factors' (e.g., worker confusion and loss of morale)	+
Modeling that replanning always results in rescheduling (e.g., not filtering the rescheduling logic based on what is cost-effective)	-
Not modeling that forecasts are increasingly inaccurate further into the future	-
Not modeling lead time compression	-
Modeling lead times that show less benefit from frequent replanning	-

Note. Adapted from Hozak and Hill (2009)

3.1). Generally, there seems to be a tendency in the literature to make the same set of assumptions within the different sub-streams. This leads to the findings of Hozak and Hill (2009) that, generally speaking: (1) the internal planning papers are critical of frequent rescheduling, (2) the shop floor papers support rescheduling, although the conclusions are less consentient, and (3) the supply chain papers endorse responding quickly to updated information (implying frequent rescheduling). The authors conclude by stating that a general conclusion on frequently rescheduling cannot be given, as there has been little effort to tie the different sub-streams of literature together.

3.2.2 Impact Categories

Over the last decades, many studies investigated plan changes. In this literature, multiple different performance measures have been used to assess the impact of plan changes. Atadeniz and Sridharan (2020) provide a comprehensive review of the literature on MPS nervousness. They state that when production orders are opened, resources are allocated to that order. Rescheduling these orders is often on short notice and can be costly, ineffective, and confusing. In particular, the authors found that rescheduling can lead to expediting, scheduling overtime or undertime, and premature breakdown of a setup for another setup. These can lead to increased costs, less productivity, and can have a negative impact on the morale of the employees on the work floor and in the planning department. On top of this, the on-time delivery performance towards customers suffers from rescheduling. To make matters worse, the negative impacts of rescheduling mentioned above, might be amplified by nervousness-inducing rescheduling in production processes with a multi-level Bill of Material (BOM) (Atadeniz & Sridharan, 2020). The authors quantify the effect of capacity constraints on the effectiveness of different policies for dampening schedule nervousness (such as freezing a portion of the MPS) under demand uncertainty. We extend this paper by looking quantitatively at the effects of different types of uncertainty in an environment with capacity constraints and a fixed policy (fixed frozen portion of the MPS). In the shop floor scheduling literature disruptions can cause rescheduling when they are sufficiently large. Disrupted schedules incur higher costs due to resource idleness, a higher WIP inventory, and missed due dates and an increased system nervousness due to frequent rescheduling (Herroelen & Leus, 2005).

Most research on scheduling under uncertainty frequently uses a (sub)set of performance measures consisting of (monetary) costs, schedule instability, and service level to study the impact of plan changes. Cost is often composed of several from the following cost elements: setup costs, inventory holding costs, ordering or raw material costs, shortage costs, and processing costs. Tunc et al. (2013) state that the cost of MRP system nervousness is difficult to measure. To this end, they presented a measure to assess this cost, in terms of ordering-, holding-, and shortage costs for different inventory replenishment policies. Schedule instability in the internal planning literature is often based on a measure provided by Sridharan et al. (1988), that measures the difference in scheduled order quantities between subsequent planning cycles. In the shop floor scheduling literature it is often measured in frequency of rescheduling interventions, starting time deviations, and sequence deviations between initial and new schedules. Service level is mostly expressed in fill rate, which is defined as the proportion of end-item demand that can be satisfied from stock, or by a measure of maximum lateness.

Internal Planning Literature

Sridharan and Lawrence LaForge (1989) found that a small amount of safety stock improved schedule stability and lowered cost. However, they also found that further increases in the safety stock level often led to increases in schedule instability and always led to higher cost. Here the lot-sizing costs consists of setup and holding cost and the schedule stability is an adaptation of the measure provided by Sridharan et al. (1988). Atadeniz and Sridharan (2020) used the same lot-sizing cost and a similar schedule instability measure, combined with a measure of fill rate, to study the effect of capacity constraints on the effectiveness of policies for dampening schedule nervousness. They found that the relative effectiveness of the policies, in terms of these measures, was not impacted by a capacity constraint. Kadipasaoglu and Sridharan (1995) investigated the effect of freezing a part of the MPS with similar cost, schedule instability, and service level measures as Atadeniz and Sridharan (2020). They concluded that freezing reduced cost, instability, and service level. Zhao and Lee (1993) investigated the impact of several MPS freezing parameters on similar measures of cost (includes shortage cost as well), stability and service levels. The results from their analysis under stochastic demand were as follows: Increases in the proportion of the schedule that got frozen, increased cost (contrasting the findings of Kadipasaoglu and Sridharan, 1995) but decreased the instability, and service level. Here, a trade-off should be made between these criteria when determining the right freezing proportion for one's manufacturing process. Additionally, less frequent replanning improved system performance. While most research focuses on the model costs before and after rescheduling, a small amount of papers also includes the cost of changing the schedule. In the research that included this cost, system nervousness would be tolerated as long as it was economical to do so (Carlson et al., 1979; Kropp & Carlson, 1984; Kropp et al., 1983). This approach was found to be effective in finding the right balance between the cost of sub-optimal lot-sizing and cost of changing the schedule. In this research the cost of changing the schedule entailed the cost of adding previously absent setups (Carlson et al., 1979; Kropp et al., 1983) or the cost of adding and canceling setups (Kropp & Carlson, 1984).

Shop Floor Scheduling Literature

Shafaei and Brunn (1999) investigated the robustness of a number of shop floor scheduling rules in a dynamic and stochastic environment using a rolling horizon approach. They used a cost-based performance measure, that includes holding-, processing-, and raw material cost, to evaluate the different rules. From the simulations, it became clear that frequent rescheduling under a rolling horizon becomes more effective in providing robustness when uncertainty increases. Church and Uzsoy (1992) tried to answer the question on whether to reschedule at every disruption event or not in a shop floor context. They did this by comparing periodic and event-driven rescheduling policies on schedule stability (frequency of rescheduling interventions) and maximum lateness performance measures. The former policy updates the schedule at a regular interval, the latter after certain disruption events occur. They found that both the periodic and event-driven policies can outperform continuous rescheduling policies as the benefit of extra rescheduling diminishes quickly. The performance of both policies depends on the scenario though, which introduces trade-offs between continuously rescheduling and the given policy. Therefore, Church and Uzsoy (1992) present a hybrid policy that updates the schedule both periodically and after certain disruption events occur. Abumaizar and Svestka (1997) compare partial-, right-shift-, and complete rescheduling methods against makespan and stability performance measures. The stability measure is composed of a starting time deviation measure and a sequence deviation measure between initial and new schedules. Partial rescheduling only considers rescheduling those tasks that are directly or indirectly affected by a disruption (Li et al., 1993). Right-shift rescheduling simply postpones every remaining task by the amount needed to make the schedule feasible again. Complete rescheduling reschedules all tasks that have not been processed so far, including those that are not affected by the disruption (Abumaizar & Svestka, 1997). They conclude that the partial rescheduling method reduces much of the deviation and computational complexity of the total rescheduling method with no significant drop in efficiency. Furthermore, they demonstrate the superior performance of the partial rescheduling method over the other two in most scenarios. Similar to the internal planning research stream, the shop floor scheduling research has also studied the inclusion of rescheduling cost, in the field of disruption management. For example, Liu and Ro (2014) studied a single machine scheduling problem with disruptions. Their model includes the rescheduling cost, composed of changing delivery times to customers and rescheduling resources, and tries to minimize make span and maximum lateness. While the shop floor scheduling literature is mainly concerned with providing scheduling policies that try to omit the negative downsides of rescheduling, this is not part of our thesis. This thesis is rather conducted to quantify the negative impacts that different types of uncertainty have given a fixed scheduling policy.

Supply Chain Scheduling Literature

Impact measures like schedule instability and service level are also present in the supply chain scheduling literature, albeit they are defined differently. Ganeshan et al. (2001) studied the sensitivity of supply chain performance to the mode of communication between echelons, and the planning frequency. They found that increasing the rescheduling frequency leads to better service, lower cycle times, and better return on investment. Additionally, using a mode of communication that facilitates information exchange yields higher service levels than a mode which does not. Here, the service level is defined as the volume-weighted average of the proportion of demand satisfied from inventory at each of the distribution centra. Sivadasan et al. (2013) challenge the notion that information sharing is always beneficial. They present a methodology for identifying complexity-adding information flows. They showed that schedule instability can be decreased for both supply chains of commodity- and customizable products by removing these complexity-adding information flows. For the measure of schedule instability, they used an information-theoretic expression for measuring the operational complexity across supplier-customer interfaces. Waller et al. (1999) state that most of the inventory reduction achieved with Vendor Managed Inventory (VMI) can be attributed to reviewing the inventory more frequently (i.e. an increased replanning frequency). Special attention in the supply chain scheduling literature is directed at the bullwhip effect. The bullwhip effect is defined as the amplification of demand variability through the entire supply chain. The nervousness in MRP systems is one of the major factors contributing to the bullwhip effect (Atadeniz & Sridharan, 2020). Therefore, addressing and reducing the effect of system nervousness in MRP systems is not only beneficial for isolated companies, but for supply chains as a whole. This is further backed by Pujawan and Smart (2012), who found that, among 230 manufacturing executives in various industries, there is major concern about the negative effects of schedule instability on the performance of supply chains. To this end, Lee et al. (1997) found that the bullwhip effect can be decreased by information lead time reduction and quick replanning. Furthermore, Pujawan (2008) investigated how different operating environments and different supply chain policies impact schedule stability in a supply chain context. They found that schedule instability, in terms of estimated order times, is propagated up the supply chain and is affected significantly by the degree of demand uncertainty from the end customer. Additionally, the applied safety stock policy by the buyer has a large impact on the schedule instability of the supplier. This impact is also affected by the degree of demand uncertainty.

3.3 Conclusion Theoretical Background

From the literature, we can make inferences on the impact of plan changes, as experienced by for example ASML. Given the fact that manufacturing environments are becoming ever more complex, it comes as no surprise that conflicting conclusions arise from the academic field on rescheduling. Hozak and Hill (2009) recognized the inconsistent conclusions between the (1) internal planning, (2) shop floor, and (3) supply chain literatures about ideal replanning and rescheduling frequencies and provided several modelling choices that may affect those conclusions (Table 3.1). The authors find that, generally speaking: (1) the internal planning papers are critical of frequent rescheduling, (2) the shop floor papers support rescheduling, although the conclusions are less consentient, and (3) the supply chain papers endorse responding quickly to updated information (implying frequent rescheduling). The authors conclude by stating that a general conclusion on frequently rescheduling cannot be given, as there has been little effort to tie the different sub-streams of literature together. This last statement applies to the problem of ASML as well, as there are clear differences between the findings in the literature and ASML's context. At ASML, the internal planning and shop floor scheduling are tightly integrated. Unlike in the literature, where the two streams seem to have strict boundaries and conclusions on rescheduling, a plan change in the MPS at ASML has clear implications for the shop floor scheduling. Here, the general idea seems to be that the closer an order is to its execution date, the more severe the impact of rescheduling is. In order to prevent plan changes from occurring too often too close to the execution dates, ASML uses time fencing systems for both the internal planning and shop floor scheduling. In the literature, time fencing systems are often considered in the internal planning literature, but not in the shop floor literature. Vieira et al. (2003) recognize the problem that these mismatches exemplify. They emphasize that more research is needed to better understand the interactions between rescheduling policies and other production planning functions such as MRP- and capacity planning. Furthermore, research in this field should extend to other decision-making systems under uncertainty, like supply chain planning (Pujawan & Smart, 2012). Similar to the literature, ASML's scheduling system includes a frozen period in which no changes can be made. In this regard however, there seems to be a mismatch between research and practice. Where the literature assumes that these frozen periods are strictly adhered to, in practice this is unlikely. Pujawan and Smart (2012) found from interviews that it is very difficult for companies not to make changes requested by the customer, even though those changes occur in the frozen period. This is very much the case for ASML, which operates in a highly dynamic environment and serves only a small customer base.

While many papers in the literature on rescheduling try to find remedies to plan changes, only a few recognize that the rescheduling itself bears a cost (e.g. Carlson et al., 1979; Ivanov et al., 2017; Kropp and Carlson, 1984; Kropp et al., 1983; Liu and Ro, 2014). Unfortunately, including the cost of rescheduling in complex manufacturing processes has not found much acceptance from the industry (Atadeniz & Sridharan, 2020). Reasons behind this is that rescheduling costs are difficult to determine, especially for different product/operation combinations (Atadeniz & Sridharan, 2020) and data collection on schedule changes is a difficult task (Pujawan, 2004). Accordingly, ASML does recognize the presence of (negative) impacts of rescheduling, but fails to pinpoint how to incorporate these changes into the decision making. These plan changes both have an effect on the scheduling system and on the morale of the employees, which are involved in handling them (Atadeniz & Sridharan, 2020).

Another topic that is relevant to ASML's problem of assessing the impact of plan changes, is raised by Koh et al. (2002). They state that the provision of a cause-and-effect structure for diagnosing uncertainty is needed to facilitate identification of underlying causes of uncertainty. A clear cause-and-effect structure can help companies gain useful insights on the impact of plan changes. Furthermore, Koh et al. (2002) argue that different organizations and industries can have different cause-and-effect relationships. Research effort should be made on the effects between all possible relationships between uncertainties, to generalize the cause-and-effect structure (Aytug et al., 2005; Koh et al., 2002; Vieira et al., 2003). Pujawan and Smart (2012) also endorse studying schedule instability empirically. They state that, while schedule instability has always been very much a practical problem, few empirical studies are presented in the literature. The holistic approach to studying the effects of uncertainty is also highlighted as a future research direction by Dolgui and Prodhon (2007). They found that while many studies focus on uncertain demand, and some on uncertain lead time, few studies take them simultaneously into account. By looking at both forms of uncertainty practical value can be provided to the industrial sector and research. Furthermore, Atadeniz and Sridharan (2020) found that there are only a few studies that have examined the effectiveness of freezing- or rescheduling the MPS when capacity is constrained. They add to this research gap themselves with their study, but the field is still understudied. While textciteatadeniz2020effectiveness address how capacity constraints impact the effectiveness of different nervousness dampening policies (such as freezing a part of the MPS) under demand uncertainty, our study focusses on the effect of different types of uncertainty in an environment with fixed capacity constraints and a fixed frozen part of the MPS. Our research aims to address the gaps in the literature, as identified in this paragraph, by empirically studying a holistic cause-and-effect structure of uncertainty at ASML, which operates in the semiconductor industry.

Chapter 4

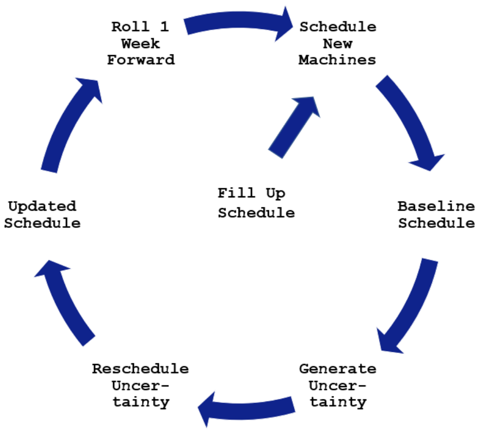
Methodology

4.1 Model

In order to generate more insight into the causes and effects of plan changes and to answer the research questions, as proposed in Chapter 1, we develop a stylized greedy algorithm. This algorithm is based on the production planning process of the machines within ASML's TF. This factory operates in the semiconductor industry. In recent years, demand is overwhelming in this industry and this is believed to remain so for years to come. The insights gained from this model can be applied to companies active in the semiconductor or similar industries, where demand for high-complexity products is high and capacity constrained. We choose a greedy algorithm as model, because the greedy behavior best describes the way of working at ASML. Namely, a production planner tries to find the earliest possible start of a machine (i.e. SI start), over all the cabins, in the blue horizon against several constraints. ASML's interest in the problematic nature of plan changes is mainly focused on the changes on the SYSTEM level (level 0 in Figure 2.1). Therefore, the MB planning (level 1 in Figure 2.1) of the modules included in this research (MF, WS, IL & LE), are only considered as an input to the greedy algorithm rather than being modelled as well. How the MB planning is simplified will be explained later on in this chapter. The current method of scheduling the machines is performed manually by the different production planning roles (long term SYSTEM, short term SYSTEM, and configuration SYSTEM). We will try to capture these activities as closely as possibly in the greedy algorithm. The greedy algorithm will operate based on the weekly drumbeat present in the production planning department (Figure 4.1).

Figure 4.1

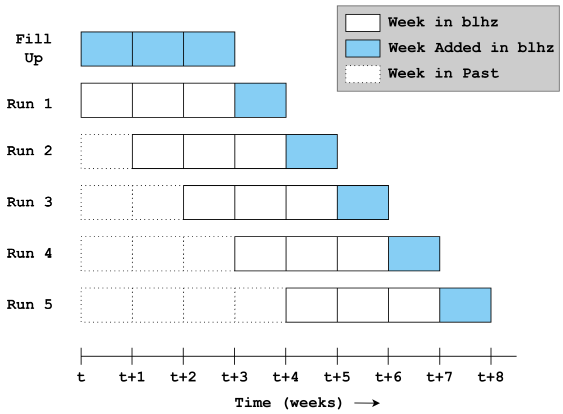
Weekly Drumbeat Cycle



The greedy algorithm that follows the weekly drumbeat (Figure 4.1) receives three forms of input every week: (1) the updated schedule from the previous week, (2) new input for the fourth week that has to be added to the end of the blue horizon, due to the rolling of schedule, and (3) uncertainty that occurs during the week, which affects the planned orders in the blue horizon. With the first two inputs, the greedy algorithm outputs the baseline schedule. The third input, the uncertainty, affects the baseline schedule and requires a rescheduling step to create the updated schedule. In turn, this updated schedule serves as part of the baseline schedule for the next weekly cycle. An overview of the blue horizon over time after five sequential runs of the greedy algorithm is given in Figure 4.2. As can be seen in Figure 4.1 and 4.2, a *Fill Up Schedule* step is needed prior to the first run. This step fills the first three weeks of the blue horizon with orders that were in the WIP or that were already planned during those weeks. The weeks that lie in the past in Figure 4.2 contain the information on the actual start- and end times of previously scheduled machines. Note that machines that have a SI start in the past weeks, can still overlap the entire blue horizon. This is due to the fact that the cycle times of the machines are greater than the blue horizon, which lasts four weeks. In the next paragraphs of this section, we will elaborate further on the different inputs, outputs, and steps in the model.

Figure 4.2

Rolling Scheduling of the Blue Horizon



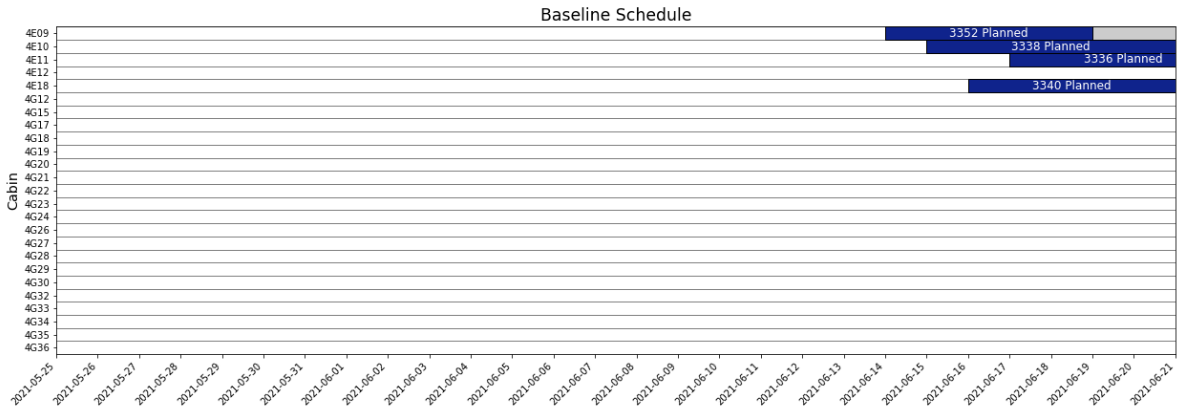
The ***baseline schedule*** and the ***updated schedule*** are the outputs of the greedy algorithm. Both schedules are work floor schedules that include the start- and end times of the SI, SP, and PP for orders in the blue horizon, divided over the cabins. At ASML, the work floor operates on a shift system: two shifts of eight hours per day on Monday through Friday and one shift of eight hours on Saturday and Sunday. On holidays, the factory is closed. This shift system is also used by the production planners to plan the machines. The baseline schedule is the same as the updated schedule from the previous week minus the week that has passed, plus the new week at the end of the horizon. For each of the runs in Figure 4.2, the white solid rectangles represent the baseline schedule inherited from the previous week. The dotted rectangles represent the past weeks, and the blue rectangles the newly added weeks.

Prior to the first simulated run of the greedy algorithm, we fill the blue horizon. We call this the ***Fill Up Schedule*** step. Here, we manually fill the first three weeks of the blue horizon with machines that were either in the WIP or planned during these weeks. To this end, we utilize historic data on the starting time and cycle times for the SI, SP, and PP steps. We manually fill the schedule, rather than using the scheduling mechanism of the greedy algorithm. We make this choice, in order to start the simulation of the greedy algorithm based on a realistic starting point.

Every week ***new input*** arrives to the greedy algorithm, which is scheduled in the ***Schedule New Machines*** step. This new input concerns the machines in the week that have to be added to the end of the planning horizon. The MPS sequence provides us weekly with up to five machines, sorted on increasing CRD date, that have to be scheduled. The greedy algorithm schedules these machines based on the First In First Out (FIFO) rule. For example, Figures 4.3 and 4.4 show two consecutive planning cycles, of four machines each, in a completely empty blue horizon (no *Fill Up Schedule* step). Figures 4.5 and 4.6 show two consecutive planning cycles four weeks later, where we see new machines being scheduled after machines that are in the WIP. We omit the Fill Up Schedule step purely for clarification of the scheduling behavior of the greedy algorithm. We will not omit the *Fill Up Schedule* step in the analysis of the model.

Figure 4.3

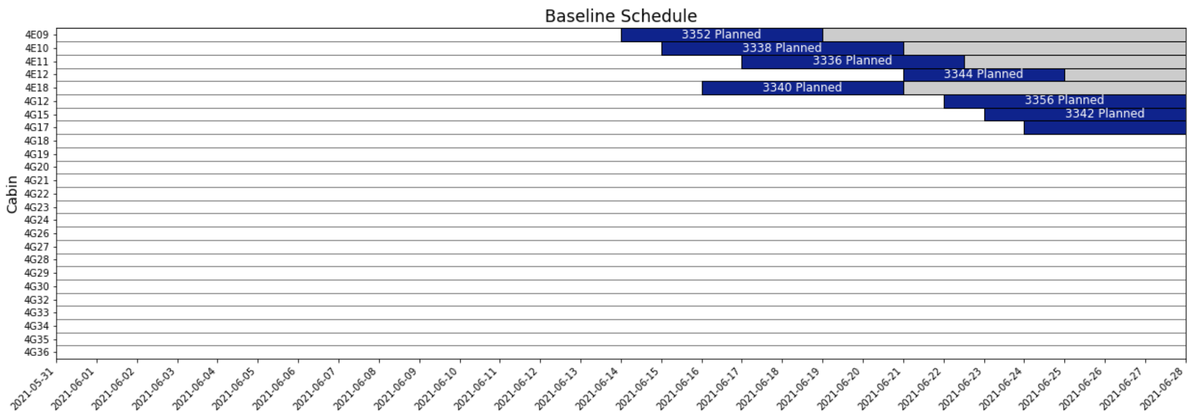
Four Planned Starts at the End of the Blue Horizon 1



Note. *Blue = SI, grey = SP.*

Figure 4.4

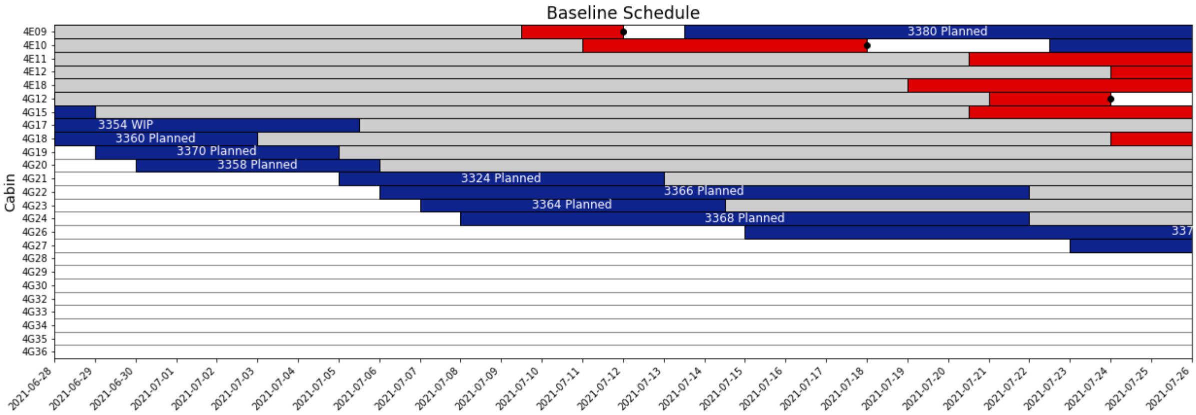
Four Planned Starts at the End of the Blue Horizon 2



Note. *Blue = SI, grey = SP.*

Figure 4.5

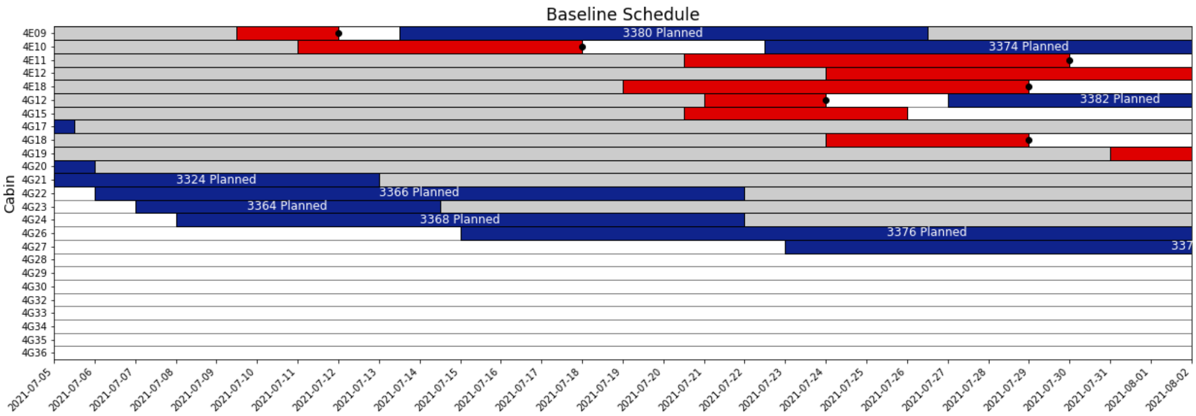
Planned Starts at the End of the Blue Horizon 1



Note. Blue = SI, grey = SP, red = PP, dots = cabin empty.

Figure 4.6

Planned Starts at the End of the Blue Horizon 2



Note. Blue = SI, grey = SP, red = PP, dots = cabin empty.

We derive the new input from the MPS. In the MPS, each order contains data on the week in which the SI needs to start and on the configuration of the ordered machine, as well as other general information. After the Fill Up Schedule step, the algorithm plans these weekly orders inside the fourth week of the horizon, marked as blue in Figure 4.2. Due to high demand for the machines, the planned starts in the MPS are generally known 18 months in advance with substantial accuracy. Therefore, we model the weekly MPS planned starts to be deterministic (i.e. no demand uncertainty in the arrival of machine orders). Furthermore, there are guideline cycle times for the assembly of the SYSTEM. These cycle times include buffer time to account for the uncertainty in the SI, SP, and PP steps. While the cycle times are stochastic in practice, we assume deterministic cycle times for the machines in our model, based on input from ASML. Their problem mainly lies in the rescheduling of SI starts rather than uncertainty in the cycle times of these machines, which is mostly captured by the buffer cycle time for XT machines. In order to keep the scheduling of the baseline schedule as close to the historic data as possible, the input of the deterministic cycle times will be based on historic cycle time data of machine orders, rather than their guideline cycle times. Realistically speaking, the final cycle time is not known before the start of the assembly. We justify the use of these deterministic historic cycle times by the observation that when machines are planned four weeks ahead in a cabin, the previously planned machine in that cabin has been in the WIP for at least some weeks already (see Figures 4.5 and 4.6). Therefore, some information from the work floor about the final cycle time of the system is already present. This behavior is present at ASML, due to the ratio between the amount of cabins, the length of cycle times, and amount of machine starts per week. The greedy algorithm produces a baseline schedule with the MPS input, that aims to schedule the new machines as soon as possible in time. It greedily finds the first possible start over all the shifts in the fourth week and over all the cabins. It does so against five constraints: (1) *Cabin Type*; some cabins cannot be used for the assembly of all machine types, (2) *Cabin Empty*; the cabin has to be empty before a new machine can be assembled in that cabin, (3) *Maximum Starts per Day*, (4) *Maximum Starts per Shift*, and (5) *Operator Capacity*; a certain amount of qualified operators must be present to assemble the machine. For the Cabin Empty constraint, the cabin is empty at the latest point in time between the IRD and CRD date ($max(IRD, CRD)$). The IRD is determined once a machine enters the WIP. This is possible due to the assumed deterministic cycle times. The IRD is calculated by adding the cycle time of a machine to the actual SI start date. The Operator Capacity constraint in the greedy algorithm is a simplification of the real world. In the real world, there is a work floor schedule that the production planners have, that shows how many operators are daily available for the SI, SP and PP steps. In practice, machines in the WIP can be put on hold when there are not sufficient qualified operators available (e.g. due to sickness). These irregularities are generally captured by the buffer cycle time. In our model, putting orders on hold is not possible, due to the assumption of deterministic cycle times. Furthermore, the operator capacity is generally only considered for the SI step. The operator capacity for SP step generally does not pose a problem and possible delays in the PP step due to operator shortage is generally captured by the buffer cycle time. For these reasons, we developed a simplified version of the Operator Capacity constraint, that constricts the maximum number of machines that are simultaneously in the SI step. For example, no more than four machines are simultaneously in the SI step at any given time in Figures 4.3, 4.4, 4.5, and 4.6. The calculation of this number will be explained in the verification section (Section 4.3). After the greedy algorithm schedules a new order, it consecutively schedules the MB starts for the four different modules based on the Just in Time (JIT) principle with additional safety cycle time per module. For example the start of the WS module for a specific order is calculated by: $WS_{start} = SI_{start}$ – Guideline CT_{WS} – Safety CT_{WS}. This is a simplification of the real world, where each MB work center has its own scheduling rules and constraints. Finally, when the greedy algorithm cannot find a SI start in the fourth week of the blue horizon, the respective machine order is postponed to the next week. Due to the FIFO rule, this machine order will be the first to be scheduled in the next week, followed by the orders that were initially planned to be scheduled in that week.

Uncertainty affects the baseline schedules generated in the *Schedule New Machines* step. This uncertainty is generated in the ***Generate Uncertainty*** step. According to the classification of plan changes (Figure 2.4), we generate demand-, supply-, and MB uncertainty.

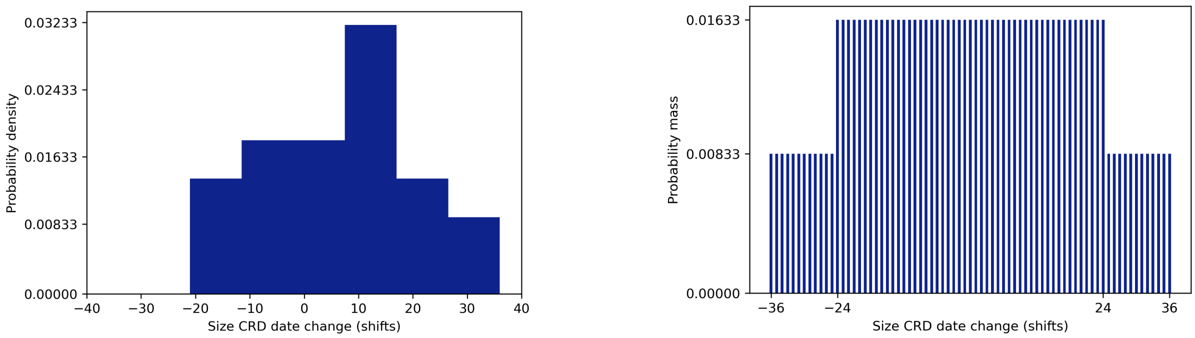
Demand Uncertainty is in the form of customers disagreeing with the date on which ASML promises to finish their machine (IRD). A customer can influence this date by changing its CRD date. They can either request a later or sooner CRD date. Take note, that these new CRD dates are not binding for the planning of the machines, but are mostly a customer push to improve on the IRD. Namely, the demand for ASML's machines is greater than the production capacity and therefore the CRD dates are often not feasible. If ASML's sales department agrees on these changes, they are mostly handled by changing which machine goes to which customer (*reallocation* in Figure 2.4). In rarer cases, the requested change is handled by postponements or preponements of scheduled machines in the blue horizon. In our model we strictly look at these changes, as they impact the timing of the planned machines in the blue horizon. These changes are reflected by changes in the starts of the SI. In the greedy algorithm, these changes are handled by changing the MPS sequence of orders. This is done by adding the (positive or negative) CRD date change to the MPS planned start, after which the new place in the sequence is determined for the impacted order. This way the impacted orders gets a new place in the FIFO sequence, but still has to undergo the rescheduling step according to all constraints. Due to the many constraints present, it is fairly uncommon for a requested CRD date change to be fully complied with. The generation of demand uncertainty is a two stage process: there is a weekly chance of occurrence per machine in the blue horizon of a CRD date change, and the sampling of the size of the CRD date change for the impacted machines. Data on the occurrence and size of the CRD date changes is only scarcely present within ASML. Data on only 23 of such changes has been gathered and used for constructing the histogram in Figure 4.7a. From the available data, we estimate the weekly chance of occurrence to be 2.3%. The limited amount of data makes it unreliable for distribution fitting on the length of the uncertainty. Therefore, we asked production planners to give estimates on the distribution of CRD date changes. The combination of the sparsely available data and the input of the production planners led to the discrete piece-wise uniform distribution of CRD date changes that can be seen in Figure 4.7b. Here; integer values in the interval [-36,-23] account for 10% of all changes; integer values in the interval [-24,24] for 80%; and integer values in the interval [25,36] for 10%. We set the boundaries of the size of the changes to plus/minus three weeks (36 shifts), since bigger changes are nearly always handled by a *reallocation*.

Figure 4.7

Demand Uncertainty

(a) *Histogram CRD Date Changes*

(b) *Chance of Occurrence of CRD Date Changes*



Note. n = 23, number of bins = 6.

Note. Each bar represents an integer value

Supply uncertainty results in supply delays for the SI start of machines. When there is a delay of supply, the SI start of a machine will have to be postponed to a later date, on which the supplies are planned to be available. We gathered estimates on the chance of occurrence and the size of supply delays from the experience of production planners. The weekly chance of occurrence per planned machine in the blue horizon is set to 2.5%, based on the input of these production planners. The size of the delay in shifts is set to a discrete uniform distribution between 2 and 6 shifts (U{2,6}). When a planned machine in the blue horizon is impacted by the 2.5% chance on supply delay, we draw the size of the delay from the uniform distribution. The drawn delay is added to the initial date of supply delivery. For simplicity, we assume that this initial date is the first planned SI start in the blue horizon, which corresponds to a JIT management of supply. For subsequent supply delays, the new initial date is the initial SI start in the blue horizon plus previous delays. Naturally, supply uncertainty can also impact MB starts, as they also require external supply. However, we plan the MB starts based on the JIT principle plus safety cycle time. This assumption removes the need to model supply delays for MB.

MB uncertainty can be seen as uncertainty in cycle times of the MF, WS, IL, and LE modules. The greedy algorithm plans the four modules based on guideline cycle times and safety cycle time. When a module enters the WIP, we calculate the actual cycle time. We draw the length of the actual cycle time from a fitted probability distribution. We fit this probability distribution on historic cycle time data for each of the four modules and their four different versions. Table 4.1 shows the result of the distribution fitting.

Table 4.1

Distribution Fitting Module Build

Module Type	n	Fitted Distribution	σ	median	μ	Location	SSE	KS test p-value
MF 400	69	Lognormal	0.48	4.51	5.76	0.72	1.89	0.96
MF 860	248	Lognormal	0.52	4.47	6.16	1.04	0.10	0.90
MF 1060	12	Lognormal	0.61	7.04	8.99	0.50	2.34	0.99
MF 1460	46	Lognormal	0.65	3.87	6.79	2.01	0.66	0.99
WS 400	57	Lognormal	0.41	8.10	7.45	-1.35	0.47	0.91
WS 860	254	Lognormal	0.45	7.59	7.55	-0.83	0.07	0.76
WS 1060	10	Lognormal	0.02	199.11	6.96	-192.18	13.96	0.97
WS 1460	43	Lognormal	0.77	5.91	9.95	1.97	0.12	0.95
IL 400	62	Lognormal	0.65	4.56	6.96	1.31	1.21	0.61
IL 860	251	Lognormal	0.40	3.93	4.54	0.27	2.23	0.03
IL 1060	10	Lognormal	0.81	2.99	6.77	2.62	12.37	0.93
IL 1460	39	Lognormal	0.41	12.09	9.65	-3.48	1.04	0.97
LE 400	60	Lognormal	0.71	2.14	3.39	0.63	2.27	0.23
LE 860	229	Lognormal	0.66	1.68	2.71	0.62	4.58	0.00
LE 1060	10	Lognormal	0.31	8.14	6.45	-2.10	13.41	0.96
LE 1460	27	Lognormal	0.51	4.21	5.81	1.00	4.50	0.91

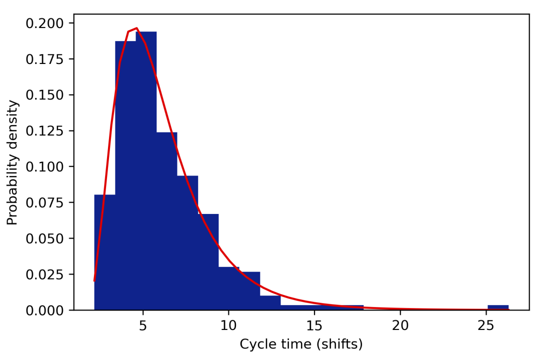
Note. *n= number of data points, σ = standard deviation, μ = mean, SSE = sum squared error, KS test = Kolmogorov-Smirnov test, MF = MetroFrame, WS = WaferStage, IL = Illuminator, LE = Lens.*

The distribution fitting in Table 4.1 is performed on the σ, median, and location parameters. Here, median $= e^{\mu_{normal}}$, the location parameter describes the horizontal shift of the distribution. The mean of the lognormal distribution has been calculated as follows: $\mu = e^{\mu_{normal}+\frac{\sigma^2}{2}} + loc$. The lognormal distribution is the best fitting distribution for most modules, based on the Sum Squared Error (SSE). Furthermore, some module types only have a few historic data points. For these modules we assume the cycle times to be lognormally distributed as well. We expect that the distribution of these modules will be lognormal when more data points were to be gathered. We justify this modelling choice by the fact that the assembly process is roughly the same as those of similar modules, for which the cycle times do follow a lognormal distribution. Figures 4.8a and 4.8b show the fitting of a lognormal distribution on the cycle time data for both a large (a) and small (b) sample. The remainder of the plots can be found in Appendix A.

Figure 4.8

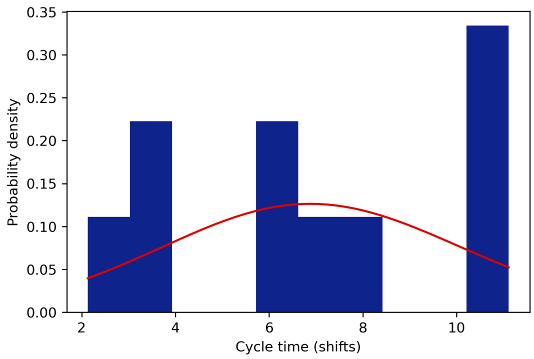
Module Build Uncertainty

(a) *Lognormal Distribution Fitting MF 860*



Note. $n = 248$, *number of bins* $= 20$, *SSE* $= 0.10$.

(b) *Lognormal Distribution Fitting WS 1060*



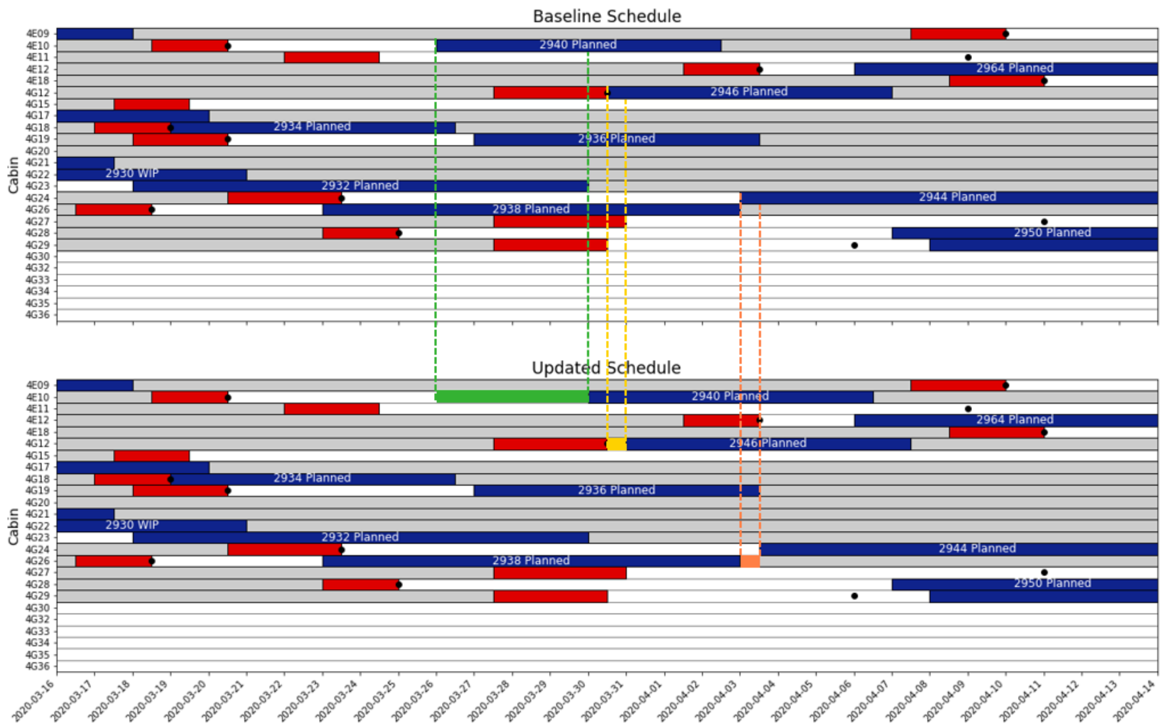
Note. $n = 10$, *number of bins* $= 10$, *SSE* $= 13.96$.

Due to the assumption that all probability distributions are lognormal, the fitted distribution in Figure 4.8b does not look like a typical lognormal distribution. This is explained by the location parameter for this distribution in Table 4.1, which shifts the distribution 192.18 shifts to the left (location = -192.18). Furthermore, we apply the one-sample KS test to test whether the historic data could have been drawn from the fitted lognormal probability distribution. Here, the null hypothesis is that the historic data is drawn from the fitted distribution. From Table 4.1, we see that 14 out of the 16 distribution have a p-value above 0.05. For these distributions we can conclude that we cannot reject that the historic data could have been drawn from the fitted distribution. This is an additional yet small confirmation that the lognormal distributions is a good distribution for estimating the MB cycle times. When a module enters the WIP, its actual cycle time is drawn from the fitted distributions. If the drawn value is negative or above the chosen upper limit of 1.5 $\cdot$ highest cycle time in historic data, we draw again. We set this upper limit to prevent the small chance of drawing an unrealistically large cycle time from the corresponding lognormal distributions. We round the drawn cycle time up towards the nearest integer number of shifts. If the drawn cycle time of any of the four modules exceeds the guideline cycle time plus safety cycle time, the corresponding machine SI start will be postponed by at least the following amount of shifts: MB postponement = max(actual CT_i − guideline CT_i − safety CT_i), for i = MF,WS,IL,LE. If the actual cycle time of all four modules of a machine is smaller than the guideline cycle time plus safety cycle time, the SI could be preponed by the following amount of shifts: MB preponement = min((guideline CT_i + safety CT_i) − actual CT_i), for i = MF, WS, IL, LE.

The final step of the greedy algorithm is the ***Reschedule Uncertainty*** step. In this step, we reschedule the planned machines in the blue horizon, according to the uncertainty that has been generated during the current week. For the rescheduling, we apply the complete rescheduling method. Complete rescheduling reschedules all tasks that have not been processed so far, including those that are not affected by the disruption (Abumaizar & Svestka, 1997). The authors found that the complete rescheduling method has greater computational complexity than other methods that only consider a subset of the jobs to be rescheduled. Still, we opt for this method in our greedy algorithm. We feel that this method best works for the production planning environment within ASML. In this context, machine orders that are affected by uncertainty can have unforeseen impacts on the timing of other machines in the blue horizon. These unforeseen effects are amplified by the fact that machine orders can be both pre- and postponed due to MPS sequence changes. Furthermore, the complete rescheduling method is suitable, since ASML would like to assembly as many machines as possible to serve the demand, that is greater than ASML's production capacity. To achieve this, every order should be checked on possible pre- or postponements in the rescheduling step. Similar to the Schedule New Machines step, the Reschedule Uncertainty step schedules the machine orders against several constraints. The (1) *Cabin Type*, (2) *Cabin Empty*, (3) *Maximum Starts per Day*, (4) *Maximum Starts per Shift*, and (5) *Operator Capacity* constraints from the Schedule New Machine step are also present in the Reschedule Uncertainty step. However, the latter step has four additional constraints: (6) *MPS Start*; machines cannot start earlier than the first shift in their MPS week, because this date is used company-wide to plan different aspects, such as external supply or sales reports, (7) *Module Build*; SI starts must account for the newly generated MB uncertainty, (8) *Module Build Earliest Start*; sets a maximum on the preponement of SI starts to prevent MB starts being pushed into the past, and (9) *Supply*; SI starts must account for the newly generated supply uncertainty. In the Reschedule Uncertainty step, it is possible that SI starts are being pushed outside of the blue horizon, due to occurrences of (large) delays. Figure 4.9 shows the baseline- and updated schedule after uncertainty occurred. Note that the schedules do not look as clean as in Figures 4.3, 4.4, 4.5, and 4.6, as we did fill the schedule at the start of the simulation run that yields Figure 4.9.

Figure 4.9

Example of a Baseline Schedule and Updated Schedule



Note. *Blue = SI, grey = SP, red = PP, dots = cabin empty, green = 6 shift delay machine 2940, yellow = 1 shift delay machine 2946, orange = 1 shift delay machine 2944.*

For the development of the greedy algorithm, we made several assumptions. An overview of these assumptions can be found in Table 4.2.

Table 4.2

Model Assumptions

	Assumption	Comment
1	Machine orders planned in the *Fill Up Schedule* step are not vulnerable to uncertainty. These orders are included in rescheduling decisions though.	*The Fill Up Schedule* step aims to provide the greedy algorithm with a starting schedule that is as realistic as possible. To this end, we used historic data on actual cycle times of these orders, which already includes uncertainty.
2	Uncertainty outside the blue horizon is handled outside the blue horizon.	Uncertainty that occurs just prior to the blue horizon could impact rescheduling decisions inside the blue horizon. We assume that these types of uncertainty are solved in the inputs of the model.
3	The cycle times of the machines are deterministic.	Uncertainty in the cycle times of the machines lies outside of the scope of this research.
4	There is no demand uncertainty in the arrival of machine orders.	The MPS is known with substantial accuracy is as realistic as possible. To this end, we used 18 months ahead.
5	Machines cannot start before the first shift in their MPS week.	This date is used company-wide for all sorts of planning activities. In practice, it might exceptionally occur that this assumption does not hold.
6	Only the SI is constrained with regards to operator capacity. SP and PP are not capacity constrained.	Operator capacity mainly impacts SI starts. SP and PP capacity problems are generally solved by buffers in cycle time.
7	The SI operator capacity constraint is a maximum value of simultaneous machines in the SI stage.	In practice, the operator capacity constraint is based on the amount of operators present each shift.
8	Supply delays for machines are assumed to follow a discrete uniform distribution (U{2,6}).	Based on experience of production planners.
9	The initial date on which supply is scheduled is the first planned SI start in the blue horizon.	In practice, the initial date is the first day of the MPS week. However, the estimates given by the production planners are based on the first SI start, as this is how they experience the supply delays that they have to handle.
10	CRD date changes for machines are assumed to follow a discrete piece-wise uniform distribution (Figure 4.7b).	Based on experience of production planners and available historic data.
11	There is no tooling constraint on the work floor.	The tooling availability rarely causes delays in the TF.
12	The probability distribution for modules with limited data points is lognormal.	Based on similar module types having the same lognormal distribution as well.
13	MB starts are planned based on the JIT principle with additional safety cycle time.	This simplification has been approved by experienced employees of the production planning department.
14	When a module is in the WIP and the corresponding SI start gets delayed due to other reasons, the module is finished as planned and is stored in a infinite buffer.	The JIT planning of MB is not impacted by the MB buffer capacity. This is confirmed by experienced production planners.
15	The laser, other modules, and submodules are always on time for the machine start.	These generally do not pose a problem for the assembly process of the machines.
16	The upper limit for drawing cycle times from the fitted lognormal distributions for MB is 1.5 · highest recorded cycle time value in the historic data.	The upper limit is set to prevent the small chance of drawing an unrealistically large cycle time value from the fitted lognormal distributions.

4.1.1 Model Implementation

In order to answer the research questions, we have to simulate the model. We implemented the greedy algorithm in Python 3.8. A simplified version of the pseudo code for the greedy algorithm, as described in the previous section, is given in Figure 4.10. Here, the blue line numbers represent the Schedule New Machines step, the green line numbers the Generate Uncertainty step, and the orange line numbers the Reschedule Uncertainty step. The elaborate pseudo code can be found in Appendix B.

Figure 4.10

Simplified Pseudocode Greedy Algorithm

```
Require: set of sorted machine jobs M, set of cabins C, set of machine data for filling up the schedule
F, empty set used to generate the planning in the blue horizon P, empty set used to generate the
rescheduled planning in the blue horizon R
1:  Generate timeline: 2 shifts per day from Monday through Friday, 1 shift per day on Saturday and
    Sunday, exclude holidays
2:  Fill Up Schedule: add jobs to P that are in WIP or planned in first 3 weeks of horizon prior to the
    start of the first planning cycle
3:  Define start- and end week (start and end) for analysis
4:  for week in [start, end]:
5:    set status = WIP in P for jobs where start SI in week-1
6:    set status = finished in P for jobs where end CT in week-1
7:    for job in P with status = WIP:
8:      set IRD = end CT in P
9:      set GSD = max(IRD, CRD)
10:   end for
      ### Schedule New Machines ###
11:   for job in M with MPS week = week+3:
12:     for shift in week+3:
13:       for cabin in C:
14:         if (1) Cabin Type, (2) Cabin Empty, (3) Maximum Starts per Day,
            (4) Maximum Starts per Shift, (5) Operator Capacity constraints = OK:
15:           add job to P, such that:
              job number = job, cabin assigned = cabin, status = Planned,
              start SI = shift, start SP = shift + CT SI, start PP = start SP + CT SP,
              start safety = start PP + CT PP, end CT = start safety + safety CT
              start MF = shift – CT MF – safety CT MF, start WS = shift – CT WS – safety CT WS
              start IL = shift – CT IL – safety CT IL, start LE = shift – CT LE – safety CT LE
16:         end if
17:       end for
18:     end for
19:     if job not added to P:
20:       MPS week of job = MPS week of job + 1 week
21:     end if
22:   end for
      ### Generate Uncertainty ###
23:   for MF, WS, IL, LE where start SI in week:
24:     Generate MB Uncertainty
25:   end for
26:   for job in P where status = Planned:
27:     Generate Supply Uncertainty
28:   end for
29:   for job in P where status = Planned:
30:     Generate Demand Uncertainty
31:   end for
```

```
32:   sort jobs in P according to new MPS sequence as set by Demand Uncertainty
      ### Reschedule Uncertainty ###
33:   add jobs with status = WIP or status = Finished to R
34:   for rjob in P where status = Planned:
35:     for shift in [week, end]:
36:       for cabin in C:
37:         if (1) Cabin Type, (2) Cabin Empty, (3) Maximum Starts per Day,
38:         (4) Maximum Starts per Shift, (5) Operator Capacity, (6) MPS Start, (7) Module Build,
            (8) Module Build Earliest Start, (9) Supply constraints = OK:
39:           add job to R, such that:
              job number = rjob, cabin assigned = cabin, status = Planned,
              start SI = shift, start SP = shift + CT SI, start PP = start SP + CT SP,
              start safety = start PP + CT PP, end CT = start safety + safety CT,
              start MF = shift – CT MF – safety CT MF, start WS = shift – CT WS – safety CT WS,
              start IL = shift – CT IL – safety CT IL, start LE = shift – CT LE – safety CT LE
40:         end if
41:       end for
42:     end for
43:   end for
44:   save copy of P for current week
45:   save copy of R for current week
46:   P = R
47: end for
```

Note. blue line numbers = Schedule New Machines step, green line numbers = Generate Uncertainty step, orange line numbers = Reschedule Uncertainty step.

4.2 Data Collection

In order to run and verify the model, as proposed in Chapter 4.1, we gathered data. The required data can be grouped into the following categories: job-, cabin-, constraint-, uncertainty-, MB-, and verification data. Below, we outline the different data sources and the data cleaning process.

We retrieved most of the data from ASML's *'Machine History'* data set (Figure 4.11). This set contains daily timestamped machine information for all the machines that have been assembled in the TF, including the XT machines (n = 2267 total machines, n = 1107 XT machines). Unfortunately, no timestamps are made during weekend days. Per machine the information includes, but is not limited to: a Work Breakdown Structure (WBS) element number and sequence number to identify the individual machine and its machine type; the machine status; the MPS start week, that shows in which week the machine was supposed to start according to the MPS schedule; dates on which the SI and PP were started and finished; the CRD date; and the cabin number in which the machine has been assembled and tested. We filter the data set to only include the relevant and complete data on XT machines between 2019 Q3 and 2021 Q2 (n = 273 machines). We choose this interval, because (accurate) data on the machine level is available in this period across the different data sources. The period is also representative of the current market in which ASML operates, where demand for the XT machines is larger than ASML's production capacity. We cut off the machine data after 2021 Q2, as it deviates too much from data in ASML's regular way of working for it to be included in the research. The deviation resulted from internal problems at ASML after the opening of its new warehouse in July 2017. Next, we use the SI and PP start- and end dates to calculate the SI, SP, and PP cycle times. Cycle times for regular XT machines lie between 2.75 and 12.5 weeks. Cycle times for special machines, such as prototypes, lie between 14.75 and 66 weeks. Note that these cycle times are often larger than the length of the blue horizon (4 weeks). We employ the resulting data to generate the list of machines (i.e. jobs) that the model uses as input to its scheduling mechanism (n = 273). We also create a second list from the *'Machine History'* data set, that is used to fill up the production schedule with jobs, prior to the jobs that the first run of the model schedules. This second list contains all machines that were in the WIP somewhere between 2019 Q3 and 2021 Q2 (n = 287). Furthermore, we utilize the data set to explore feasible values for the Operator Capacity constraint by computing the mean- and maximum amount of machines that were simultaneously in the SI stage.

Figure 4.11

Snippet from the Machine History Dataset

Timestamp	WBS	Sequence Number	Machine Type	Status	MPS Week	SI Start	SI Finish	PP Start	PP Finish	CRD Date	IRD	Cabin
3/31/2020	XT400L-2020	1234	XT:400L	blue horizon	2015	2014.3E	2015.4E	2018.4E	2019.2E	2016	2020.1	
4/1/2020	XT400L-2020	1234	XT:400L	blue horizon	2015	2014.3E	2015.4E	2018.4E	2019.2E	2016	2020.1	
4/2/2020	XT400L-2020	1234	XT:400L	blue horizon	2015	2014.3E	2015.4E	2018.4E	2019.2E	2016	2020.1	4G23
4/3/2020	XT400L-2020	1234	XT:400L	blue horizon	2015	2014.3E	2015.4E	2018.4E	2019.2E	2016	2020.1	4G23
4/4/2020	XT400L-2020	1234	XT:400L	blue horizon	2015	2015.1E	2016.1E	2018.7E	2019.5E	2016	2020.1	4G23
4/5/2020	XT400L-2020	1234	XT:400L	blue horizon	2015	2015.1E	2016.1E	2018.7E	2019.5E	2016	2020.1	4G23
4/6/2020	XT400L-2020	1234	XT:400L	SI	2015	2015.1L	2016.1L	2019.1E	2019.6E	2016	2020.1	4G23
4/7/2020	XT400L-2020	1234	XT:400L	SI	2015	2015.1L	2016.1L	2019.1E	2019.6E	2016	2020.1	4G23
4/8/2020	XT400L-2020	1234	XT:400L	SI	2015	2015.1L	2016.1L	2019.1E	2019.6E	2016	2020.1	4G23
4/9/2020	XT400L-2020	1234	XT:400L	SI	2015	2015.1L	2016.1L	2019.1E	2019.6E	2016	2020.1	4G23
4/10/2020	XT400L-2020	1234	XT:400L	SI	2015	2015.1L	2016.1L	2019.1E	2019.6E	2016	2020.1	4G23
4/11/2020	XT400L-2020	1234	XT:400L	SI	2015	2015.1L	2016.1L	2019.1E	2019.6E	2016	2020.1	4G23
4/12/2020	XT400L-2020	1234	XT:400L	SI	2015	2015.1L	2016.1L	2019.1E	2019.6E	2016	2020.1	4G23
4/13/2020	XT400L-2020	1234	XT:400L	SI	2015	2015.1L	2016.1L	2019.1E	2019.6E	2016	2020.1	4G23
4/14/2020	XT400L-2020	1234	XT:400L	SI	2015	2015.1L	2016.3L	2019.1E	2019.6E	2016	2020.1	4G23
4/15/2020	XT400L-2020	1234	XT:400L	SI	2015	2015.1L	2016.3L	2019.1E	2019.6E	2016	2020.1	4G23
4/16/2020	XT400L-2020	1234	XT:400L	SP	2015	2015.1L	2016.3L	2019.3E	2019.6E	2016	2020.1	4G23
4/17/2020	XT400L-2020	1234	XT:400L	SP	2015	2015.1L	2016.3L	2019.3E	2020.3E	2016	2020.3	4G23
4/18/2020	XT400L-2020	1234	XT:400L	SP	2015	2015.1L	2016.3L	2019.3E	2020.3E	2016	2020.3	4G23
4/19/2020	XT400L-2020	1234	XT:400L	SP	2015	2015.1L	2016.3L	2019.3E	2020.3E	2016	2020.3	4G23
4/20/2020	XT400L-2020	1234	XT:400L	SP	2015	2015.1L	2016.3L	2019.3E	2020.3E	2016	2020.3	4G23
4/21/2020	XT400L-2020	1234	XT:400L	SP	2015	2015.1L	2016.3L	2019.3E	2020.3E	2016	2020.3	4G23

Note. Manually generated data

From the *'Machine History'* data set the Weekly Operational Planning Alignment (WOPA) data set is made. The *'WOPA'* data set is similar to the *'Machine History'* data set, but timestamped only once per week (i.e. the *'WOPA'* data set is a subset of the *'Machine history'* data set). We make use of the *'WOPA'* data set for the verification of the model. The verification requires the planned SI start of each individual order the first week it enters the blue horizon (the fourth week from present day). For each individual XT machine order that has been planned inside the blue horizon between 2019 and 2021 (n = 402) , we select these planned SI starts from the *'WOPA'* data set. By setting the interval between 2019 and 2021, we make sure that all orders that the model simulates can be verified. The 'WOPA' data set also contains comments on why certain XT jobs have been pre- or postponed. One of the reasons being priority setting by the sales department (n = 20). The production planners also manually constructed a list, between March 2020 and July 2021, that contains XT machines that were involved in sequence changes due to priority setting by the sales department (n = 18). The union of these two sources serves as input to the estimation of the parameters for the demand uncertainty (n = 28).

We estimate parameters for the MB uncertainty by using both the *'Norm Review'* database and start- and end dates of each individual module in SAP (ASML's ERP system) between June 2016 and July 2021. The *'Norm Review'* database contains cycle time and labor hour information for each individual module (n = 412, 563, 471, 468 for MF, WS, IL, LE). The time period of the data differs from that of the machine data. After June 2016, ASML's TF started working according to the Lean factory principles. Up until July 2021 (the opening of the warehouse), cycle times for the modules have been reasonably consistent, due to no significant changes in their assembly process. We filter incorrect and missing data from both data sets (n = 4, 168, 79, 101 for MF, WS, IL, LE). Furthermore, we exclude mismatches between SAP and *'Norm Review'* data (n = 26, 18, 19, 14 for MF, WS, IL, LE), as well as orders where the documented labor hours are at least 2.5 times above or below the target amount of labor hours (n = 6, 13, 11, 26 for MF, WS, IL, LE). These orders signal an incorrect way of data recording. This results in four data sets including 376, 364, 362, and 327 modules for the MF, WS, IL, and LE work centers respectively. Finally, we transform the cycle times, that are expressed in days, into cycle times that are expressed in shifts. In this transformation, we consider the planning structure of the different module work centers (e.g. one shift per day versus two shifts per day). Furthermore, we check whether any weekends (maximum one shift per weekend day) or holidays (no shifts on holidays) lie between the starting- and end times from SAP.

We could not find the remaining input data for the model in existing data sets within ASML. Therefore, we gathered this data through a combination of information in ASML's internal network and experienced employees with relevant domain knowledge. We sourced a complete list of available XT cabins (n = 25) and each cabin's compatible XT machine types in the internal planning environment that the production planners use. Data on supply uncertainty is dispersed across different departments within ASML, each having different data structures. Therefore, we cannot draw coherent estimates of the supply uncertainty from these datasets within the time window of the Thesis. We also sourced values of the maximum amount of starts per day and week; guideline cycle times for the different modules of MB; and safety times for the different modules of MB through the responsible production planners and the documents that they use in their daily work.

4.3 Model Verification

In this section, we assess the validity of the proposed greedy algorithm. The outcome of the verification will help in determining the extent to which the insights, gained from the analysis of the model, are relevant for the production planning department of the TF. We compare the scheduled SI starts of the model against the scheduled SI starts from historic data. The uncertainty that we generate in the model is random. Thus, we cannot verify the *Reschedule Uncertainty* step of the greedy algorithm against historic data, and therefore we exclude it from the verification of the model. Since we exclude the uncertainty, the scheduled SI starts of each machine will remain the same for the weeks that the machine is in the blue horizon. Without uncertainty, this period is four weeks. Additionally, we do not allow the algorithm to reschedule the machines that have been planned in the *Fill Up Schedule* step. In the analysis of the model, we do allow these machines to be rescheduled, but in the verification we keep the filled up schedule true to the historic data. By doing so, we allow for better verification of the scheduled SI starts after the filled up schedule.

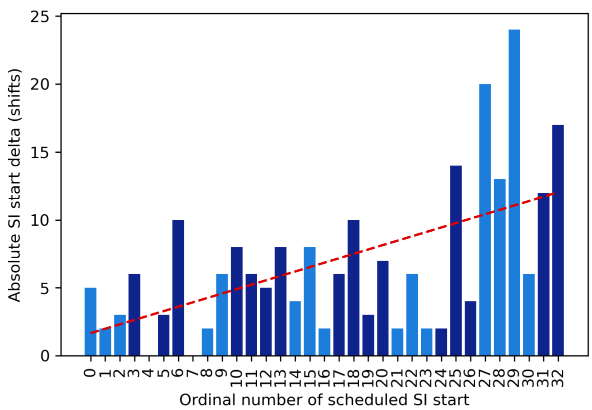
Before we start the verification, we have to decide which historic data we use as our benchmark. We can compare the greedy algorithm's SI starts against: (1) the historic planned SI starts when the machines entered the blue horizon or against (2) the historic actual SI start when the machine entered the WIP. There is no definite best choice for this matter. When excluding the uncertainty from the model, the model's planned SI start is the same as the model's actual SI start. Intuitively, comparing these model SI starts against the actual SI starts in the historic data makes sense. However, the actual historic SI start has been impacted by the real world uncertainty that occurred in the blue horizon. This real world uncertainty is less present in the planned SI starts when the machine entered the blue horizon. On the other hand, we use actual historic cycle times for filling up the schedule and planning the new orders in the verification. In practice, these cycle times were not known exactly when the machine entered the blue horizon. Here, we have to decide whether the cycle time uncertainty of the machines or the rest of the uncertainty in the blue horizon impacts the planned SI starts more. Based on input of production planners, we decide to compare the greedy algorithm's planned SI starts against the historic planned SI starts when the machine entered the blue horizon.

A second decision we have to make is on the value for the *Operator Capacity* constraint for different time periods in the verification. To help make this decision, we simulate the first eight planned machines for different periods and for different values of the capacity constraint. We compare the simulated SI starts against the historic planned SI starts when the machines entered the blue horizon. From this comparison, we compute the average of the absolute difference between the SI starts. We choose the first eight planned machines, since this represents at least two weeks of scheduling for nearly every period between Q3 2019 and Q2 2021. We consider two weeks as a sufficient base for determining the best value for the capacity constraint. We sample eleven periods between week 26 2019 and week 22 2021, with a ten week interval between each, to cover the entire interval between Q3 2019 and Q2 2021. We derive initial guesses for the Operator Capacity value by computing the maximum and average amount of machines that were simultaneously in the SI step from the SI Start and SI Finish timestamps in the *Machine History* data set (Figure 4.11). The maximum value is 11 machines and the average value 3.4. Here, the average value gives us a better estimate than the maximum value, as in the real world the SI can be put on hold when there are insufficient operators available. Hence, the high maximum value. From the results, we find that, generally speaking, a value of 3 for the *Operator Capacity* constraint yields the lowest average absolute difference between SI starts for 2019 and a value of 4 the lowest for 2020 and 2021. The increase from 3 to 4 can also be explained by the real world data. For example, the number of weekly machine starts has increased steadily between the last two quartiles of 2019 (1.96), 2020 (2.63), and the first two quartiles of 2021 (3.35). The bottleneck of the machine assembly process in the TF is mostly determined by the amount of qualified operators. Between 2019 and 2021, the amount of operators for the SI step has also increased.

We perform the verification of the scheduling mechanism of the greedy algorithm with the design choices from the previous paragraph. The error measure we adopt for this verification is the absolute SI start difference between the model SI starts and the historic SI starts when the machines entered the blue horizon. For example, Figure 4.12 shows the results of the verification for the planned starts in the first ten weeks after the start of the greedy algorithm, beginning in week 2 of 2021.

Figure 4.12

Verification of SI Starts

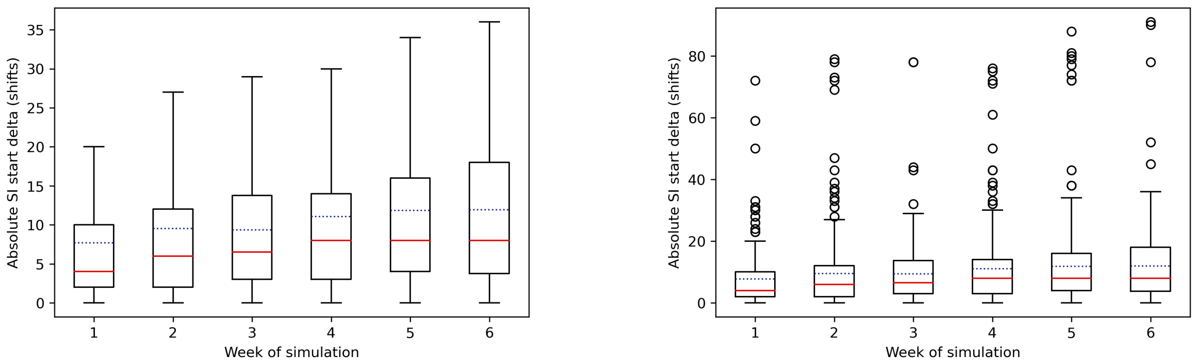


Note. Starting point is week 2 2021, each cluster of bars represents starts planned in the same week.

From Figure 4.12, we see that the absolute SI start difference increases the further the simulation runs into the future. We expected this behavior, because the historic data includes uncertainty which the modeled SI starts do not account for. The further the simulation runs in the future, the more uncertainty is accumulated on this historic data and the larger the difference with the model's planned starts. We repeated this simulation 105 times, where each simulation starts in one of the 105 consecutive weeks between Q3 2019 and Q2 2021. We summarize the results of these simulations in the boxplots shown in Figure 4.13a (without outliers) and 4.13b (with outliers). Here, the first six weeks (e.g. the first six clusters in Figure 4.12) of scheduled orders in the 105 simulations are shown in the boxplots. For example, the sixth week on the x-axis of Figures 4.13a and 4.13b denotes the sixth cycle of the greedy algorithm in which the SI starts are planned in the fourth week of the blue horizon.

Figure 4.13

Boxplots of Verification between Q3 2019 and Q2 2021
(a) *Without Outliers* **(b)** *With Outliers*



Note. Red line = median, blue dotted line = mean, box extends from first quartile to third quartile, whiskers extend from the box by 1.5 times the inter-quartile range, n = 183, 246, 270, 267, 277, 280 for weeks 1, 2, 3, 4, 5, 6.

From Figure 4.13a we see that the average behavior of increased differences holds for the 105 simulations. Furthermore, we learn from Figure 4.13a that the differences of the SI start in the first couple of cycles of the greedy algorithm remain under a week (12 shifts) for about three quarter of the scheduled machine starts. Still, there are many outliers as shown in Figure 4.13b. Possible explanations for the (large) differences are: incomplete, erroneous and/or outdated SI start-, MPS-, or cycle time data; scheduling of special orders; uncertainty that is accounted for in the historic SI start data, but not in the modeled SI starts; simplifications and assumptions made in the greedy algorithm, for example the *Operator Capacity* constraint; and human decision making that is excluded in the greedy algorithm, for example deviations from standard procedures. Given the possible explanations of the (large) differences, we conclude that the scheduling mechanism of our greedy algorithm is fairly accurate. We consider mismatches between SI starts of under a week acceptable in an uncertain environment where guideline cycle times of the machines range between four to ten weeks. While the modeled SI starts should remain fairly close to the reality, the point of our analysis is to show the relative impact of rescheduling rather than perfectly scheduling SI starts. The results of the verification should be considered when deriving insights from the results of the analysis of the model. Appendix

C shows the results of the verification when comparing the model SI start against the actual historic SI start rather than against the historic SI starts when the machines entered the blue horizon.

4.4 Analysis

4.4.1 Performance Measures

In order to provide an answer to the research question *"How do timing plan changes inside the frozen horizon impact production planning?"*, we define six KPIs. Since we are dealing with an empirical study within ASML, these KPIs have to be in line with ASML's context and data. Therefore, these performance measures allow us to gain insights into plan changes for both the literature and ASML. In this study, we take a comprehensive stance towards plan changes. Therefore, we will not study the direct impact of plan changes on the defined KPIs, but rather the impact of uncertainty, that causes these plan changes, on the KPIs.

The first three KPIs are defined to give insights into the ***schedule instability*** that arises from the demand, supply, and MB uncertainty (sub research question 2.1). Schedule instability is the difference between schedules of two subsequent planning cycles. In the proposed greedy algorithm, this is reflected by the difference between the baseline schedule and updated schedule for each week in the analysis horizon. Logically, in a week with no uncertainty there is no difference between the schedules. In our research, we modify and extend the schedule instability measure as defined by Wu et al. (1993). Their measure included: the starting time deviations between the new schedule and the original schedule, and a measure of the sequence difference between the two schedules. We add a third measure that quantifies the percentage of orders in the blue horizon that are impacted by uncertainty. These three measures give us insights in how uncertainty causes plan changes. Formulas 4.1 and 4.2 show how the (1) average weekly percentage of orders in the blue horizon, that are impacted by uncertainty, is computed. We consider a planned machine order to be impacted when its SI start has changed. Here, we use SI to denote the start of the SI, n_j as the number of machines in the blue horizon in week j (i.e. in the baseline or updated schedule) with status Planned, and w as the number of weeks in the horizon of the analysis.

$$impacted = \begin{cases} 1, & SI_{baseline} - SI_{updated} \neq 0 \\ 0, & SI_{baseline} - SI_{updated} = 0 \end{cases} \tag{4.1}$$

$$\text{Percentage Impacted} = \frac{1}{w} \sum_{j=1}^{w} \sum_{i=1}^{n_j} \frac{1}{n_j} \cdot impacted_i \cdot 100 \tag{4.2}$$

Formula 4.3 shows how the (2) average amount of SI start deviation in shifts is calculated for the machines that are impacted by uncertainty.

$$\text{SI Start Deviation} = \frac{\sum_{j=1}^{w} \sum_{i=1}^{n_j} |SI_{baseline,i} - SI_{updated,i}|}{\sum_{j=1}^{w} \sum_{i=1}^{n_j} impacted_i} \tag{4.3}$$

Formulas 4.4 and 4.5 show how the (3) total number of machines over the entire horizon of the analysis, that have been impacted by a sequence change, is calculated.

$$sequence\_change = \begin{cases} 1, & sequence\_number_{baseline} - sequence\_number_{updated} \neq 0 \\ 0, & sequence\_number_{baseline} - sequence\_number_{updated} = 0 \end{cases} \tag{4.4}$$

$$\text{Sequence Deviation} = \sum_{j=1}^{w} \sum_{i=1}^{n_j} sequence\_change_i \tag{4.5}$$

We also considered the Levenshtein distance as the measure for *Sequence Deviation*. The Levenshtein distance between two sequences is the minimum number of insertions, substitutions or deletions required to change one sequence into the other. However, we dropped this metric, since it is more useful for the production planners to know the total amount of machine orders that are included in a sequence change. This can be explained by the fact that the production planners have to update the planning of all these planned machines manually.

We also use the first three KPIs to gather insights that can help answer the sub-research questions that addresses the difference between preponing and postponing machine orders (sub-research question 4) and the relation between the timing of a plan change and its impact (sub-research question 5). The answers to these sub-question require the impact of individual plan changes though. Therefore, we adapt KPIs 1,2, and 3 to only look at the impact on the baseline schedule in the single week j where the plan change occurred. In order to prevent intercorrelation in the impact of multiple plan changes in a single week, we only analyze these adapted KPIs for weeks where a single plan change occurred. Formulas 4.6, 4.7, and 4.8 show the adapted KPIs.

$$\text{Percentage Impacted}_j = \frac{\sum_{i=1}^{n_j} impacted_i}{n_j} \cdot 100 \tag{4.6}$$

$$\text{SI Start Deviation}_j = \sum_{i=1}^{n_j} |SI_{baseline,i} - SI_{updated,i}| \tag{4.7}$$

$$\text{Sequence Deviation}_j = \sum_{i=1}^{n_j} sequence\_change_i \tag{4.8}$$

The next set of KPIs aim to give insights into how uncertainty impacts ***on-time start performance***. Note that the corresponding sub-research question (2.2) reads: *"How does uncertainty impact the on-time delivery performance?"*. While most of the research and industry uses its delivery performance as a KPI, we opt for start performance as our measure. We make this choice for two reasons. Firstly, our model assumes deterministic cycle times, thus the on-time start and finish performance of the machine orders in the simulated model tell the same story. Secondly, ASML actively uses the SI starts to assess the performance of the TF. They set goals based on the amount of SI starts and use these starts for the calculation of quarterly financial figures. To elaborate, the customer deadlines are often not feasible due to demand being greater than the production capacity. Therefore, basing the performance of the model on these deadlines is not insightful. At ASML, an SI start is considered on time if the SI starts inside the machine's MPS week. To assess the on-time start performance we define two KPIs: the (4) percentage of machines that were started in their MPS week, and the (5) average amount of SI start deviation from the last shift in the MPS week, for the machines that were started later than their MPS week. Formulas 4.9 and 4.10 show how the percentage of machines stared in their MPS week is calculated. Formulas 4.11 and 4.12 show the calculation of the average amount of SI start deviation from the MPS week. Here, m is used to denote the number of machines with status WIP or Finished out of all the scheduled machines in the horizon of the analysis (= number of machine starts).

$$in\_week = \begin{cases} 1, & week\_actual\_SI - MPS\_week = 0 \\ 0, & week\_actual\_SI - MPS\_week \neq 0 \end{cases} \tag{4.9}$$

$$\text{Percentage in MPS week} = \frac{\sum_{i=1}^{m} in\_week_i}{m} \cdot 100 \tag{4.10}$$

$$SI\_delta = \begin{cases} SI - last\_shift, & SI > last\_shift \\ 0, & SI \leq last\_shift \end{cases} \tag{4.11}$$

$$\text{MPS week Deviation} = \frac{\sum_{i=1}^{m} SI\_delta_i}{\sum_{i=1}^{m} 1 - in\_week} \tag{4.12}$$

The last KPI helps to answer how uncertainty impacts the production output (sub research question 2.3). In the context of ASML, we measure the production output by the ***number of SI starts*** over a period of time. Once again, we opt for measuring the start performance rather than the output performance, for the same reasons given in the previous paragraph. We define the KPI that measures this as follows: (6) the total number of machines with status *WIP* or *Finished* out of all the scheduled machines in the horizon of the analysis. We also use this measure in the calculation of the other KPIs, denoted as m.

4.4.2 Parameters

We have to decide on the value of several parameters that the greedy algorithm uses as input. Firstly, we decided to set the starting and ending week of the horizon of the analysis to week 27 2019 and week 26 2021 respectively. These weeks mark the start of Q3 2019 and the end of Q2 2021. In this interval, sufficient data is available to run the model plus this interval is representative for the market where ASML currently operates in. Secondly, we set the maximum SI starts per shift and day both to 1. This basically implies that there is a maximum of one machine start per day. We choose this value in collaboration with the production planners of the TF. They state that the value of 1 has been used for the entirety of the chosen horizon of analysis. Thirdly, we set the safety cycle time of the MF, WS, IL, and LE modules to 6, 12, 6, and 6 shifts respectively. While the amount of safety time which the production planners use in the different module work centers has varied quite a bit over the last years, these are the most up-to-date guidelines. Fourthly, we set the *Operator Capacity* constraint to 4. This implies that there is a maximum of 4 orders that can simultaneously be in the SI stage. In the Model Verification section (4.3) we found that the best fitting values for this constraint are 3 for 2019, and 4 for 2020 and 2021. We opt for a single value to lower the computational burden of the analysis. We choose the value 4 over 3, since three quarter of the analysis horizon is optimal under the value 4, against one quarter under the value 3.

The remaining parameters have to do with the uncertainty that we introduce in the model. In order to examine how uncertainty impacts production planning and processes, we manipulate the parameters of the demand-, supply-, and MB uncertainty. In Section 4.1 we estimated parameters for these three types of uncertainty based on historic data and input from production planners. These estimations are based on the actual uncertainty levels that ASML experienced over the analysis horizon. We manipulate these estimates to investigate the changes in impact when these actual uncertainty levels increase or decrease. Table 4.3 shows the resulting uncertainty levels with the manipulated parameters. Here, the *medium* level refers to the current levels of uncertainty at ASML. The remaining parameters remain as estimated in Section 4.1.

Table 4.3

Uncertainty Levels

	Level			
	no	low	medium	high
Demand Uncertainty (piecewise discrete Uniform	chance = 0	chance = 0.0115	chance = 0.023	chance = 0.046
Supply Uncertainty (discrete Uniform)	chance = 0	chance = 0.0125	chance = 0.025	chance = 0.05
MB Uncertainty (lognormal)	chance = 0	chance = 1 $\sigma_{new} = \sigma/2$	chance = 1 σ	chance = 1 $\sigma_{new} = \sigma \cdot 2$

Note. chance = weekly chance of occurrence per planned machine/module, σ = standard deviation, MB = Module Build.

For the *Demand Uncertainty* and *Supply Uncertainty* in Table 4.3, we manipulate the weekly chance of occurrence by a factor of 2 between the *low*, *medium*, and *high* levels. These uncertainty levels give us insights into what the change in impact is when uncertainty would be twice as low or high as current levels of uncertainty (*medium*). We choose not to increase or decrease boundary values of the size of the uncertainty in shifts for the *Demand Uncertainty* and *Supply Uncertainty*. Increasing the positive or negative size of *Demand Uncertainty* is not useful for analysis, since CRD date changes bigger or smaller than the current maximum and minimum values (see Section 4.1) are handled via reallocations rather than via timing plan changes. Similarly, we choose not to change the boundary values of the *Supply Uncertainty* as production planners mention that the size of the supply delay is fairly consistent. We modeled the *MB Uncertainty* differently than the other two uncertainties in our model. Since every module is vulnerable to cycle time uncertainty, we set the weekly chance of occurrence per module to 1 for all three uncertainty scenarios. Here, we choose to manipulate the standard deviation of the fitted lognormal distributions by a factor of 2. By changing the standard deviation, the fitted distributions move closer to, or further away from their mean. Therefore, the drawn cycle time values from these distributions are more likely to be either closer to the mean (*low*) or further away from the mean (*high*). In the *high* level, this results in more postponements or possible preponements of SI starts due to MB uncertainty. The opposite holds for the *low* level. We choose a factor 2 for impacting the standard deviation as this seems reasonable given the context. How this manipulation impacts the percentage of drawn cycle times that are on time for the SI start is shown in Appendix D.

The final set of parameters that we set, are the random seeds for generating the three types of uncertainty. We choose the Common Random Numbers (CRN) method for comparing the different scenarios of the analysis. Glasserman and Yao (1992) state that variance reduction is guaranteed whenever changing the order of some events does not radically change the evolution of the system. This is the case for most standard queueing systems with a single class of jobs and a first-come-first-served (FCFS) discipline. Our greedy algorithm also schedules a single class of jobs, based on the FCFS policy, therefore we can use CRN to reduce variance in generated uncertainty between different analysis scenarios. Furthermore, we feel that the amount of runs we simulate per scenario in the analysis, does not make up for the variance in the generated uncertainty when not using CRN.

Chapter 5

Results

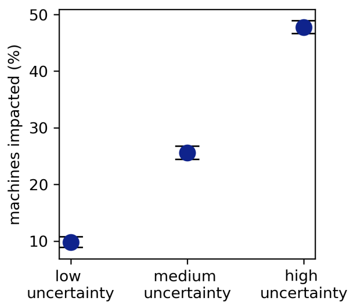
5.1 Schedule Instability

The results of the first three KPIs give us insights into how uncertainty impacts schedule instability. The results of the three KPIs are shown in Figure 5.1a, 5.1b, and 5.1c. To retrieve these results, the demand, supply, and MB uncertainty are set at the low, medium, and high levels. Here, each scenario is run 20 times with different random seeds.

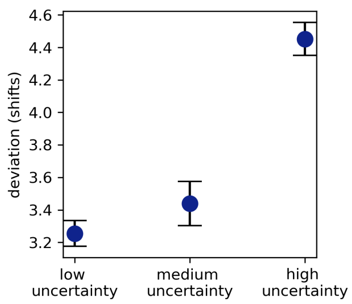
Figure 5.1

Schedule Instability

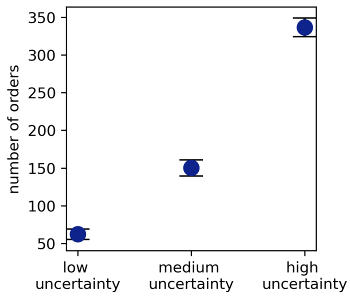
(a) *Percentage Impacted*



(b) *SI Start Deviation*



(c) *Sequence Deviation*



Note. Number of runs per scenario = 20, blue dots = μ, error bars are set at the 95% confidence interval.

Figure 5.1a shows the results of the average weekly percentage of planned machines impacted by plan changes in the blue horizon, as defined in Formulas 4.1 and 4.2. This statistic shows us the percentage of planned SI starts that have changed between the baseline and updated schedules. Figure 5.1b reports on the average absolute number of shifts deviation for the planned machine orders that are impacted by uncertainty in the blue horizon, as defined in Formula 4.1 and 4.3. In other words, Figure 5.1a shows how many orders are impacted, and Figure 5.1b by how much those orders are impacted. From the results we learn that the amount of machines that are impacted by uncertainty roughly decrease or increase by a factor 2 when going from the medium level to the low or high level respectively (Figure 5.1a). Furthermore, we see that the average amount of shifts these impacted orders deviate between the baseline and updated schedule also increases with the uncertainty level (Figure 5.1b). Note that the decrease in deviation due to less uncertainty is lower than the increase in deviation due to more uncertainty. So when uncertainty increases, both the quantity of plan changes and the size of plan changes increases between the baseline- and updated schedules.

Figure 5.1c tells us the total amount of planned machine orders in the horizon of the analysis for which the sequence changed in the blue horizon, as computed by Formulas 4.4 and 4.5. Note that the sequence of a planned machine order can change multiple times when it is in the blue horizon. We see that the amount of orders that change sequence over the entire analysis horizon increases with the level of uncertainty as well (Figure 5.1c). Dividing the 62.35 (low), 150.15 (medium), and 336.65 (high) values for the amount sequence changes by the analysis horizon length of 105 weeks yields us the average amount of weekly sequence changes. This results in 0.59 (low), 1.43 (medium), and 3.21 (high) sequence changes per week. This indicates that for both medium and high levels of uncertainty weekly changes to the MPS sequence have to be investigated and made.

Summarizing, the results of the schedule instability KPIs show us how the amount of instability increases with the amount of uncertainty. Notably, both the percentage of orders impacted by uncertainty (Figure 5.1a) and the amount of orders included in sequence changes (Figure 5.1c) increase substantially with uncertainty. The amount of shifts deviation between schedules (Figure 5.1b), seems to be impacted less by uncertainty. However, there seems to be exponential growth when uncertainty increases.

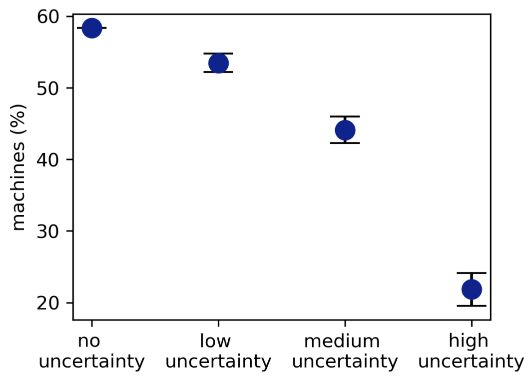
5.2 On-time Start Performance

The next two KPIs report on the on-time start performance of our greedy algorithm. Figure 5.2a shows the results computed by Formulas 4.9 and 4.10. It shows us the percentage of machines in the analysis horizon for which the actual SI start lies inside its MPS week. Figure 5.2b depicts the results of the fifth KPI, that measures the average amount of SI start deviation from the last shift in the MPS week, for those machines that were started later than their MPS week. Formulas 4.9, 4.11, and 4.12 give the underlying calculations. As expected, we see a decline in the percentage of orders planned inside their MPS week when uncertainty increases (Figure 5.2a). The drop in performance is quite significant. Compared to the no uncertainty statistic, the amount of machines planned in their MPS week in the low, medium, and high uncertainty scenario drop with 4.88, 14.25, and 36.52 percentage points respectively. Interestingly, the average percentage of orders planned inside their MPS week when no uncertainty is present is fairly low at 58.37%. Upon closer investigation, we learn that this is caused mainly by a backlog in the scheduling of machine starts that starts in week 16 of 2020 and last all the way through week 5 of 2021. This simulated backlog is also roughly present in the historic data on weekly planned SI starts, where planned machine orders between these dates remain longer in the blue horizon than the regular four weeks. Furthermore, we see that amount of shifts that machines start too late increases with uncertainty (Figure 5.2b). For both KPIs we see diminishing returns, as increases in uncertainty have a bigger negative impact on system performance than decreases in uncertainty have a positive impact, compared to the medium level.

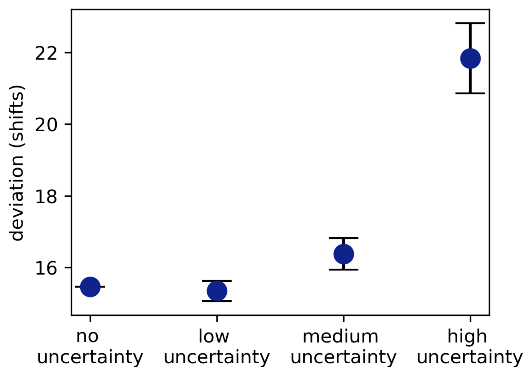
Figure 5.2

On-time Start Performance

(a) *Percentage in MPS Week*



(b) *MPS Week Deviation*



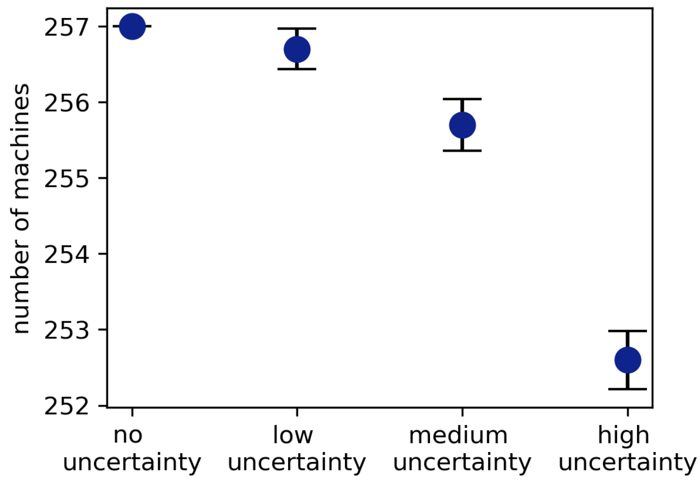
Note. Number of runs per scenario = 20, blue dots = μ, error bars are set at the 95% confidence interval.

5.3 Number of Starts

The sixth KPI measures how the production output over the analysis horizon, as measured in machine starts, is impacted by uncertainty. Figure 5.3 shows the results of the analysis. We learn that, generally speaking, the amount of machine starts over the analysis horizon decrease with the amount of uncertainty. Once again we see diminishing returns, where increases in uncertainty impact the model more negatively than decreases in uncertainty impact it positively, compared to the medium level. The difference in the number of machines that are started between no and high uncertainty is only small: 257 versus 252.6 machines respectively. However, the machines that ASML sell are costly and complex, so every extra machine that can be built is significant.

Figure 5.3

Total Number of Machine SI Starts



Note. Number of runs per scenario = 20, blue dots = μ, error bars are set at the 95% confidence interval.

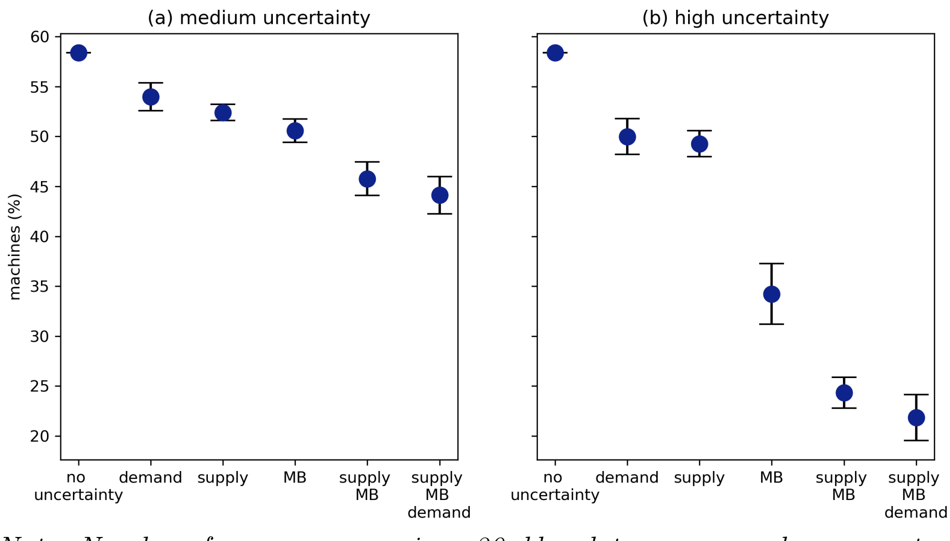
5.4 Different Types of Uncertainty

We are also interested in how different types of uncertainty impact the KPIs. To this end, we analyze the difference between scenarios in which different types of uncertainty are present. The uncertainty levels that we analyze, are the medium and high levels, since these allow us to investigate the (small) differences between individual uncertainty types well. For each of the sub-figures in Figures 5.4, 5.5, and 5.6, we only include the uncertainty that is denoted on the x-axis with the amount of uncertainty that is indicated above the sub-figures. The remainder of the uncertainty is set to 0. We include both a scenario with all three types of uncertainty included (*supply MB demand*) and a scenario that only excludes demand uncertainty (*supply MB*). We include the latter in the analysis, since employees in the production planning department state that adapting the production planning to demand uncertainty requires a significant amount of manhours. However, the impact that demand uncertainty (or rather the exclusions of it) has on production output and on-time performance is not yet clear. Take note that it is difficult to compare the individual types of uncertainty in the sub-figures, as different probability distributions are used with different parameters that impact the model differently. However, the medium level uncertainty is closest to the real world uncertainty, and therefore we regard this as a significant base to draw conclusions from. Furthermore, we add the high level of uncertainty in the analysis, as the individual differences between the scenarios are greater, thus allowing us to better draw conclusions.

Figure 5.4 shows the percentage of machines that were started in their MPS week. In both Figure 5.4a and 5.4b, we see that the more types of uncertainty we include in the model, the less we score on this measure. On average, demand and supply uncertainty seem to impact the on-time performance less than MB uncertainty. This could also be explained by the fact that the MB uncertainty is manipulated differently than the other two (Section 4.4.2). Furthermore, we see that by excluding demand uncertainty (supply MB vs. supply MB demand), the average percentage of on-time starts improves by 1.65% (from 44.11% to 45.76%) under medium uncertainty (Figure 5.4a) and improves by 2.50% (from 21.84% to 24.34%) under high uncertainty (Figure 5.4b).

Figure 5.4

Percentage of Machines Started in their Planned MPS Week

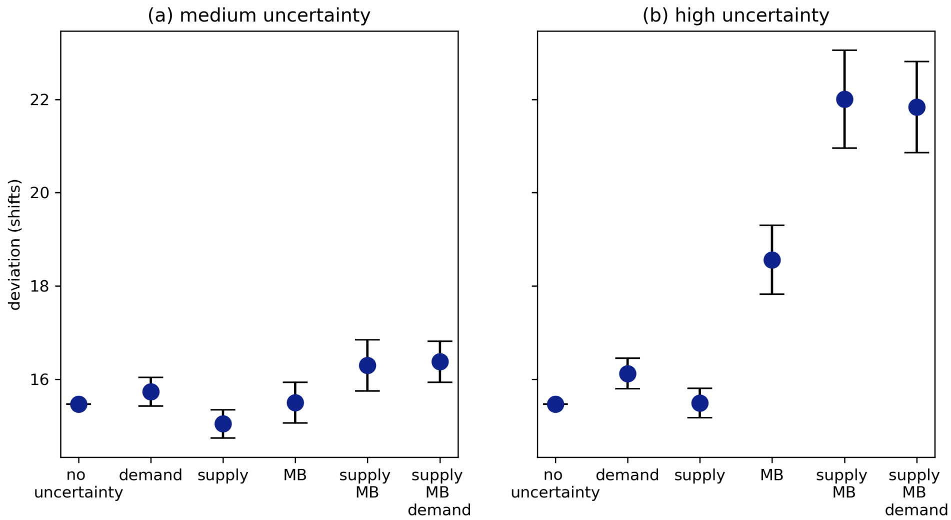


Note. Number of runs per scenario = 20, blue dots = μ, error bars are set at the 95% confidence interval.

Figure 5.5 shows the average amount of SI start deviation from the last shift in the MPS week, for the machines that were started later than their MPS week. In Figure 5.5a, we see that the amount of shifts that machine starts deviate from the last shift of the MPS week changes only marginally when analyzing different types of uncertainty under medium uncertainty. For high uncertainty (Figure 5.5b), both supply and demand uncertainty do not increase much when compared to medium uncertainty. This is likely the result of the manipulation of supply and demand uncertainty. Namely, only the chance of occurrence is manipulated and not the length of delays. The scenario with only MB uncertainty does increase significantly between the medium and high levels of uncertainty. Once again, this can be explained by the manipulation of the uncertainty, as MB uncertainty does increase in length between medium and high levels. Furthermore, the scenarios with multiple types of uncertainty present (*supply MB* and *supply MB demand*) increase more than the sum of their parts.

Figure 5.5

Average Number of Shifts Deviation from MPS Week

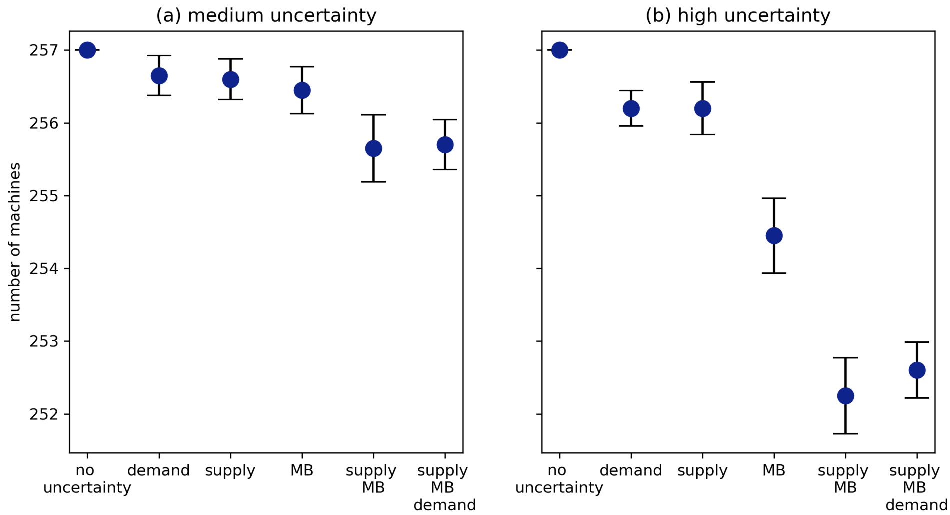


Note. Number of runs per scenario = 20, blue dots = μ, error bars are set at the 95% confidence interval.

Figure 5.6 shows the output performance of the model, expressed in the number of machine SI starts. From both Figure 5.6a and Figure 5.6b, we learn that the amount of machines starts generally improves when excluding different types of uncertainty from the model. This effect is minimal for medium levels of uncertainty (Figure 5.6a), but becomes greater for high levels of uncertainty (Figure 5.6b). Notably, in both sub-figures we see a slight decrease in performance when excluding demand uncertainty (*supply MB demand* vs. *supply MB*). We suspect this is due to the negative demand uncertainty (i.e. preponement requests). Namely, these request can sometimes fill up the freed capacity from postponements that arise from supply, MB, or positive demand uncertainty.

Figure 5.6

Total Number of Machine SI Starts



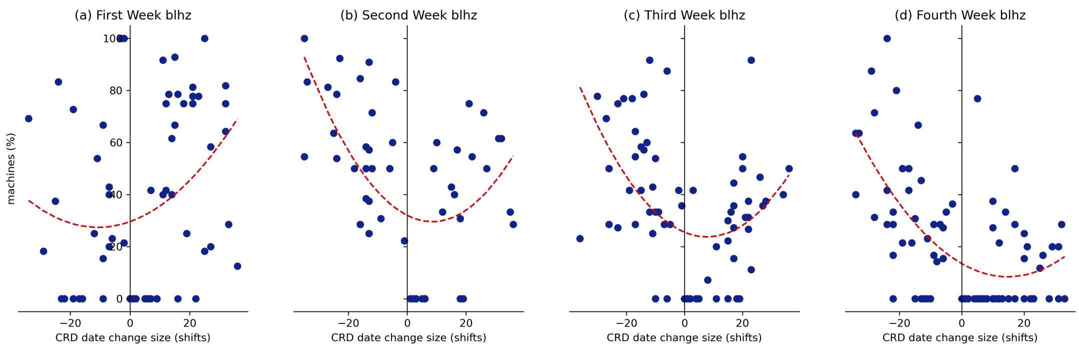
Note. Number of runs per scenario = 20, blue dots = μ, error bars are set at the 95% confidence interval.

5.5 Preponing versus Postponing

Figures 5.7, 5.8, and 5.9 show how preponing and postponing affect the schedule instability KPIs between the baseline and updated schedules. Here, we study demand uncertainty, as this type of uncertainty includes both preponements and postponements. Supply- and MB uncertainty generally lead to postponements, thus we exclude them from this analysis. We split each figure into the four weeks of the blue horizon, as impacts of demand uncertainty are substantially different depending on where they occur in the blue horizon. Furthermore, we only include individual occurrences of demand uncertainty in the results, as we want to prevent intercorrelation in the impact of multiple occurrences of uncertainty. Figure 5.7 shows the percentage of planned machines in the blue horizon that are impacted (Formulas 4.1 and 4.6). Figure 5.8 the total number of shifts SI start deviation between the baseline and updated schedule (Formulas 4.1 and 4.7). Figure 5.9 the total number of machines for which the sequence changed between the baseline and updated schedule (Formulas 4.4 and 4.8).

Figure 5.7

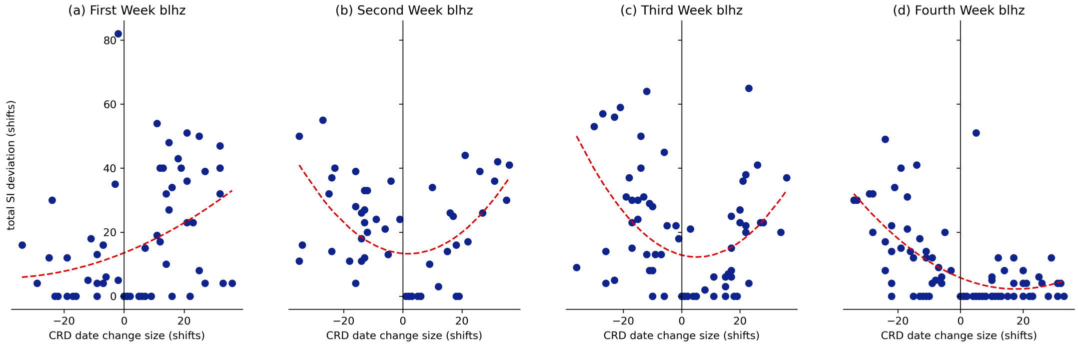
Percentage Impacted



Note. n = 63, 51, 68, 80, blhz = blue horizon, CRD = Customer Requested Delivery.

Figure 5.8

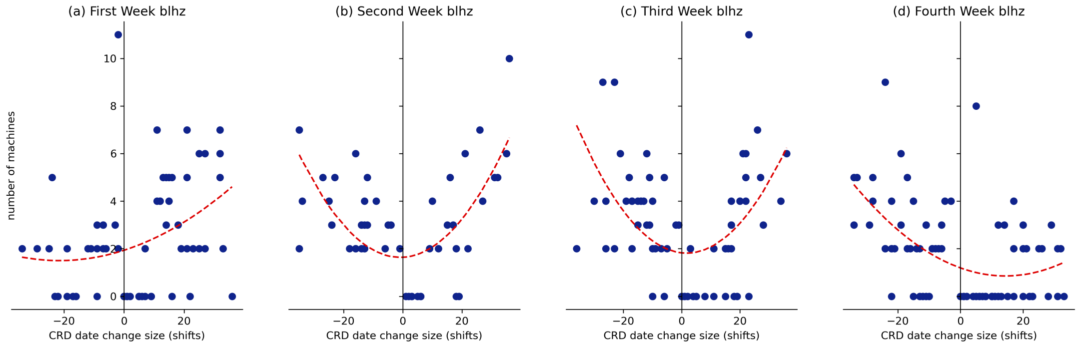
SI Start Deviation



Note. n = 63, 51, 68, 80, blhz = blue horizon, CRD = Customer Requested Delivery.

Figure 5.9

Sequence Deviation



Note. n = 63, 51, 68, 80, blhz = blue horizon, CRD = Customer Requested Delivery.

The general behavior that we observe in the first week of the blue horizon (Figures 5.7a, 5.8a, and 5.9a), is that positive CRD date changes (i.e. a postponement request) impact the baseline schedule more than negative changes (i.e. a preponement request). This is in line with our expectations, as request for preponements of machine orders which are close to their start can generally not be adhered to. In other words, machine starts cannot be rescheduled into the past. We do however, see quite some negative CRD date changes in the first week that do impact the schedule severely. Upon closer investigation, we found multiple reasons for this behavior. Firstly, there are periods where there is only a small amount of planned machines in the blue horizon. This can lead to a seemingly large percentual effect (Figure 5.7a) while the actual amount of machines impacted is only small. Secondly, an error in the input data of a single machine that allowed rescheduling to the past (see the extreme outlier in the first week of Figure 5.8a and 5.9a). Thirdly, a planned machine in the first week can still have up to four planned machines before it, for which the sequence number can be impacted by preponements (see Figure 5.9a).

The general behavior that we observe in the second and third week of the blue horizon (Figures 5.7b/c, 5.8b/c, and 5.9b/c), is represented by the parabolic trendlines. The larger the negative or positive size of the demand uncertainty, the bigger the impact. Here, negative uncertainty results more often in plan changes and these changes are generally more impactful on the baseline schedule. Take note, that the plotted trendlines in the figures do not represent the actual behavior of the demand uncertainty, but merely the general behavior. For example, in the actual behavior, a CRD date change of zero shifts would logically result in zero impact.

The general behavior, that we observe in the fourth week of the blue horizon (Figures 5.7d, 5.8d, and 5.9d), is that negative CRD date changes impact the baseline schedule more than positive changes. This is the opposite behavior present in the first week of the blue horizon.

Remarkably, there are multiple datapoints in Figures 5.7, 5.8, and 5.9 that have zero impact on the baseline schedule. There are several reasons behind this. Firstly, requested changes in the CRD dates are not strictly adhered to. There are multiple constraints present in the greedy algorithm that limit the free rescheduling of the impacted machines. This can lead to orders not being rescheduled at all, hence zero impact. Secondly, some preponement requests in the first week do not result in plan changes as they cannot be rescheduled to the past. Thirdly, postponement requests at the end of the blue horizon do not impact the baseline schedule as they are planned greedily and will not be delayed by the model until new machine orders arrive as input. Fourthly, postponement requests do not impact the schedule if the planned machine has already been planned at a later date, due to a backlog.

5.6 Timing of Uncertainty

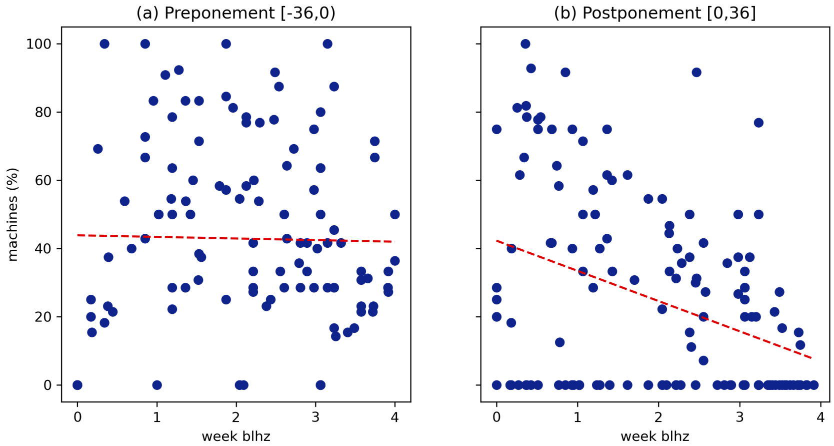
The last part of the analysis will address the impact of the timing of demand uncertainty in the blue horizon on schedule instability. This analysis serves as an extension to the previous section (5.5) by looking more closely at the timing of uncertainty and less at the size of uncertainty. Note that the same set of data points is used between the two analyses. Therefore, the explanation for the data points with zero impact given in Section 5.5 also holds for this part of the analysis. We will only analyze demand uncertainty, as plan changes due to this uncertainty are experienced as the most impactful on the weekly blue horizon schedules, as mentioned by the production planners. Furthermore, MB uncertainty is not fit for this analysis as it only occurs at the beginning of the blue horizon, and supply uncertainty would only allow us to analyze small delays. Moreover, we split the demand uncertainty into preponements (subfigures a) and postponements (subfigures b), as they show differences in impact (see Section 5.5).

Figure 5.10 shows the percentage of planned machines in the blue horizon that are impacted (Formulas 4.1 and 4.6). On the x-axis, we plot the timing inside the blue horizon of the machine that is impacted by uncertainty. In other words, how far away the planned machine is from entering the WIP in weeks. In Figure 5.10b, we see that the impact of positive uncertainty decreases with the week of the blue horizon. The opposite does not hold for the negative uncertainty in Figure 5.10a. We refer to the explanation of why negative CRD date changes at the beginning of the blue horizon do significantly impact the baseline schedule given in Section 5.5.

Figure 5.11 shows the total number of shifts SI start deviation between the baseline and updated schedule (Formulas 4.1 and 4.7). Figure 5.12 the total number of machines for which the sequence changed between the baseline and updated schedule (Formulas 4.4 and 4.8). In both figures, we do see opposite behaviors between negative (Figures 5.11a and 5.12a) and positive (Figures 5.11b and 5.12b) occurrences of CRD date changes. Here, preponements increase in impact when further away from the start of the blue horizon, while postponements decrease in impact when moving away from the start of the blue horizon.

Figure 5.10

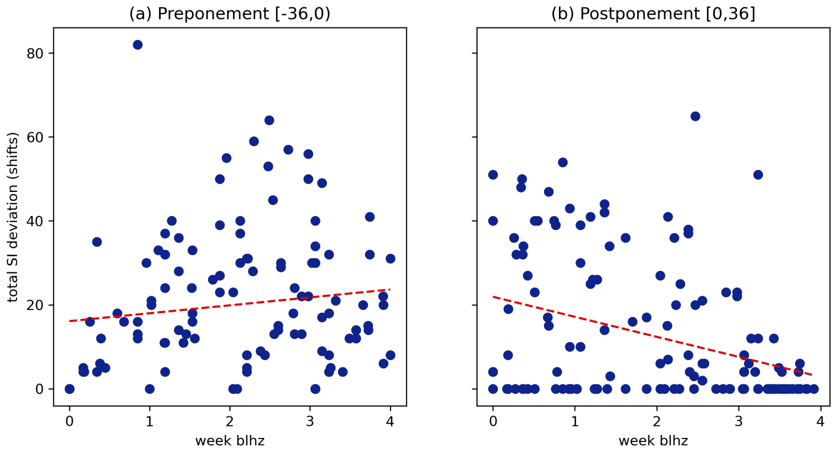
Percentage Impacted



Note. n = 119, 143, blhz = blue horizon.

Figure 5.11

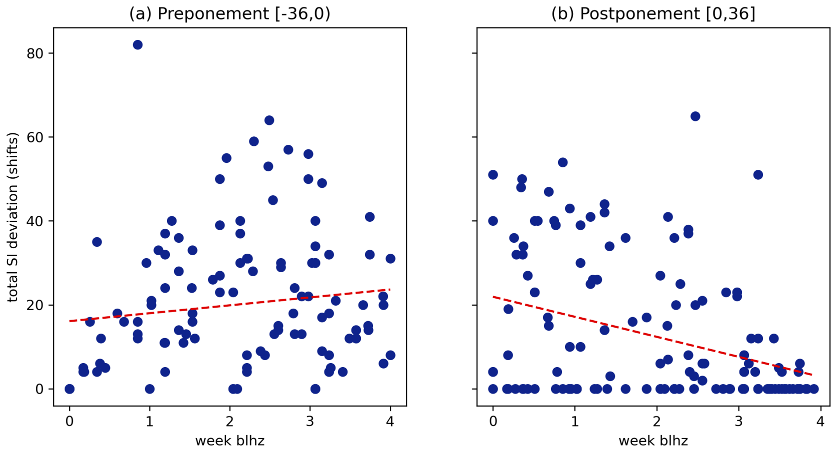
SI Start Deviation



Note. n = 119, 143, blhz = blue horizon.

Figure 5.12

Sequence Deviation



Note. n = 119, 143, blhz = blue horizon.

Chapter 6

Discussion and Conclusion

6.1 Answers to Research Questions

The main goal of this research is to give insights into the hidden costs of late plan changes. Following from this, the main research question reads: *"How do timing plan changes inside the frozen horizon impact production planning?"*. To be able to provide an elaborate answer to this question, we drew several sub-research questions. These sub-questions have guided the analysis of this study and will be answered in the next paragraphs.

The first sub-question reads: *"What types of uncertainty cause these changes?"*. In their review of MRP systems under uncertainty, Koh et al. (2002) classified uncertainty that causes changes in production planning. The authors divide uncertainty into two categories: input and process uncertainty. Here, input uncertainty is further divided into external supply and external demand uncertainty. After thorough investigation within ASML, we adhere to this classification of uncertainty by categorizing the present uncertainty into supply uncertainty, process uncertainty, and demand uncertainty. Here supply uncertainty can stem from both independent companies as well as own production facilities located elsewhere. External demand uncertainty is in the form of customers changing their previously placed orders. Currently, the uncertainty of the quantity of future demand is fairly low in the semiconductor industry, given the fact that the world-wide demand is greater than the present-day production capacity. The main demand uncertainty lies in the configuration and the timing of demand. Note that in the current study, we only investigate the latter. This uncertainty is high, given the continuously evolving and highly complex nature of the industry. The process uncertainty is present at the internal processes of the companies active in this industry, which carries uncertainty due to the complexity of the processes.

The second sub-question reads: *"How does uncertainty impact the schedule instability?"*. From the results, we learn that the higher the level of uncertainty, the more instability is present in the schedules. Here, instability is expressed in the percentage of machines impacted, the amount of machine start deviation, and the amount of sequence changes of machines. We learn that the modelled uncertainty has a great negative impact on schedule stability. For example, the weekly percentage of machines included in plan changes is already significant at low uncertainty, and increases sharply with additional uncertainty (see Figure 5.1a). The sharp increase might be a possible explanation for the negative connotation of schedule instability in the literature that addresses rescheduling of MPS and MRP systems under uncertainty. In this research stream, the general consensus is to eliminate schedule instability (i.e. system nervousness). Furthermore, results show that for medium and high levels of uncertainty, weekly changes to the MPS sequence have to be made. These changes have been shown to be especially troublesome in multi-level production processes, due to their nervousness-inducing behavior (Atadeniz & Sridharan, 2020).

The third sub-question reads: *"How does uncertainty impact the on-time delivery perfor-*

mance?". The results of this research report on the on-time start performance rather than the delivery performance. Due to the assumption of deterministic cycle times, the conclusions from these results are similar to the on-time delivery performance conclusions, which are widely present in the literature. The results of the analysis show that increasing the amount of uncertainty generally decreases the on-time start performance. Furthermore, the drop in performance increases the higher the uncertainty becomes. Once again, we see that increases in uncertainty can lead to drastic decreases in on-time start performance (Figure 5.2a). It is of importance to prevent these decreases, especially in industries similar to the one ASML operates in, where delivery of produced goods is critical. The high and sometimes unrealistic demand requirements are reflected in the results, as on-time start performance is already low when no uncertainty is present.

The fourth sub-question reads: *"How does uncertainty impact the production output?"*. In this research, we expressed this in the number of machine starts over a two year period. While the decrease in the number of machine starts becomes bigger when uncertainty becomes high, the overall decrease remains fairly low. For low levels of uncertainty, this seems in line with the findings of Aytug et al. (2005). They state that rescheduling more frequently is not negatively affecting system performance significantly, but beyond a certain threshold it is not affecting it positively either. However, most of the other findings in our study contradict this, since increases in uncertainty (i.e. more rescheduling) negatively impact the performance. This might be explained by the fact that the focus on uncertainty is extremely narrow in the literature, while this study considers a holistic view of uncertainty. Furthermore, capacity constraints are often not present in the literature on rescheduling (Atadeniz & Sridharan, 2020), but are present in our model. These constraints might tamper with the effectiveness of rescheduling found by Aytug et al. (2005).

The fifth sub-question reads: *"How do the results vary for the different types of uncertainty that cause these changes?"*. Most literature on rescheduling is about providing remedies to uncertainty rather than clarifying the cause-and-effect structure of uncertainty. By analyzing the effects that different types of uncertainty have on system performance within ASML, we aim to add to this literature gap as identified by Aytug et al. (2005), Koh et al. (2002), and Vieira et al. (2003). In our study, it is difficult to compare the relative impact of different types of uncertainty, as they are different in characteristics. Nonetheless, we deem a comparison based on the medium and high levels of uncertainty a solid base for deriving insights. We found that the three individual sources of uncertainty (demand, supply, and process) impact the system performance measures differently in size and variance. Although, generally speaking, their impact behavior is similar. Notably, the negative impact of MB uncertainty increases more than supply and demand uncertainty when increasing the level of uncertainty from medium to high. This effect likely rises from the fact that MB uncertainty is impacted on its length and supply and demand uncertainty on their chance of occurrence. Interestingly, for some measures the sum of the negative impact of the individual uncertainties is greater than the negative impact when all three types of uncertainty are present in the model. This would imply that for some performance measures, there is an interplay between the different types of uncertainties. For example, postponements on a machine due to supply uncertainty, could potentially allow preponements of other machines due to early finishes at previous steps in the process (process uncertainty) or due to demand uncertainty. Furthermore, for some KPIs, there are multiple instances in the data where the negative impact in scenarios with uncertainty is lower than in the scenario without, indicating that some uncertainty can potentially improve system performance. Finally, eliminating demand uncertainty has only a marginal positive effect on two measures of system performance, and a marginal negative effect on the third measure. While these results advocate for allowing demand uncertainty to fulfill customer needs, one must not forget the cost of rescheduling that demand uncertainty entails.

The sixth and seventh sub-questions read: *"What is the difference in impact between prepon-*

ing orders and postponing orders?", and *"Is there a relation between the timing of a timing plan change inside the frozen horizon and its impact?"*. Both these questions seem to have gotten little attention in the literature so far. We aim to add to this scarce literature, by addressing these questions through analysis of demand uncertainty on schedule stability. Namely, demand uncertainty gives us the opportunity to investigate both preponements and postponements. We limit the impact analysis to schedule stability, as we want to investigate individual occurrences of demand uncertainty. These cannot be analyzed over the long run in our model, due to interplay between occurrences of demand uncertainty. Our results show that, at the start of a rolling-horizon schedule, postponements impact the schedule instability more than preponements. The opposite effect holds for the end of the rolling horizon schedule. In the middle of the schedule, the impact increases with the absolute size of the demand uncertainty. Generally, preponements impact the schedule more often and more drastic than postponements. The results for the timing of uncertainty are in line with those of preponement versus postponement. For postponements, the impact becomes larger the closer to the start of the rolling horizon schedule. And for postponements, the impact becomes generally smaller the closer to the start of the rolling horizon.

6.2 Managerial Insights

We derive several insights from the outcomes of our study. While different organizations and industries can have different cause-and-effect relationships (Koh et al., 2002), we believe that most of the insights can be generalized across organizations and industries, especially those that are close in behavior to the semiconductor industry. While most research on uncertainty in production planning is experimental, we performed an empirical study. Therefore, our insights aim to build upon, and challenge current insights by providing a practical analysis of a system under uncertainty.

Firstly, we recommend that the focus within companies, which have an established production process, should lie on preventing more uncertainty, rather than eliminating the current levels of uncertainty. Our results generally show that increases in uncertainty have a bigger negative impact on system performance, than decreases in uncertainty have a positive impact. In other words, decreasing uncertainty has diminishing returns. This effect might be explained by the fact that there seems to be an interplay between the different sources of uncertainty that impact system performance. On the other hand, eliminating uncertainty becomes more attractive the more uncertainty an organization experiences. Therefore, companies should carefully assess their levels of uncertainty to identify potentially substantial gains in system performance. Unfortunately, it proves to be difficult to eliminate uncertainty in practice. This is also the case for ASML, where the factory struggles with tackling the troublesome uncertainty that impacts their production planning. Pujawan and Smart (2012) found from interviews that it is very difficult for companies not to make changes requested by the customer, even though those changes occur in the frozen period. This is very much the case for ASML, which operates in a highly dynamic environment and serves only a small customer base. Therefore, we pose that managers learn to deal with marginal amounts of uncertainty rather than putting an emphasis on removing all uncertainty. This especially holds if uncertainty is inherent to the industry. For example in the semiconductor industry, which handles cutting edge technology. This contradicts the findings of the field-based research on schedule instability by Krajewski et al. (2005). They found that suppliers with higher levels of annual revenue, that produce components with high value and complexity, use uncertainty reducing strategies rather than strategies that help cope with uncertainty. While increases of uncertainty have a negative impact on system performance, a significant hidden impact category is schedule instability. This leads to our next insight.

Secondly, we advocate for the recognition of the cost of rescheduling, especially those that require human intervention. From the results of the impact of uncertainty on schedule instability, we learn that even low amounts of uncertainty lead to very unstable schedules. Furthermore, our results show that due to uncertainty, schedules have to be updated periodically (at least weekly for medium and high levels of uncertainty). Both findings require scheduling interventions that bear cost. Unfortunately, including the cost of rescheduling in complex manufacturing processes has not found much acceptance from the industry, as rescheduling costs are difficult to determine (Atadeniz & Sridharan, 2020). Nonetheless, we feel that tackling this challenge holds invaluable benefits for organizations. Furthermore, the cost of human intervention in rescheduling is absent in the literature. More and more automated systems are used to perform production planning. However, there is still a significant portion of production planning in the industry that is performed manually. This is even the case for large companies such as ASML, where the production planning of the highly complex machines has lots of dependencies and irregularities that require human input. In the literature, most studies focus on the effects of plan changes on system performance, and not on human factors. We pose that the human factors should be included in research on rescheduling as well, to achieve more complete models. There is a limited amount of papers that do include the cost of rescheduling into their model (e.g. Carlson et al., 1979; Ivanov et al., 2017; Kropp et al., 1983; Kropp and Carlson, 1984). In those papers, rescheduling would be permitted, as long as it was economical to do so. However, the cost of rescheduling is limited to adding or cancelling setups. More recently, including the cost of uncertainty has gained momentum under the Disruption Management literature stream. For example, Liu and Ro (2014) included rescheduling cost that consists of rescheduling resources and changing delivery times. We would like to build on this literature stream, by emphasizing that human aspects, such as invested manhours and motivation, can be seriously impacted by uncertainty. In order to assess the human factors that handle the plan changes, appropriate data must be gathered within organizations.

Thirdly, as introduced by the previous paragraph, we endorse the recording of data on uncertainty that impacts production planning and processes. In the current study, we tried to estimate the uncertainty as accurately as possible, based on data. Unfortunately, data on uncertainty was scarce, and therefore qualitative date in the form of experience of production planners was necessary. Nonetheless, we found that the level of uncertainty can have serious impact on system performance. Therefore, to get accurate insights into how uncertainty impacts performance, better data collection is a must. This would allow for models that are closer to the reality. While data collection on schedule changes is a difficult task (Pujawan, 2004), we believe that a clear cause-and-effect structure helps assessing the cost of uncertainty, and ultimately can be taken advantage of to diminish or deal with uncertainty. To help establishing this structure, data on the type of uncertainty and the impact on the production schedule (e.g. size of preponement, postponement, sequence change, etc.) should be recorded. Additionally, as highlighted before, accurate data on invested manhours (e.g. FTE) by the production planning should be collected in parallel. This data can help in getting a grip on uncertainty and could help quantify the cost of uncertainty.

Fourthly, the impacts of uncertainty should be discussed between different departments within organizations and between organizations in the supply chain. It became clear that there are different conclusions in the literature about the effectiveness of rescheduling (Hozak & Hill, 2009). These different conclusions can partly be explained by a misalignment between different parties about rescheduling. For example, it became clear that plan changes often result from a mismatch of interests between the marketing and production departments. Taylor III and Anderson (1979) stated that the conflicting objectives of these departments are largely the result of different evaluative criteria employed. For many organizations, plan changes can be due to unforeseeable causes or choice. Here, unforeseeable causes can be material breakdown, operator absence, material unavailability, etc. Plan changes due to choice can, amongst others, be caused by trying to satisfy changing customer demands late in the process. In this scenario, the customer and sales department would like to reach an agreement. This agreement will likely impact the production department negatively. Although, removing demand uncertainty from our model did not unambiguously increase system performance, it does add to schedule instability. Accordingly, Pujawan and Smart (2012) found that rescheduling open orders to serve customer due dates can in turn lead to less overall profitability. Therefore, we put forward that a comprehensive overview on the impact of uncertainty should be integrated in decision making on plan changes. Here, the tradeoff between the negative impact of uncertainty on the internal production and the benefits of accepting uncertainty should be made. For example, a cost-benefit analysis could be done, which includes the negative impact of uncertainty that can be estimated when a clear cause-and-effect structure is present.

6.3 Limitations

There are several limitations in the current research that might impact the results. The first set of limitations has to do with the uncertainty that is present in the model. In our study, we modelled the scheduling of the machines, and modelled the three types of uncertainty as inputs to the model. For example, both the process uncertainty at MB and supply uncertainty are modelled based on the JIT principle. In practice, MB uncertainty stems from the different planning rules and constraints present at the individual work centers where the modules are assembled. The same holds for the supply and demand uncertainty, behind which entire departments handle the incoming supplies and customer requests. All three of these departments work in close cooperation with the production planning departments. The decision making around uncertainty is a complex and context dependent process that requires inputs from the different departments. In our model the uncertainty is simply fed as input to the production planning department. This can lead to exaggerations of the impact of uncertainty in our model, as in the real world custom solutions can prevent the need for drastic plan changes. Furthermore, supply and demand uncertainty have been estimated with the use of experience of production planners, rather than quantitative data. This might introduce human bias into the model. Lastly, the manipulation and comparison of the different types of uncertainty has its limitations. Due to time constraints, we limited the amount of uncertainty scenarios to three (low, medium, and high). More scenarios would have allowed us to better analyze the behavior of increases and decreases in uncertainty. The comparison of the different types of uncertainty is limited, since they are modelled differently and impact the model differently. A more analogous implementation of the different types of uncertainty would have enabled us to investigate how increases or decreases in uncertainty compare between the individual types.

There are also limitations in the amount of uncertainty included in the model. Although we provide a complete classification of uncertainty within ASML in our study, some uncertainty had to be excluded to keep the size of the model manageable. For example, the model only includes uncertainty of four main modules of the machines. There are also modules that are manufactured at different locations, and many submodules from suppliers. These are assumed to have no uncertainty or to be included in the supply uncertainty. Furthermore, we assumed that internal logistics incur no uncertainty. While the uncertainty that is included in the model has a greater impact on the factory, according to experienced employees, the excluded uncertainty could also impact scheduling. Additionally, the cycle times of the machines are stochastic in practice. Machines in the WIP can be put on hold when, for example, work floor employees call in sick. We assumed deterministic cycle times, and posed a simplified employee capacity constraint. All these exclusions of uncertainty might have changed the results of our analysis, especially since we concluded that there seems to be an interplay between the different types of uncertainty. We expect that additional uncertainty would increase the negative impacts. However, in specific scenarios, it could also increase performance by providing unforeseen flexibility that could help diminish the effects of uncertainty.

Finally, we limit our research by only looking at periods in which the factory operated as usual. In the high tech sector, many technological breakthroughs, unpredictable events (e.g. COVID-19), and restrictions can have disruptive effects on the supply chain. These disruptions have very different effects on system performance than the operational uncertainty that we included in our model. Furthermore, it is likely that there is an interplay between disruption uncertainty and operational uncertainty.

6.4 Future Research Directions

Several interesting future research directions arise from our study. Firstly, one could build on this research by addressing the limitations. Firstly, more consistent implementations of the different types of uncertainty could ensure a better analysis of the differences in impact. By doing so, research could better relate manipulations in uncertainty parameters to differences in impact. Secondly, our research includes multiple types of uncertainty, but some is left out. Future research could address how a more complete inclusion of uncertainty within an organization impacts system performance. By analyzing how different types of uncertainty and combinations of uncertainty impact system performance, additional insights into the holistic behavior of uncertainty could be found. Furthermore, this adds to the mapping of cause-and-effect structures within different organizations and industries. Thirdly, studying uncertainty in different environments (e.g. with or without major disruptions) could provide useful insights into how production processes and planning are impacted. For example, our results imply that changing the size of uncertainty (i.e. more major disruptions) impacts system performance differently than changing the chance of occurrence of uncertainty. Research that studies these different environments and uncertainty types could provide useful insights that could be used to design processes that are robust to different uncertainty environments.

We identified that the cost of rescheduling is hardly recognized in the literature, while in practice the amount of rescheduling activities is heavily impacted by increases in uncertainty. This is an interesting avenue for future research. By investigating a complete overview of the monetary costs and work hours, that are required for plan changes, companies can better decide on which uncertainty to accept and which to prevent or avoid. Furthermore, future research could extend on this study by investigating how different types of uncertainty impact schedule instability. In this research, schedule instability can be linked to the cost of rescheduling to gain insights into how much the cost of rescheduling changes with uncertainty.

In order to generalize the results within ASML further to other companies in similar or different industries, research should be conducted in those contexts. This research should address the cause-and-effect structures present in the specific organizations or industry, as they are likely different from that of the current study. Here, research should not only consider impacts within singular companies, but rather in a supply chain context. This is especially relevant for high tech industries, where supply chain are becoming more integrated over time.

Moreover, research attention should be directed towards ways to integrate uncertainty into the standard processes for handling production. Currently, most focus lies on the development of policies and methods that minimize the amount of plan changes. However, as we see from ASML, plan changes are inevitable in highly complex environments. In this context, plan changes even occur in parts of the process that have explicitly been designed not to allow any changes. Therefore, the focus should not only lie on diminishing uncertainty, but also on how to internalize it. For example, future studies could investigate different levels of time that are allocated to rescheduling within an organization. By studying how these varying levels impact system performance, within a model that considers a holistic overview of all uncertainty, new guidelines for process design could be found. Once again, this future research could benefit greatly from studies that provide ways to estimate the cost of rescheduling.

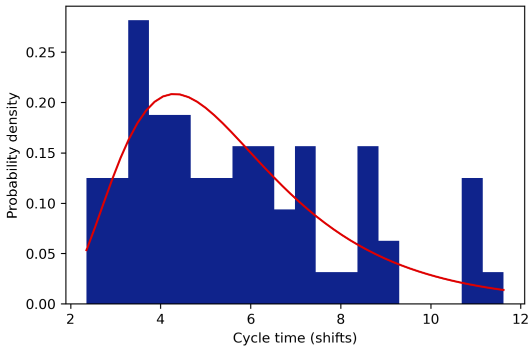
Appendix A

Distribution Fitting Module Build

Figure A.1

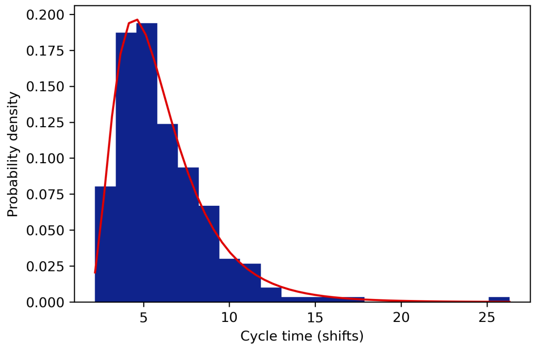
Module Build Uncertainty 1

(a) *MF 400*



Note. number of bins = 20.

(b) *MF 860*

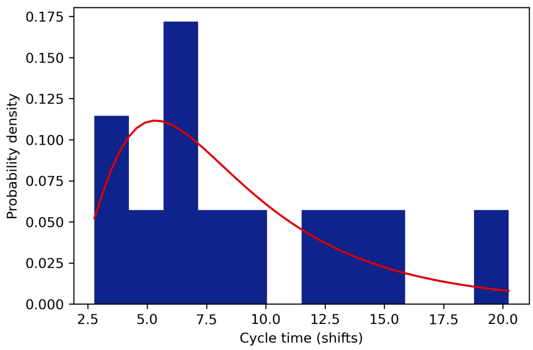


Note. number of bins = 20.

Figure A.2

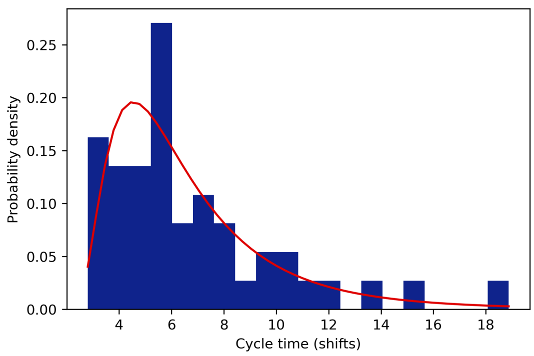
Module Build Uncertainty 2

(a) *MF 1060*



Note. number of bins = 12.

(b) *MF 1460*

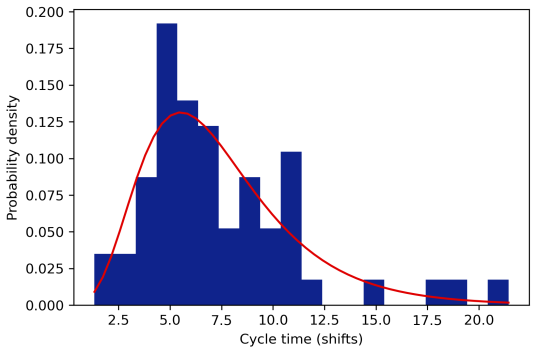


Note. number of bins = 20.

Figure A.3

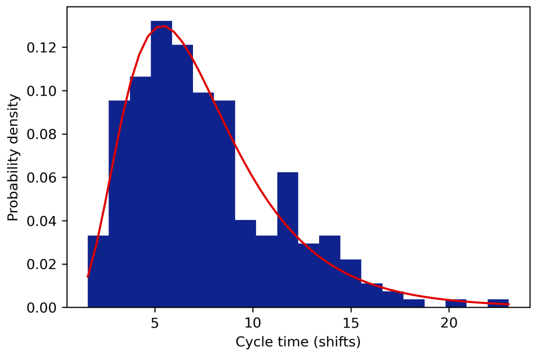
Module Build Uncertainty 3

(a) *WS 400*



Note. number of bins = 20.

(b) *WS 860*

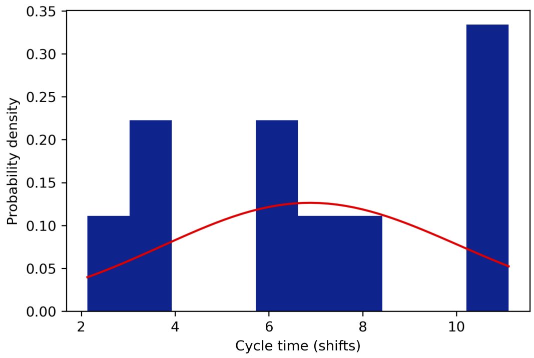


Note. number of bins = 20.

Figure A.4

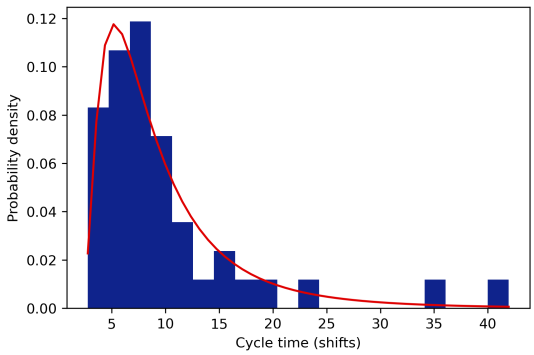
Module Build Uncertainty 4

(a) *WS 1060*



Note. number of bins = 10.

(b) *WS 1460*

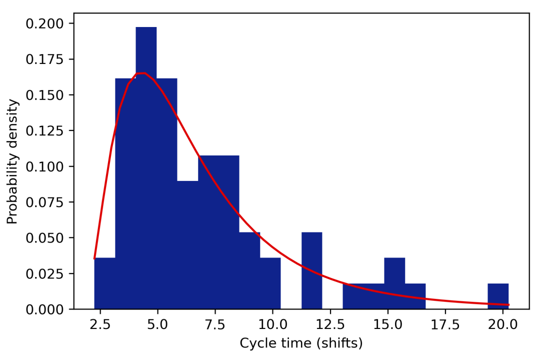


Note. number of bins = 20.

Figure A.5

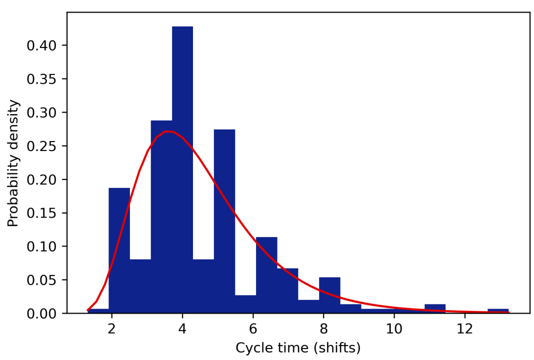
Module Build Uncertainty 5

(a) *IL 400*



Note. number of bins = 20.

(b) *IL 860*

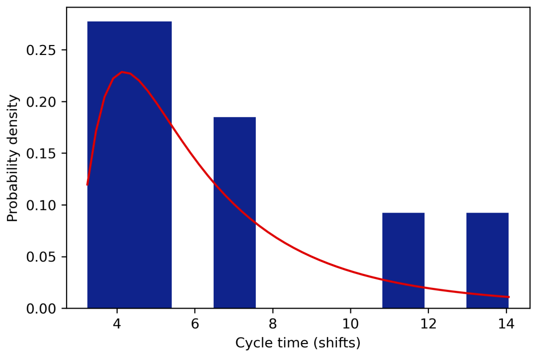


Note. number of bins = 20.

Figure A.6

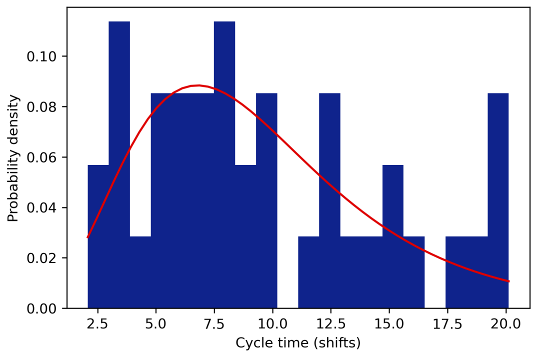
Module Build Uncertainty 6

(a) *IL 1060*



Note. number of bins = 10.

(b) *IL 1460*

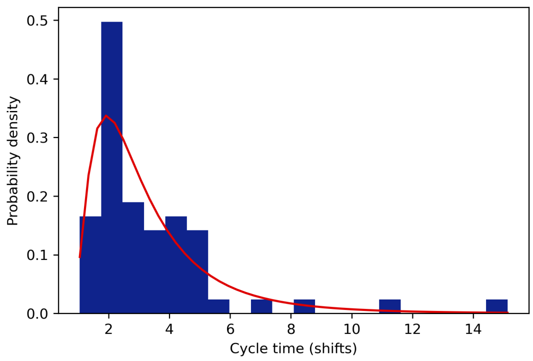


Note. number of bins = 20.

Figure A.7

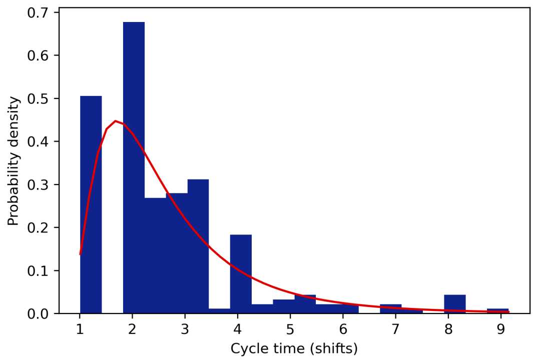
Module Build Uncertainty 7

(a) *LE 400*



Note. number of bins = 20.

(b) *LE 860*

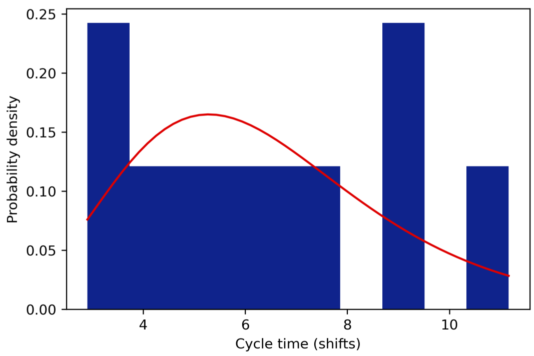


Note. number of bins = 20.

Figure A.8

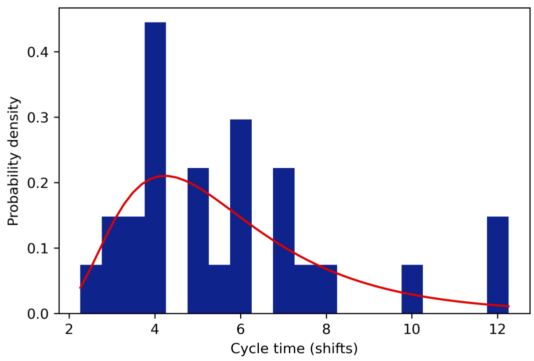
Module Build Uncertainty 8

(a) *LE 1060*



Note. number of bins = 10.

(b) *LE 1460*



Note. number of bins = 20.

Appendix B

Model Implementation

Figure B.1

Elaborate Pseudocode Greedy Algorithm

```
Require: set of sorted machine jobs M, set of cabins C, set of machine data for filling up the schedule
F, empty set used to generate the planning in the blue horizon P, empty set used to generate the
rescheduled planning in the blue horizon R

Generate timeline: 2 shifts per day from Monday through Friday, 1 shift per day on Saturday
and Sunday, exclude holidays
Fill Up Schedule: add jobs to P that are in WIP or planned in first 3 weeks of horizon prior to the
start of the first planning cycle
Define start- and end week (start and end) for analysis
for week in [start, end]:
  set status = WIP in P for jobs where start SI in week-1
  set status = finished in P for jobs where end CT in week-1
  for job in P with status = WIP:
    set IRD = end CT in P
    set GSD = max(IRD, CRD)
  end for
  ### Schedule New Machines ###
  for job in M with MPS week = week+3:
    for shift in week+3:
      for cabin in C:
        constraints = [empty list]
        if cabin type = correct:     >>> constraint (1)
          add OK to constraints
        end if
        if shift >= max(end CT,CRD) of job currently in cabin:     >>> constraint (2)
          add OK to constraints
        end if
        if number of starts per day < max number of starts per day:     >>> constraint (3)
          add OK to constraints
        end if
        if number of starts per shift < max number of starts per shift:     >>> constraint (4)
          add OK to constraints
        end if
        if number of jobs in SI in P in interval [start SI of job, end SI of job] < max jobs SI:
          add OK to constraints     >>> constraint (5)
        end if
        if constraints = [OK,OK,OK,OK,OK]:
          add job to P, such that:
          job number = job
          cabin assigned = cabin
          status = Planned
          start SI = shift
          start SP = shift + CT SI
```

```
            start PP = start SP + CT SP
            start safety = start PP + CT PP
            end CT = start safety + safety CT
            start MF = shift – CT MF – safety CT MF
            start WS = shift – CT WS – safety CT WS
            start IL = shift – CT IL – safety CT IL
            start LE = shift – CT LE – safety CT LE
          end if
        end for
      end for
      if job not added to P:
        MPS week of job = MPS week of job + 1 week
      end if
    end for
    ### Generate Uncertainty ###
    for MF, WS, IL, LE where start SI in week:     >>> MB Uncertainty
      if actual finish not set yet:
         actual cycle time = random variate from fitted lognormal distribution
         actual finish MF, WS, IL, LE = start MF, WS, IL, LE + actual cycle time
      end if
    end for
    for job in P where status = Planned:     >>> Supply Uncertainty
      if random number in [0,1] < supply uncertainty chance:
        supply delay = random variate from discrete Uniform distribution
        supply available = first SI start in blue horizon + previous supply delays + supply delay
      end if
    end for
    for job in P where status = Planned:     >>> Demand Uncertainty
      if random number in [0,1] < demand uncertainty chance:
        CRD date change = random variate from piece-wise discrete Uniform distribution
        CRD date = CRD date + CRD date change in M
        MPS week = MPS week + CRD date change
      end if
    end for
    sort jobs in P according to new MPS week sequence
    ### Reschedule Uncertainty ###
    add jobs with status = WIP or status = Finished to R
    for rjob in P where status = Planned:
      for shift in [week, end]:
        for cabin in C:
          constraints = [empty list]
          if cabin type = OK:     >>> constraint (1)
            add OK to constraints
          end if
          if shift >= max(end CT,CRD) of job currently in cabin:     >>> constraint (2)
            add OK to constraints
          end if
          if number of starts per day < max number of starts per day:     >>> constraint (3)
```

```
        add OK to constraints
      end if
      if number of starts per shift < max number of starts per shift:     >>> constraint (4)
        add OK to constraints
      end if
      if number of jobs in SI in R in interval [start SI of job, end SI of job] < max jobs SI:
        add OK to constraints     >>> constraint (5)
      end if
      if shift >= first shift MPS week:     >>> constraint (6)
        add OK to constraints
      end if
      MB constraints = [empty list]     >>> constraint (7)
      for MF, WS, IL, LE:
        if shift >= actual finish:
          add OK to MB constraints
        end if
      end for
      if MB constraints = [OK,OK,OK,OK]:
        add OK to constraints
      end if
      first MB start = min(start MF, start WS, start IL, start LE)     >>> constraint (8)
      start second week = first shift (week+1)
      if first MB start > start second week:
        earliest possible start = start SI – (first MB start – start second week)
        if shift >= earliest possible start:
          add OK to constraints
        end if
      else:
        add OK to constraints
      if shift >= supply available:     >>> constraint (9)
        add OK to constraints
      end if
      if constraints = [OK,OK,OK,OK,OK,OK,OK,OK,OK]:
        add job to R, such that:
        job number = rjob
        cabin assigned = cabin
        status = Planned
        start SI = shift
        start SP = shift + CT SI
        start PP = start SP + CT SP
        start safety = start PP + CT PP
        end CT = start safety + safety CT
        start MF = shift – CT MF – safety CT MF
        start WS = shift – CT WS – safety CT WS
        start IL = shift – CT IL – safety CT IL
        start LE = shift – CT LE – safety CT LE
      end if
    end for
```

```
    end for
  end for
  save copy of P for current week
  save copy of R for current week
  P = R
end for
```

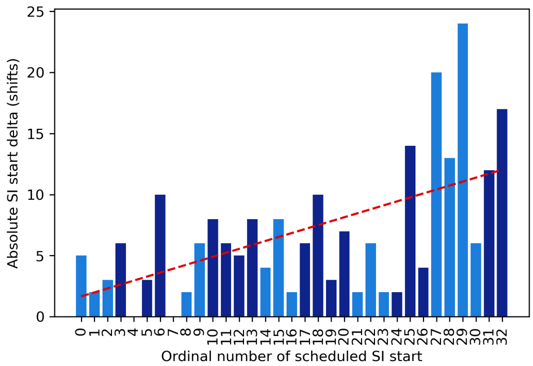
Appendix C

Model Verification

Figure C.1

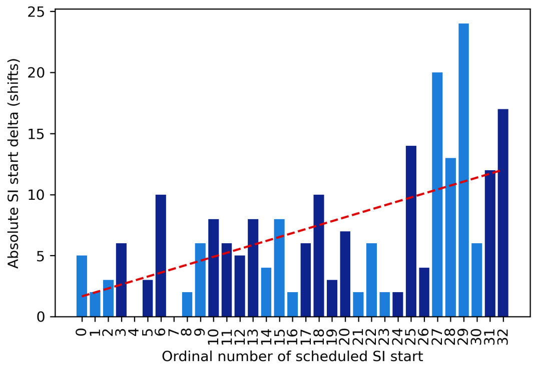
Verification of SI Starts

(a) *Against First Planned SI Start in Blue Horizon*

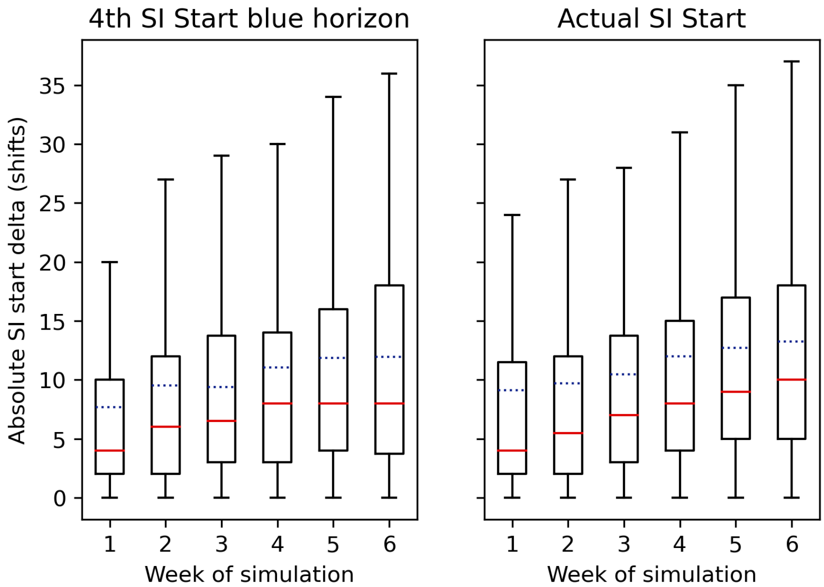


Note. Starting point is week 2 2021, each cluster of bars represents starts planned in the same week.

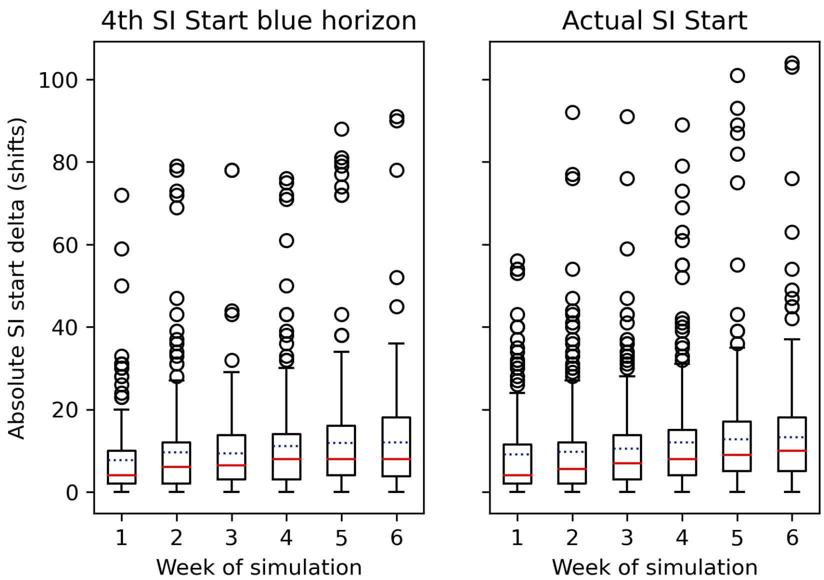
(b) *Against Actual SI Starts*



Note. Starting point is week 2 2021, each cluster of bars represents starts planned in the same week.



Note. Red line = median, blue dotted line = mean, box extends from first quartile to third quartile, whiskers extend from the box by 1.5 times the inter-quartile range, n = 183, 246, 270, 267, 277, 280 for weeks 1, 2, 3, 4, 5, 6.



Note. Red line = median, blue dotted line = mean, box extends from first quartile to third quartile, whiskers extend from the box by 1.5 times the inter-quartile range, n = 183, 246, 270, 267, 277, 280 for weeks 1, 2, 3, 4, 5, 6.

Appendix D

Distribution Manipulation Module Build

Table D.1

Percentage of drawn Random Variates that are On-time

Module Type	Interval [0,guideline CT + safety CT] in shifts	Percentage in interval low	medium	high
MF 400	[0,11]	99.97	95.80	80.71
MF 860	[0,11]	99.91	93.79	78.12
MF 1060	[0,11]	90.46	74.73	62.89
MF 1460	[0,11]	99.46	90.16	74.36
WS 400	[0,24]	100	99.74	90.51
WS 860	[0,24]	100	99.63	89.96
WS 1060	[0,24]	100	98.73	86.13
WS 1460	[0,24]	99.96	95.44	80.16
IL 400	[0,11]	98.94	87.66	71.88
IL 860	[0,11]	100	99.35	89.48
IL 1060	[0,11]	99.49	90.08	73.59
IL 1460	[0,12]	88.79	72.74	56.03
LE 400	[0,9]	99.92	97.30	82.76
LE 860	[0,9]	100	99.24	88.76
LE 1060	[0,9]	97.75	84.01	67.70
LE 1460	[0,10]	99.82	92.99	77.09

Note. *number of random variates drawn = 100,000, MF = MetroFrame, WS = WaferStage, IL = Illuminator, LE = Lens*

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