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MASTER

Shop floor control system design within a maintenance depot environment

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Award date:
2018

Link to publication

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EINDHOVEN UNIVERSITY OF TECHNOLOGY

MASTER THESIS

Shop floor control system design within a maintenance depot environment

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14-12-2017

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It should be noted that all numbers and costs mentioned in this thesis are fictitious due to confidentiality reasons

Abstract

This study examines how existing theory about shop floor control can be applied within a maintenance depot environment such that a 98% service level target is met at minimum costs. The shop floor control mechanisms are evaluated through 17 different simulation models. Based on the simulation experiments, we show that the sequencing rule Earliest Due Date always outperforms the sequencing rule First-Come First-Served in terms of service level. Next, we show that for low to medium workforce cost factors, a partially cross-trained workforce policy outperforms a fully cross-trained workforce policy. Finally, since current lead times are often set too low during regular demand periods, we recommend a deterministic lead time control rule equal to 14 hours. This lead time control rule results in (i) a 98% service level performance, (ii) a 24.1% decrease in the average lead time experienced by asset holders and (iii) an operational workforce costs reduction during regular demand periods equal to 62.1%.

Executive Summary

Companies using high-value capital assets in their primary processes extremely depend on the availability of their capital assets (Arts & Flapper, 2015). In order to minimize asset downtimes, these companies have developed a maintenance spare parts supply chain (Muckstadt, 2005). Within those maintenance spare parts supply chain, maintenance depots (MDs) are responsible to perform the diagnosis and maintenance activities (Keizers et al., 2001). Minimizing the time required to perform these diagnosis and maintenance activities is important, since downtime costs due to lost production are 0.5$ million to 1.5$ million per day for Chemical manufacturers (Peterson, 1994). Despite its importance, most literature conducted in the maintenance spare parts supply chain field have only studied the spare parts inventory control problem and the repair shop control problem (cf. Keizers et al., 2001; Basten & van Houtum, 2014). As such, this study aims to complement the literature by bridging the gap between existing theory about shop floor control and a maintenance depot environment. In cooperation with the MD under analysis, a main research question is specified that incorporates the MD's minimal costs objective as well:

How to design a shop floor control system for a maintenance depot which minimizes costs, while meeting a 98% aggregate service level target?

The 98% service level target is proposed, since we expect, in line with Keizers et al. (2001), that the operational availability of the customer's technical systems can only be controlled if the delivery performance of the diagnosis and maintenance activities are controlled as well.

Research Approach

According to Law and Kelton (2015), a system can be studied in various ways. In this study, simulation is selected as the approach to evaluate various MD shop floor control system designs. In total 17 different simulation models are designed in which various control mechanisms are evaluated. These control mechanisms can be categorized regarding sequencing rules, workforce allocation policies and lead time control rules.

Sequencing rules determine the order in which jobs are processed (Nahmias & Cheng, 1993). Workforce allocation policities specify how operators are allocated. In this study, 5 policies are established. The first three policies consider only workforce flexibility using various degrees of cross-trained workforce. As such, we distinguish the no cross-trained workforce (NOCTW) policy, partially cross-trained workforce (PACTW) policy, fully cross-trained workforce (FUCTW) policy. Next, workforce allocation policy 4 (FUCTWAE) consists of fully cross-trained workforce and ample equipment, i.e. maximum machine flexibility. Last, the 3PU model relies on the principles of the Eindhoven Planning Framework (EPF). In this policy, the valve overhaul process is decomposed into three production units (PUs) which can process jobs without having information of other production units. Furthermore, this 3PU model apply partially cross-trained workforce within their PUs. Last, the lead time control rule is aimed to specify for each job arrival a lead time such that service level targets are met at minimum costs and the average aggregrated lead time can be reduced.

The control mechanisms are simulated in two different cases. The first case is established to evaluate alternative solution designs regarding a regular demand period, i.e. a period in which no Turn Around (TAR) is executed. Within the second case, data regarding a TAR is inlcuded in the simulation experiments such

that a TAR demand period is mimicked. As such, durin a TAR demand period regular demand continious while at the same time demand is peaked because of the existence of the TAR. The results from each simulation experiment is used to decide the total number of simulation models required. Table 1 depicts the differences between each of the 17 simulation models.

Table 1: Overview of all simulation models involved.

Sequencing rule		FCFS					EDD				
Workforce flexibility											
Lead Time	**Demand period**	**NOCTW**	**PACTW**	**FUCTW**	**FUCTWAE**	**3PU**	**NOCTW**	**PACTW**	**FUCTW**	**FUCTWAE**	**3PU**
From data	**Regular**	SM1	SM2	SM3	SM4	SM5	SM6	SM7	SM8	SM9	SM10
From data	**TAR**						SM11	SM12	SM13	SM14	SM15
Decision variable	**Regular**		SM16 & SM17								
Decision variable	**TAR**										

Although most input parameters for the simulation model are derived from data that was not available within PLVS' ERP system, the outcomes from the simulation model fits surprisingly well with the expected outcomes from the system. That is, we have validated the simulation model in terms of the expected total processing times as derived from Sabic Europe's Calculation Data Onderhoud handbook (2009) (Table 2). The table shows that, from a statistical point of view, the simulation model does not predict the outcomes well. However, and explained in more detail in Chapter 5, the relative differences are at maximum 6.8%. The model is also confirmed being valid by MD's management. As such, the results are based on the proposed simulation models.

Table 2: Results of the hypothesis tests on the mean total processing times used to validate the simulation model.

Job type d	CDO	Simulation model	t_n^d	$t_{n-1,1-\alpha/2}$
DN-25	100%	-3.5%	129.6	2.064
DN-50	100%	+6.8%	243.8	2.064
DN-80	100%	+3.5%	139.0	2.064

Results & Recommendations

The results are displayed in terms of the service level or the tardiness level. Tardiness is defined as the proportion of jobs finished after their due date, which is the opposite of the service level metric (Nahmias & Cheng, 1993). The results show that, independent from the workforce allocation policy applied, the sequencing rule Earliest Due Date (EDD) always outperforms the sequencing rule First-Come First-Served (FCFS) in terms of average tardiness levels (e.g. Figure 1). As such, the first recommendation to MD's management is:

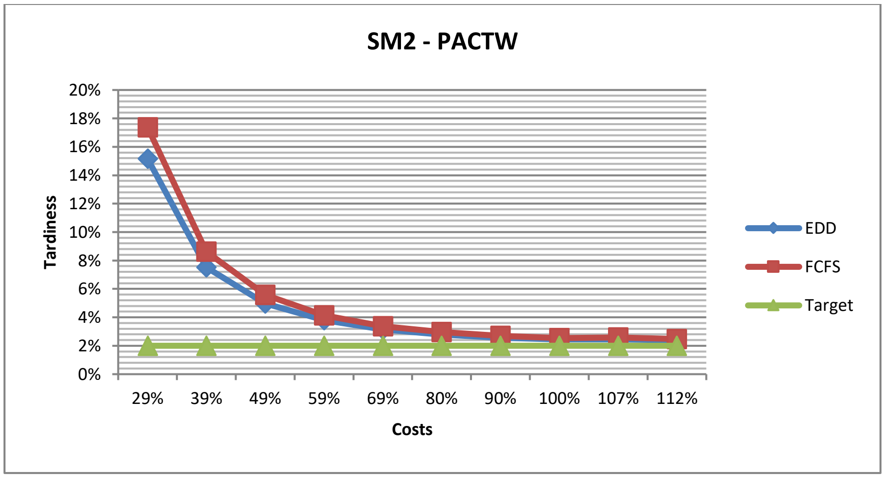

Figure 1: Results regarding the sequencing rules for the PACTW model. In here, the average tardiness is plotted against the relative costs.

Next, the proposed workforce allocation policies are analyzed using both the regular demand case and the TAR demand case. Although Figure 2 depicts the results regarding the regular demand case, the results are similar for the two cases. It is concluded that the workforce allocation policy that results in the lowest tardiness level relates to the partially cross-trained workforce policy for low cost levels. However, for high cost levels, the FUCTWAE workforce allocation policy performs best. For current workforce cost levels, we will recommend the PACTW workforce allocation policy. However, the only model that achieves a 98% service level target during both the regular demand case and the TAR demand case is the FUCTWAE workforce allocation policy. Applying this policy results in a cost increase of 146.1% and 243.5% for Regular and TAR demand periods respectively.

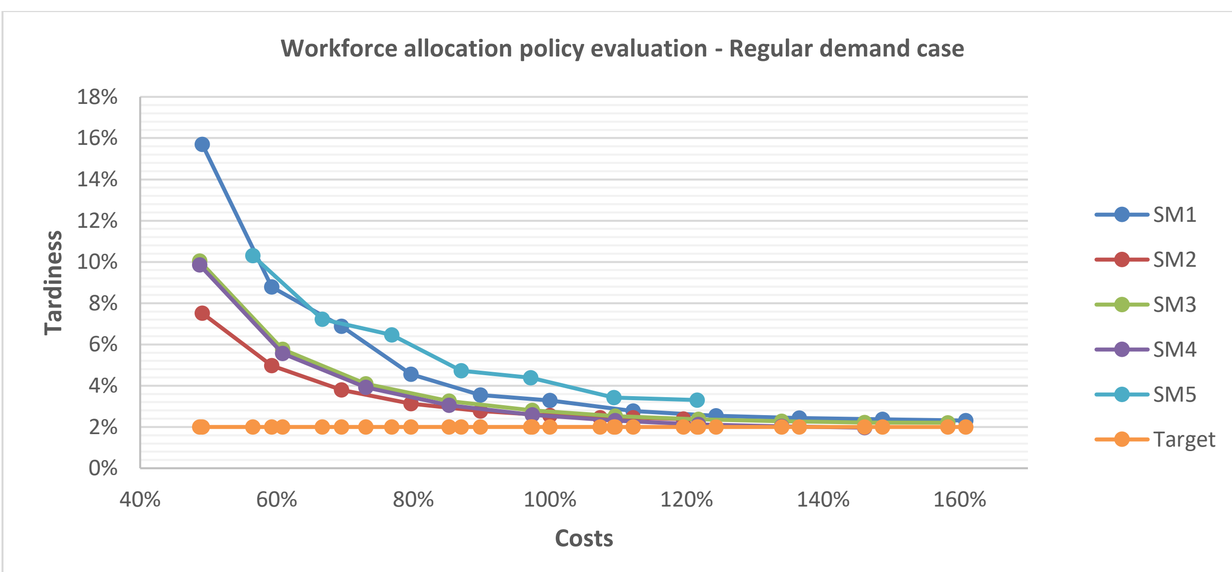

Figure 2: Results regarding the tardiness performance levels during a regular demand period.

Last, since it is impossible to meet a 98% service level target during regular demand periods without making investments in both workforce and equipment, a different lead time control rule is proposed which contains promising results. When a job arrives at the system and the MD can reserve 840 minutes to perform the overhaul while applying a PACTW workforce allocation policy, then this will result in the following outcomes. (i) The 98% service level will be met, (ii) the average lead time as experienced by customers decreases by 24.1% and (iii) the operational workforce costs during regular demand periods can be reduced by 62.1%.

As such, taking the above into account, we recommend MD's management to either:

R2a: ***Invest*** *in both* ***workforce and equipment*** *such that full flexibility of the system is achieved and the 98% service level target can be met; or*

R2b: ***Decrease*** *the* ***service level target*** *and apply a partially cross-trained workforce policy. This will not result in making workforce investments during both regular and TAR demand periods; or*

R2c: ***Negotiate*** *with* ***customers*** *the* ***minimum lead time*** *provided to overhaul a valve and make maximum use of the available workforce capacity, i.e. increase operator utilization levels.*

Preface

This report is the result of a Master Thesis project, performed to receive a Master of Science degree in Operations Management and Logistics at Eindhoven University of Technology. The project is conducted at Product Line Valve Services at the company under analysis in Elsloo, The Netherlands.

The project has been a long journey in which I was frequently introduced to a new 'me'. As always, I started the project with a 'big smile' and perhaps with a bit too idealistic view: *my thesis will significantly improve current business performances!* After months of research, I have to conclude that it is not all that easy. But it was worth it. Besides the in-depth knowledge about my research topic, I have learnt a lot about myself. Sometimes this was pleasant, at other times it was confronting. I really believe that these experiences will help me in my future career.

For sure, completing this master thesis project would not have been possible without the support of others. First of all, I would like to thank my first supervisor from the TU/e, Rob Broekmeulen. Rob, thank you for your constructive feedback and thank you so much for the time you have invested in guiding me throughout the project. As I have told you before, I really appreciated that you always trusted me in completing the master thesis project. Second, I want to thank my second supervisor from the TU/e, Rob Basten. Although we haven't been in meetings that often, you have helped me a lot when I got stuck in my project. You inspired me to start designing the simulation model and you have furthermore introduced me to an employee at NedTrain, who helped me with his practical point of view.

Besides my supervisors at the TU/e, I also would like to thank my company supervisor for providing me this opportunity. I really appreciated that despite your full agenda, you always found a moment to discuss my project and answer questions. Furthermore, I would thank the employees within the company. Without them, I was not able to build a simulation model, which was one of the phases I was very motivated for.

Finishing my master thesis also means that I have reached the end of my student life. Therefore, I would like to thank some people for making my student life such a great experience. First of all, my parents. I know I have made many choices you did not expect or understand, but you always supported me. I have never told you, but I really appreciated your support. Next, I want to thank my Eindhoven friends. You guys have made my Eindhoven student time unforgettable. From the countless hours we studied together to the many liters beer we have drunk in The Villa. Thank you, Eindhoven!

Tijmen van Middelaar

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List of Abbreviations

Abbreviation	Meaning
CDF	Cumulative distribution function
CR	Critical ratio
CRN	Common random numbers
CT	Cycle time
EDD	Earliest due date
EPF	Eindhoven planning framework
ERP	Enterprise resource planning
FCFS	First-Come First-Served
FPS	Field problem solving
FUCTW	Fully cross-trained workforce
FUCTWAE	Fully cross-trained workforce and ample equipment
HPP	Hierarchical production planning
KPI	Key performance indicator
LT	Lead time
MD	Maintenance Depot
MS	Minimum slack
MSPSC	Maintenance spare parts supply chain
MTO	Make-to-order
NOCTW	No cross-trained workforce
OEM	Original equipment manufacturer
PACTW	Partially cross-trained workforce
PLVS	Product Line Valve Services
PU	Production units
SCOP	Supply chain operations planning
SCP	Supply chain planning
SFC	Shop floor control
SL	Service level
SPT	Shortest Processing Time
TAL	Turn around light
TAR	Turn around
TH	Throughput rate
WIP	Work in progress

1 Introduction

In many industries companies use high-value capital assets in their primary processes (Keizers et al. 2001; Cavalieri et al., 2008; Driessen et al., 2015; Arts & Flapper, 2015). In order to be competitive, these companies highly depend on the availability of their capital assets since downtime results in lost revenues (Sarker & Hague, 2000), customer dissatisfaction, customer claims or public safety risks (Driessen et al., 2015). Moreover, besides lost revenues, the costs associated with downtimes are significant. A recent study shows that unplanned downtime costs industrial manufacturers $50 billion each year (Coleman et al., 2017). In order to minimize system's downtime, companies apply maintenance programs in which maintenance strategies are included for each asset individually (Driessen et al., 2015; Van Houtum & Kranenburg, 2015). We refer to the work of Van Houtum and Kranenburg (2015) for a detailed description about the maintenance strategies.

Apart from the strategy applied, whenever an asset is maintained it automatically means that the asset is faced with downtime. To minimize the time required to perform the maintenance activities, companies have designed a maintenance spare part supply chain (MSPSC) such that a repair-by-replacement strategy* is applied (Muckstadt, 1973; Driessen et al., 2015; Van Houtum & Kranenburg, 2015). For companies that apply a repair-by-replacement policy, two factors determine the maintenance downtime (Driessen et al., 2015. First, the time required to perform the diagnosis and maintenance activities. Second, the maintenance delay caused by unavailability of the required resources (e.g. spare parts) to perform the diagnosis and maintenance activities (Driessen et al., 2015). As such, reducing either the time required to perform the diagnosis and maintenance activities or increase the availability of resources result in a decrease of an asset's downtime.

Literature gap

Before we introduce how this study aims to complement the existing literature, one first needs to understand the principles of the MSPSC. Figure 3 visualizes a simplified model of the maintenance spare parts supply chain, which is based on the MSPSC design introduced by Driessen et al. (2015). In short, whenever an asset requires maintenance, it is removed from the production facility (i.e. factory) and transported to a maintenance depot (MD). The MD is responsible for performing the diagnosis and maintenance activities (Keizers et al., 2001). If the MD requires spare parts to perform the maintenance, these spare parts are replenished from a stocking point. The parts that are taken out are scrapped or sent to a repair shop for repair. The spare part stocking point is replenished with spare parts repaired by the repair shop or through buying new valves from original equipment manufacturers (OEM).

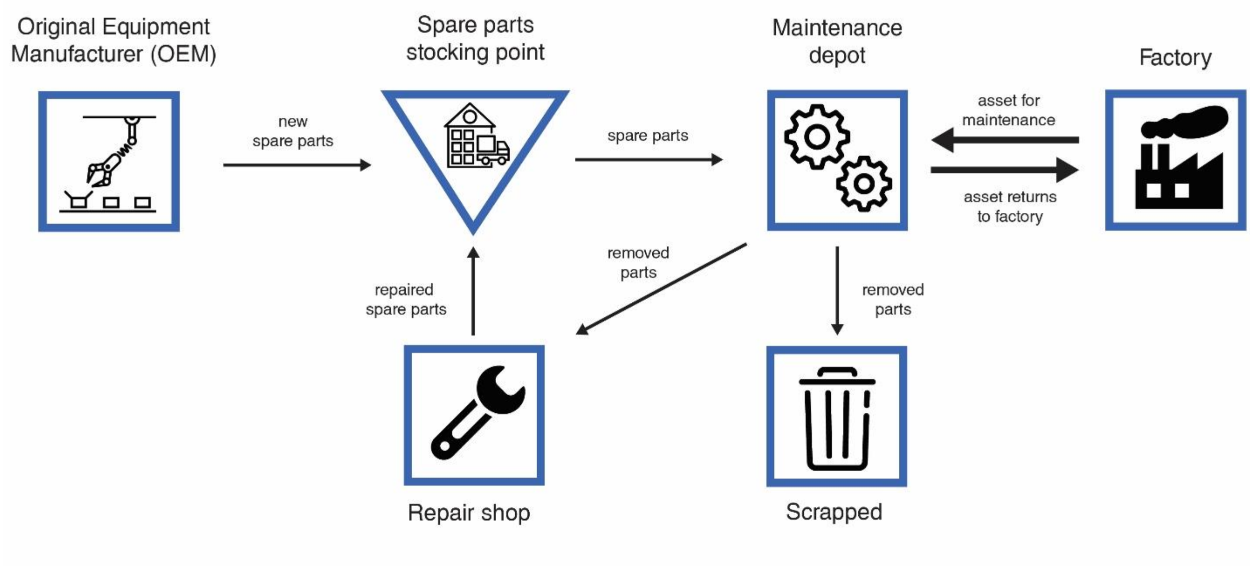

Figure 3: Simplified model of the maintenance spare parts supply chain introduced by Driessen et al. (2015). In here the thick lines represent a valve transport, whereas the thin lines represent a (spare) part movement.

Most literature conducted in the MSPSC field discusses two topics, which are the spare parts inventory control problem (cf. Guide & Srivastava, 1997b; Kennedy et al., 2002; Sherbrooke, 2006; Basten & van Houtum, 2014; Van Houtum & Kranenburg, 2015) and the repair shop control problem (Cf. Guide Jr & Srivastava, 2000; Keizers et al., 2001; Vernooij, 2011). Although earlier research has mentioned the existence of maintenance depots (cf. Vernooij, 2011; Driessen et al., 2015), no literature is available on the maintenance depot control problem explicitly. As such, providing a solution for the maintenance depot control problem is interesting from a theoretical point of view.

Besides the academic relevance, this research is also relevant from a practical point of view. As mentioned, the annual associated costs of unplanned downtimes cost manufacturers $50 billion (IndustryWeek, 2017). Furthermore, downtime costs due to lost production are 0.5$ million to 1.5$ million per day for Chemical manufacturers (Peterson, 1994). Since MDs are responsible for performing the diagnosis and maintenance activities (Keizers et al., 2001), manufacturing companies can save costs if maintenance depots are able to optimize their shop floor processes (which is called shop floor control (SFC) problem in literature).

Optimizing the MD SFC system can reduce downtime costs for manufacturers in two ways. First, when the average time required to perform the diagnosis and maintenance activities can be reduced, it is expected that the asset's downtime can be reduced as well. Second, if the percentage of jobs overhauled within the planned maintenance time (i.e. service level) can be enhanced, it is expected that the manufacturer's downtime can be reduced. This claim is in line with Keizers et al. (2001), who stated that if the time required to perform the diagnosis and maintenance activities is uncontrolled, the operational availability of the customer's technical systems is uncontrolled as well. However, from a MD perspective, an optimized SFC system design is only appropriate if it meets the system's requirements and costs are reduced.

Taking all of the above into account, this study aims to complement the literature by bridging the gap between existing theory about shop floor control and a maintenance depot environment. More specifically, we aim to design a shop floor control system that minimizes costs, while meeting a 98% aggregated service level target. This research objective is translated into the main research question which is leading throughout this study:

How to design a shop floor control system for a maintenance depot which minimizes costs, while meeting a 98% aggregate service level target?

In order to design a shop floor control system which is relevant for practice, a case study is elaborated at a company which offers maintenance services. The next section therefore discusses the company under analysis. In cooperation with this company, the 98% service level target is proposed. We expect that if a 98% service level target is achieved at the maintenance depot, the operational availability of the customer's technical system can be better controlled and downtimes are decreased.

1.1 Company Description

The company under analysis is a Dutch international business originated in 1868. After some mergers and acquisitions the company was bought by an American enterprise in 2016. Its vision is to be the worldwide leading provider of knowledge-based Asset Integrity services in markets like the oil & gas, chemical and power industries. The company is headquartered in Utrecht (The Netherlands) and production operations are located in Africa, Asia-Pacific, Europe, Middle-East, and South-America. Nowadays, the company employs over 20,000 people all over the world and its turnover is about 1.5 billion euro per year.

This research is executed on behalf of the Product Line Valve Services, which is one of the specialist services present within the International Services Continental Europe division. Section 1.2 provides a description about this product line.

1.2 Valve Services

The Product Line Valve Services (PLVS) offers maintenance services on valves. A valve is a mechanical asset that controls the flow of gases, liquids, or loose materials through apertures (e.g. piping) by opening, closing or partially obstructing passages (Dictionary.com, 2016). The product line currently operates at three different locations in The Netherlands, which are situated nearby the chemical parks Chemelot, Farmsum and the Botlek (Figure 4). Note that the facility which mainly operates in the Botlek is acquired in February 2016. Since these three operations are located nearby chemical parks, most of PLVS customers are operating in the chemical and oil & gas industry. These customers apply maintenance programs to control their asset availability and outsource the required maintenance activities through annual maintenance contracts to maintenance service providers such as PLVS.

Figure 4: Geographic plot of PLVS' operations located in The Netherlands.

Company's motivation of study

As mentioned, maintenance depots like PLVS have to plan their resources (e.g. workforce and equipment) such that due dates are met at minimum costs in order to remain competitive. Since PLVS has acquired facility C early 2016, management became aware about different shop floor management (Hendriks & Geurts, 2016). More specifically, facilities A and B allocate operators to valves such that operators and valves move together from one process to another. In this policy, operators need to be cross-trained. On the contrary, facility C assigns operators to processes such that only valves are moved from one process to another. This policy does not allow operators to be cross-trained. Since both policies result in different performance levels (i.e. costs, service level, etc.), management wants to know how to allocate operators at the shop floor. Furthermore, management wants to know how these policies affect the decision and costs to hire additional workforce capacity during peak demand periods.

In summary, PLVS management wants to know how to plan resources (i.e. operators) such that due dates are met at minimum costs.

1.3 Research Scope

This master thesis project is aimed to reduce asset's downtime by improving the shop floor processes at MDs. As such, only the MD's shop floor processes are within the research scope. This indicates that, when considering the maintenance spare parts supply chain (Figure 3), the downtimes regarding the transportation of an asset from or to the customer's facility or downtimes due to unavailability of a spare parts are out of scope. A more detailed scope about the research project is given in Section 4.3, in which the simulation's scope is explained.

1.4 Research Methodology

In this study, the research methodology follows the approach of the regulative cycle (van Strien, 1997). This approach is especially useful for field problem solving (FPS) projects. According to van Aken et al. (2012), a FPS project's objetive is to improve business performances. Since we aim to improve MD's shop floor control management, this project can be labeled as a FPS project. Figure 5 shows the five phases that are included in the regulative cycle. The regulative cycle starts with formulating a problem definition, which is provided in this chapter. Next, the analysis and diagnosis phase is aimed to obtain specific knowledge to solve the defined problem and to gather insights about the nature and the context of the problem. Based on these knowledge and insights, alternative solutions can be designed and evaluated which finally results in the proposed solution design (van Strien, 1997). The intervention and learning and evaluation phases are excluded from this research due to the time frame in which the master thesis project is executed. The next section explains how this methodology is captured within this master thesis report.

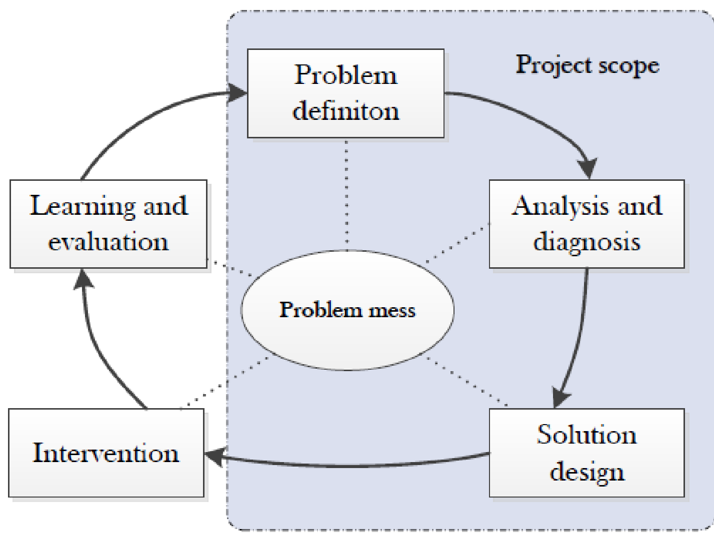

Figure 5: Regulative cycle introduced by van Strien (1997)

1.5 Thesis Outline

Figure 6 visualizes the thesis outline, which is structured according to the first three phases of the regulative cycle as discussed in the research methodology (Section 1.4). First, the problem definition phase is captured in this chapter. Next, during the analysis and diagnosis phase, literature is reviewed (Chapter **Error! Reference source not found.**: Theoretical Background) to obtain knowledge about general shop floor control mechanisms. Furthermore, a case study (Chapter 3) is analyzed to gain insights about the nature and the context of the problem. Based on the information obtained in these chapters, Chapter 0 concludes the analysis and diagnosis phase by describing the research context. The analysis and diagnosis phase is followed by the solution design phase. In this phase, first the model (Chapter 5) is described after which the results (Chapter 6) are provided regarding the research questions and conclusions and recommendations (Chapter 7) are given.

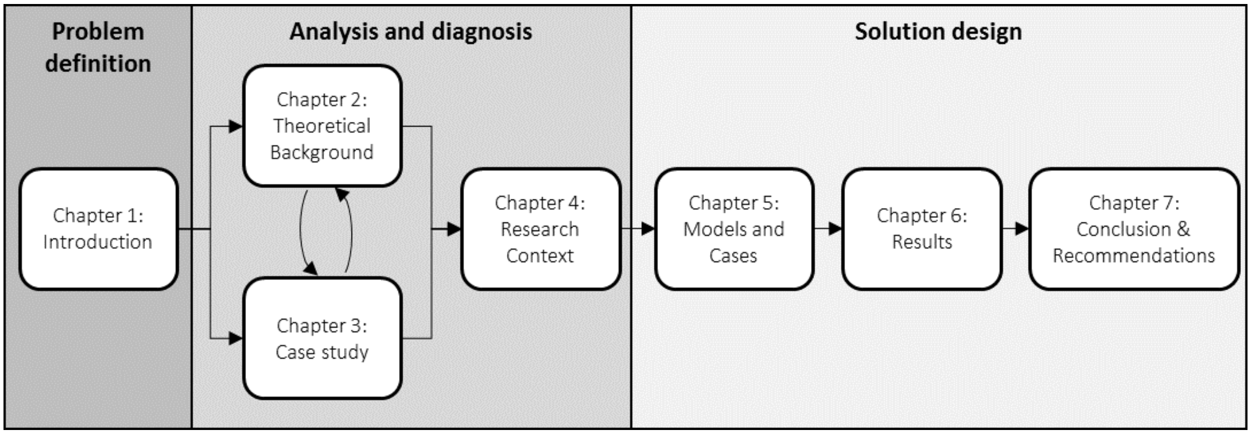

Figure 6: Thesis outline

2 Theoretical Background

Literature is reviewed to establish how the maintenance depot (MD) shop floor control system can be designed. As mentioned, the shop floor control problem in general is about planning resources such that due dates are met at minimum costs (Keizers et al., 2001). A measurement for due date reliability is called service level, which is defined in this study as the aggregate percentage of valves overhauled on or before their due date. According to Hopp & Spearman (2011) and Bertrand et al. (1998), Service level (SL) depends on both a job's cycle time and a job's lead time. Lead time (LT) is defined as the time between a job's due date and its arrival time (Nahmias & Cheng, 1993), whereas cycle time (CT) equals the time a job is in the system. Using these definitions, then service level can be expressed in terms of cycle time and lead time as follows: $SL = P(CT \leq LT)$ (Hopp & Spearman, 2011; Bertrand et al., 1998). It follows that one needs to control both cycle times and lead times to obtain a predetermined service level target.

Section 2.1 and Section 2.2 discuss respectively how cycle time and lead times can be controlled. Subsequently, Section 2.3 provides a framework which is developed by researchers to cope with complexity in production systems. This is included, since MDs contain complex characteristics. Finally, Section 2.4 summarizes the literature review.

2.1 Cycle time

According to Little (1961), cycle time (CT) is a function of the work in progress (WIP) divided by the throughput (TH):

$$CT = \frac{WIP}{TH}$$

Here, WIP relates to the workload in the system and TH depends on the processing time(s) and the available resources in the system (i.e. capacity such as machines, operators). According to this formula, the cycle time increases either if TH decreases relatively more than WIP or if the WIP level increases relatively more than the TH rate. The cycle time will only be stable in case WIP and TH remain proportional to each other (Hopp & Spearman, 2011). As such, shop floor control management has to control both WIP and TH levels in order to control cycle times.

2.1.1 WIP

According to Bechte (1988), WIP can be controlled during three moments in time. After the decision is made to accept a customer order (1), a decision has to be made when which order is released to the shop floor (2). The third decision to control the WIP takes place at the shop floor. Then, in case a machine becomes idle and jobs are waiting in queue, a decision is made which job is processed next (3).

In this research, the decision whether or not to accept a customer order is out of scope and is assumed to be given. Therefore, techniques to control the WIP levels regarding the first control moment are not discussed in this section. The WIP levels for the second and third moment can be controlled through the use of release methods. Release methods are developed to determine when which job is released. These methods can be divided into sequencing rules and triggering mechanisms (Bergamaschi et al., 1997). Sequencing rules determine the order in which jobs are processed (Nahmias & Cheng, 1993). Various sequencing rules exist in literature which are established for different objectives and different problem types (cf. Nahmias & Cheng, 1993; Thomas et al., 1997; Silver et al., 1998; Pinedo, 2008; Hopp & Spearman, 2011). Simple sequencing rules often outperform more difficult ones (Lawrence & Sewell, 1997; Stockton et al., 2008) and, additionally, are relatively easy to understand, use, and implement (Nahmias & Cheng, 1993). As such, the paragraphs below explains only simple sequencing rules. Most of these sequencing rules contain due date related objectives.

First-Come First-Served

When jobs are scheduled according to the first-come first served (FCFS) sequencing rule, jobs cannot bypass another while waiting in a queue (Pinedo, 2008). FCFS results in low flow time variance (Nahmias & Cheng, 1993). This sequencing rule is often applied to analyze queueing systems such as e.g. the lines at the cashiers, lines in front of ATMs or lines at call centers.

Earliest Due Date

Earliest due date (EDD) schedules jobs with the earliest due date next (Pinedo, 2005). This sequencing rule results in an optimal solution for minimizing the maximum lateness (Nahmias & Cheng, 1993). In addition, the sequencing rule performs well in minimizing the number of late jobs and minimizing the variance of the time jobs are late (Rajendran & Holthaus, 1999).

Shortest Processing Time

Shortest processing time (SPT) is a static sequencing rule which schedules jobs in increasing order of their processing time such that the job with the lowest processing time is executed first (Nahmias & Cheng, 1993). According to Nahmias and Cheng (1993), SPT minimizes the mean flow time, mean waiting time and the mean lateness. The rule functions well in environments where jobs arrive simultaneously. However, in practice jobs arrive dynamically over time which may result that jobs faced with long processing times are processed too late regarding their due date since new arrived jobs with shorter processing times are processed first (Pinedo, 2008).

Minimum Slack

A dynamic rule which operates in a similar way as the EDD sequencing rule is called minimum slack (MS). This rule selects among all jobs in queue the one with the lowest value of the current time subtracting its processing time (Pinedo, 2008). MS tends to minimize due date related objectives (Pinedo, 2005).

Critical Ratio

Critical ratio (CR) is widely adopted within make-to-order (MTO) systems, because the ratio serves as a measurement to determine the urgency of a job to be scheduled next while taking in mind the jobs' expected remaining completion time (Stockton et al., 2008). A job's critical ratio is calculated using the formula:

$$Critical\ Ratio = \frac{due\ date - current\ time}{expected\ remaining\ processing\ and\ waiting\ time}$$

The critical ratio is a useful indicator of a job's status (Nahmias & Cheng, 1993; Stockton et al., 2008). $CR > 1$ Shows that a job is ahead of schedule, $0 < CR < 1$ demonstrates that a job is behind schedule, and a job is late if $CR < 0$ (Stockton et al., 2008). According to this sequencing rule, late jobs are always scheduled first using the SPT policy. In case no jobs are late, the next job scheduled is the one with the lowest CR value (Nahmias & Cheng, 1993). A disadvantage of this method is that each time a job is completed, the critical ratios for all jobs have to be determined again (Nahmias & Cheng, 1993).

Next to the sequencing rules, triggering mechanisms are a form of the second moment in time to control WIP levels and determine when the next job is released (Bergamaschi et al., 1997). Kingsman (2000) claims that triggering mechanisms are a stronger tool to control the WIP levels compared to sequencing rules, since sequencing rules lose effectiveness when queues are relatively small. Triggering mechanisms can be decomposed into four categories in which triggering mechanisms are based on 1) customer order conditions (e.g. due date, processing time), 2) shop floor conditions (e.g. (CON)WIP levels), 3) a combination of order and shop floor conditions, or neither based on order or shop floor conditions (e.g. immediate release) (Hales & Laforge, 2006).

2.1.2 Throughput

As mentioned, cycle time is a function of the WIP level and the throughput rate (Little, 1961). When the WIP level increases, the throughput rate has to increase simultaneously in order to achieve the same cycle times. According to Hopp and Spearman (2011), the throughput rate of a line equals the bottleneck utilization multiplied by the bottleneck throughput rate. Improving one of these factors will improve system's throughput. The bottleneck rate can be increased by increasing its effective rate through e.g. adding equipment and flexible labor. Bottleneck utilization can be increased through buffering with WIP to prevent for starving (i.e. idled by a lack of parts to work on) or blocking (i.e. idled by a lack of space in the downstream buffer toward completed parts are sent), or by buffering the bottleneck with capacity by increasing effective rates of non-bottleneck processes (Hopp & Spearman, 2011). As such, increasing the effective process rate of any process may increase throughput rates.

According to Hopp and Spearman (2011), an upper limit on the throughput of a production system is its capacity. Capacity can be constrained by equipment and/or workforce. In production systems where equipment constraints the available capacity, the throughput is bounded by the bottleneck workstation. This bottleneck workstation throughput rate can be increased through adding equipment or by investing in machines with lower processing times (Hopp & Spearman, 2011). On the other hand, in production systems where workforce constraints the available capacity, the maximum throughput rate equals the number of operators divided by the total processing time (Hopp & Spearman, 2011). This is the case in systems where labor works on one job at a time. Furthermore, this only yields in the ideal situation that workers are never blocked (i.e. ample equipment capacity) and are fully cross-trained. However, often equipment is less than ample, operators are not fully cross-trained or other system variabilities can cause workers to be blocked (Hopp & Spearman, 2011). As such, the throughput rate and, accordingly, the performance of the system depends on how effectively workers are allocated to promote flow through the system. Nahmias and Cheng (1993) claim that a system's throughput can already provide near optimal solutions for low flexible workers (i.e. partially cross-trained workforce). Then, chaining policies and bucket brigade are mechanisms that provide insights how to deal with the flexible workforce allocation problem.

Hopp and Spearman (2011) conclude that systems with high process variability and parallel machine processes are most susceptible for cross-trained workforce.

2.2 Lead time

As mentioned in this chapter's introduction, service level depends on both the job's cycle time and its lead time (Hopp & Spearman, 2011; Bertrand et al., 1998). When assuming that cycle times follow a certain distribution, it automatically follows that lead time can be expressed in terms of the cycle time distribution parameters for any targeted service level. Hopp & Spearman (2011) and Bertrand et al. (1998) assume that cycle times are normally distributed and introduced the following formula to determine the minimum lead time to satisfy a particular service level:

$$LT = CT + z_{SL} * \sigma_{CT}$$

In this formula, z_{SL} equals the value in the standard normal table for which $\Phi(z_{SL}) = SL$. The term $z_{SL} * \sigma_{CT}$ is called the safety lead time (Hopp & Spearman, 2011).

2.3 Hierarchical Production Planning

Similar to MDs, the supply chain planning (SCP) problem is faced with complex characteristics (de Kok & Fransoo, 2003). We assume that concepts developed for the SCP problem might be applied within a MD as well. As such, this section describes how hierarchical production planning are established and explains how one works.

According to McKay et al. (1995), SCP concepts are developed and studied by many researchers over time, which finally resulted in the development of hierarchical production planning frameworks (e.g. Hax & Meal, 1973; Orlicky, 1974; Bertrand et al., 1998). A hierarchical production planning (HPP) framework is defined as: "*a structural approach to the problem of coordinating activities within the primary process of the firm where authority and responsibility to make decisions is divided over levels and each higher level specifies the constraints in which lower level hierarchies are free to achieve local objectives*" (Bertrand et al., 2016, pp. 16-17).

The MIT framework and the MRP II framework practice are the most commonly used HPPs in today's practice (cf. Hax & Meal, 1973; Bitran, Haas, & Hax, 1981, 1982; Hax & Candea, 1984; Vollmann et al., 1984; Bitran & Tirupati, 1993). This study however proposes the Eindhoven Planning Framework (EPF). First of all, because the EPF provides a solution concerning the issues involved with the commonly used frameworks (Bertrand et al., 2016). Secondly, because the EPF has already been adapted within a maintenance and repair shop environment in the study of Bertrand et al. (1991).

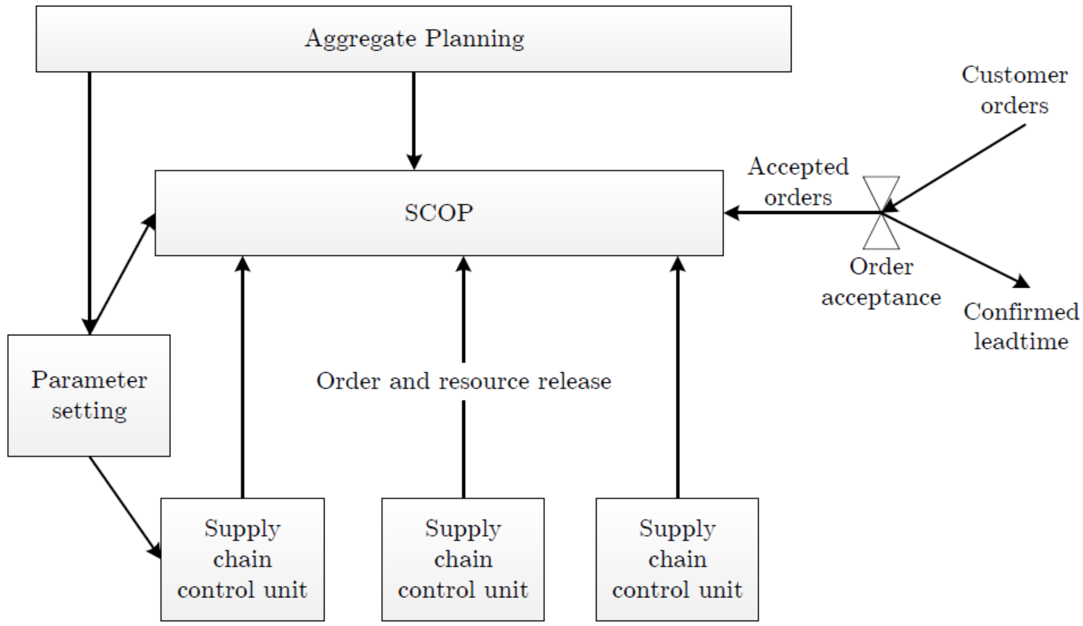

Figure 7: The Eindhoven Planning Framework as introduced by Bertrand et al. (2016).

The EPF can be seen as a supply network of production units (PUs) separated by controlled stock points that add value to the goods flow and to which production orders are released by a central coordination authority denoted as the supply chain operations planning (SCOP) function (Bertrand et al., 2016) Figure 7. Both the SCOP -and the PUs' decisions are constrained by parameter settings which determine values for e.g. costs, service targets, (fixed planned) lead times, and safety stocks. Within these parameters, the SCOP is responsible to coordinate the release of materials and resources such that customer service constraints are met at minimal costs (de Kok & Fransoo, 2003). The PUs, on the other hand, are responsible for processing jobs from a specific start process level towards a specific next process level within the agreed constraints. From the SCOP's point of view, PUs are black boxes that transform inputs into outputs (Bertrand et al., 1990, 1998, 2016; de Kok & Fransoo, 2003). As such, PUs are self-contained which means that a PU can achieve its performance targets without having information about how the design problem of any other PU function nor how the SCOP function is solved (Bertrand et al., 1990, 1998, 2016). To make this work, PUs are constrained with fixed planned lead time targets.

2.4 Conclusion

In Chapter 2 the principles of shop floor control were discussed and a framework (i.e. EPF) was provided which copes with maintenance depot's complexity.

In this study, service level is defined as the aggregate percentage of valves overhauled on or before their due date. According to Hopp & Spearman (2011) and Bertrand et al. (1998), service level can be expressed in cycle time and lead time: $SL = P(CT \leq LT)$. As such, in order to achieve a high due date reliability, both the job's cycle time and its lead time need to be controlled (Keizers et al., 2001)

According to Little (1961), cycle time is a function of the WIP level divided by the throughput rate (TH). This indicates that cycle times are stable in case both WIP and TH decrease or increase proportional to each other (Little, 1961). Mechanisms used to control WIP levels relate to sequencing rules and triggering mechanisms (Bergamaschi et al., 1997). Sequencing rules determine the order in which jobs are processed (Nahmias & Cheng, 1993). Triggering mechanisms are used to decide when the next order is released (Bergamaschi et al., 1997).

Whenever the WIP level increases, the throughput rate should increase simultaneously in order to remain the same cycle times (Little, 1961). According to Hopp and Spearman (2011), a system's throughput rate can be most effectively increased by increasing either the bottleneck utilization rate or the bottleneck effective throughput rate. The effective throughput rate is often constrained by capacity restriction in terms of equipment or workforce. Increasing both equipment and workforce levels will result in higher throughput levels (Hopp & Spearman, 2011). In systems where workforce constraints system's throughput, cross-trained workers can significantly increase throughput rates without increasing equipment or workforce levels (Nahmias & Cheng, 1993).

Lead time can be controlled in case a cycle time's distribution is known. When assuming cycle times to be normally distributed, the minimum lead time that satisfies the targeted service level (SL) equals:
$LT = CT + z_{SL} * \sigma_{CT}$ (Bertrand et al., 1998; Hopp & Spearman, 2011).

Finally, HPP frameworks are established for the SCP problem in order to reduce system's complexity (Bertrand et al., 1990). Such a HPP relates to the EPF, which is a supply network of production units (PUs) separated by controlled stock points that add value to the goods flow and to which production orders are released by a central coordination authority (i.e. SCOP function) (Bertrand et al., 2016). The PUs are self-contained, which means that a PU can achieve its performance without having information about how the design problem of any other PU function nor how the SCOP function is solved (Bertrand et al., 1990, 1998, 2016).

In conclusion, we expect that MD's shop floor control can benefit from control mechanisms provided in literature. These control mechanisms relate to sequencing rules and triggering mechanisms to control WIP, cross-trained workforce to enhance throughput rates, establishing the cycle time distribution to determine lead times, and decomposing the production system to reduce maintenance depot's complexity. The next chapter discusses the MD's characteristics and describes how shop floor control is currently organized at the MD under analysis.

3 Case Study

Chapter 3 is aimed at gaining insights about nature and the context of the shop floor control problem for a MD. On the one hand, this is required to get a thorough understanding of the MD shop floor control problem. On the other hand, analyzing a MD is required to obtain inputs for the mathematical model which will be built in Chapter 5.

As will be explained in the upcoming sections and summarized in Section 4.3, the case study describes (except for the sections regarding the demand analysis) how the shop floor is currently structured at Facility B and, even more specifically, we only analyze the product group safety valves. This scope is set because of the absence of data available to analyze these product groups and operations mathematically. In addition, it is expected that insights provided at this product group can be used for other product groups and operations as well.

Information in this chapter is derived from data analysis, interviews with employees and researcher's shop floor observations. In total, data from three different sources is analyzed. First, data from the enterprise resource planning (ERP) system is collected, which includes data about the valves overhauled from January 2014 till August 2016. Second, data about a turn around which is executed in March 2017 is analyzed to obtain input values for the mathematical model regarding this demand type. Last, data from a valve tracking procedure (Appendix A2, Figure 20) is used to specify the input values for the mathematical model for regular demand periods.

This chapter is structured as follows. First, to understand how higher planning functions influence the shop floor control, Section 3.1 discusses how planning is hierarchically structured within PLVS. In here, the incoming customer order demand is analyzed as well. Next, the valve overhaul process and the resources involved with the valve overhaul process are explained in Section 3.2. Then, Section 3.3 discusses the current shop floor performances. Last, Section 3.4 summarizes the findings from Chapter 3.

3.1 Planning and Control

The BWW-framework introduced by Bertrand et al. (1990) is used as a basis to describe the current planning and control structure at PLVS Figure 8. In here, control functions (blue rectangles) are specified on three hierarchical planning levels. These three hierarchical planning levels relate to planning at department level (i.e. PLVS), planning at facility level and planning at shop floor level. These levels are displayed on the right hand side.

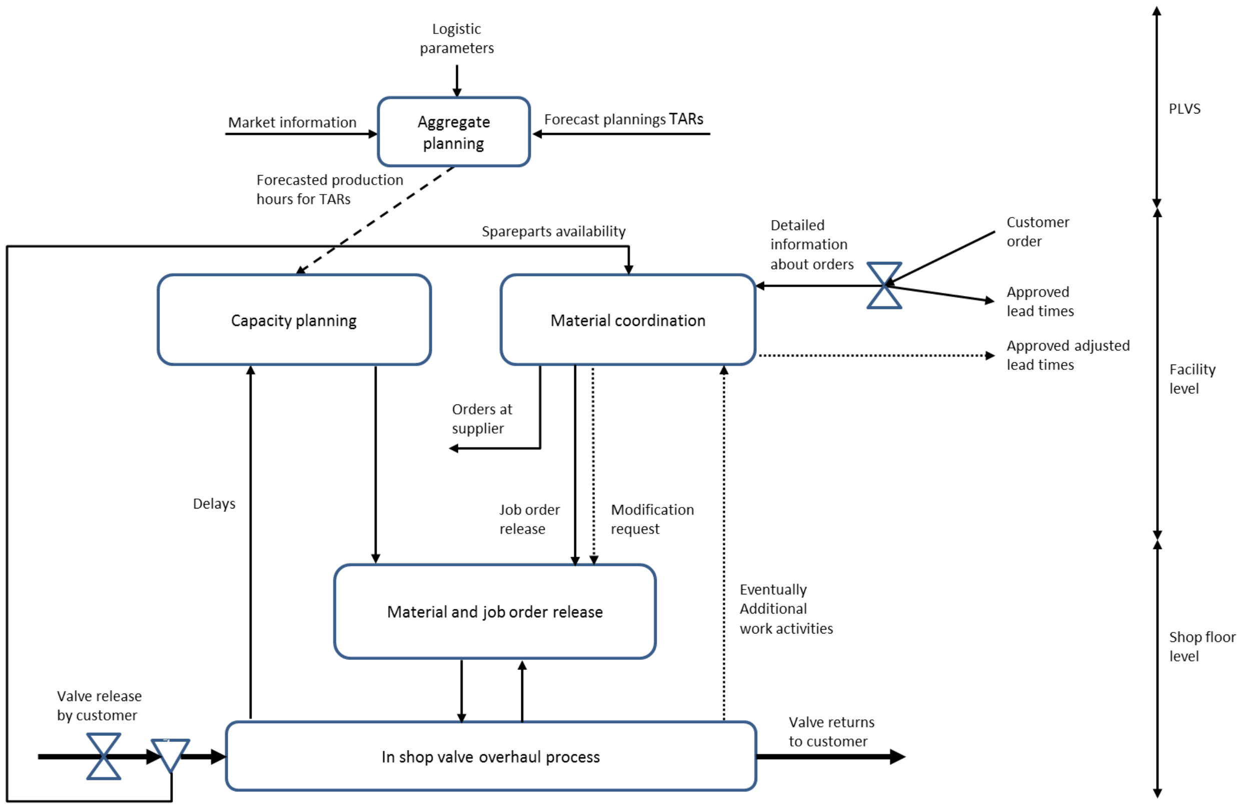

Figure 8: Planning and control structure at PLVS, which is based on the principles of the BWW-framework introduced by Bertrand et al. (1990)

The highest planning level at PLVS refers to the aggregate planning. This aggregate planning consists of budget plans about total sales volumes expressed in terms of revenue and billable hours. Input for the aggregate planning are the planned turn arounds (TARs, we will explain this demand type in Section 3.1.1), market information, and a logistic parameter about billable hours set by higher management. The aggregate planning is input to the production management at facility level. The production management at facility level consists of two decision functions: capacity planning and material coordination. Planners are responsible for the material coordination function. A planner is allowed to accept all customer orders besides TARs (i.e. TARs are input from aggregate planning) and to discuss the start and completion dates of these orders. The start and completion dates is negotiated based on the available workforce capacity and the availability of spare parts. Ideally, operators are planned fully utilized to ensure billability targets (see Section 3.3) are met. Next, an operations manager is responsible for the capacity planning, which deals with equipment and workforce levels. In here, short term capacity extensions are made if foremen request more temporary capacity. Long term capacity changes are made for planned TARs. Then, the operations manager hires operators up to a workforce level which equals the expected total processing times required to overhaul all the valves during the TAR multiplied by a factor which is based on his experience from TARs with similar scopes. Equipment is only extended during TARs and is also based on operations manager experiences.

Each valve within an accepted customer order is transformed to a job order by the planning department. A job order consists of information such as the maximum time allowed to overhaul the valve and the (additional) activities that have to be executed. At the end of each week, these job orders are handed over to the foremen of each product group during the material and job order release meeting. However, the actual release of materials take place once the valves regarding a customer order arrive at PLVS facility. Then, production management at the shop floor starts.

Foremen are responsible for the shop floor management, which is about the planning and control of the available capacity such that arriving valves (henceforth called jobs) are overhauled within their due dates. They are authorized to (re)allocate operators to workstations or to valves. In general, operators are assigned to jobs such that they execute all processes involved with a valve overhaul from start to finish. Since operators are not always allowed (i.e. competent) to execute all the required processes themselves, specialized operators are sometimes assigned to perform particular processes. Based on the way operators are allocated, it is concluded that the current shop floor management contains 1 production unit.

Customer Order Acceptance

The decision to accept a customer order differs per demand type and contractor. First, TARs are input to facility's management from aggregate planning. Next, customer order arrivals from contractors having a maintenance contract at PLVS are always accepted by planners, independent whether or not a TAR is planned in the same time period. On the other hand, customer orders arriving from contractors without having a maintenance contract at PLVS are accepted if capacity is sufficient. The capacity check is based on the expected total processing time of a standard valve overhaul (Table 4) (i.e. no capacity is reserved to perform rework or additional work activities) and the available workforce capacity in that particular time period. The expected total processing times are derived from the Sabic Europe's Calulation Data Onderhoud handbook (2009) in which processing times are specified for 30 different safety valves. In here, the characteristic which mainly affects the total processing time is the valve size, i.e. DN-size (SABIC Europe, 2009). Unfortunately, this capacity check is inappropriate since actual valve arrival dates highly deviate from planned arrival dates (Figure 9 and Figure 10).

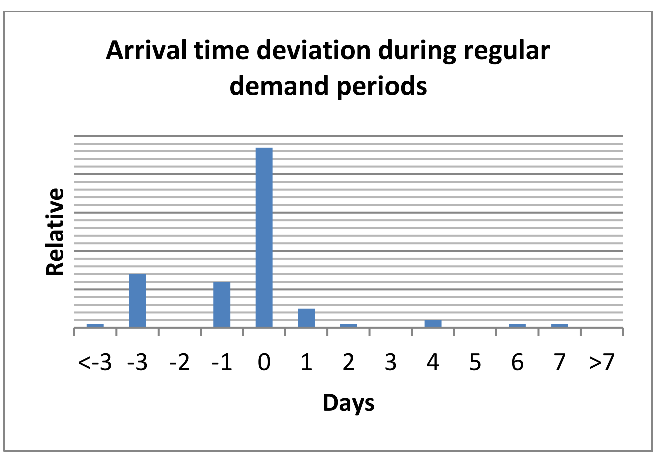

Figure 9: Comparison of the actual arrival times versus the planned arrival times during regular demand periods

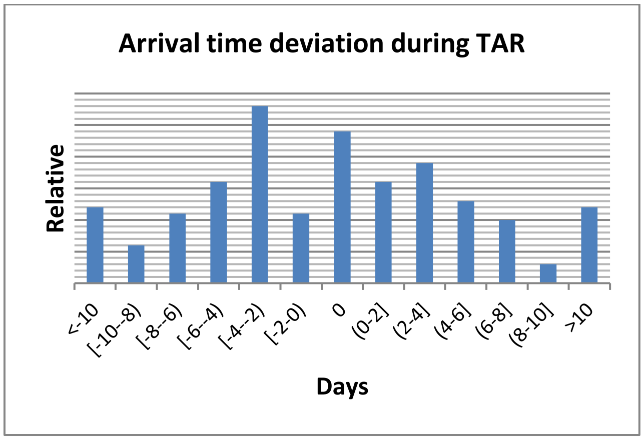

Figure 10: Comparison of the actual arrival times versus the planned arrival times during TAR demand periods

Note that in practice all customer orders are always accepted outside TAR periods and have to be discussed with the operations manager during TAR periods.

Release methods

Arriving jobs are always immediately released to the production area. In here, shop floor management is organized such that operators are always (if possible) busy performing a valve overhaul. As such, no upper bound on the WIP is determined to limit the WIP levels. This is inappropriate, since high WIP levels negatively influence the performance of the system (Little, 1961; Hopp & Spearman, 2011). Next, foremen have to decide which job is processed next in case an operator becomes idle. This decision is important, because jobs have different priority levels. On the one hand, because jobs contain different lead times which are approved by planners in an earlier stage. On the other hand, actual valve arrival times highly deviate from planned arrival times (Figure 10). Based on observations and interviews, it is concluded that foremen however are not familiar with sequencing rules and use a combination of FCFS and EDD.

3.1.1 Demand

This section provide the results of the demand analysis which is based on data from January 2014 till August 2016. We first explain the four demand types that are recognized by PLVS, which result from the maintenance programs applied by PLVS' customers. Each demand types contains different characteristics. In general, Turn arounds (TAR) and turn around lights (TAL) are preventive maintenance strategies that are used for assets that are marked being critical. During TARs and TALs, the customer's facility or a part of the facility is shut down for a particular period in order to carry out maintenance activities on all asset types. Since these down time periods are planned as short as possible, TALs and especially TARs result in immense volume peaks at PLVS.

PLVS recognizes furthermore standard demands. These customer orders are most often ordered from customers that have contracted PLVS as their main maintenance service provider. The orders often consist of one or several assets and are executed in periods that these assets are marked less critical to meet customer's production targets. Often, PLVS can influence the start and finish dates as well. A fourth demand type relate to emergency orders. An emergency order is placed, in case an asset requires maintenance and is marked being critical to satisfy customer's production targets.

Figure 11 visualizes the sales volumes for each demand type based on data from 1 January 2014 till 31 August 2016. The figure shows similar patterns for facilities A and B (data regarding the demand types at Facility C is not available). It is remarkable that almost no emergency orders are observed. Last, it is concluded that most jobs are overhauled regarding the standard demand type.

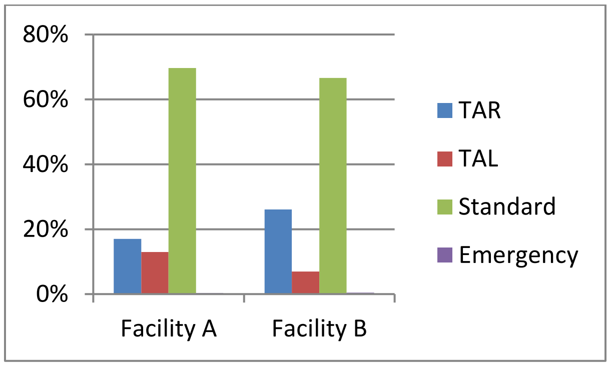

Figure 11: Relative sales volumes per demand type as observed at facilities A and B during January 2014 till August 2016.

Next, the demand is analyzed for each facility and for each product group (Table 3). Based on the outcomes provided in these tables, we conclude that most overhauls are performed at Facility B. Furthermore, most overhauls are performed regarding the group safety valves.

Table 3: Relative annual demand per facility {A, B, C} and per product group {On/off, Safety, Control}. Note that the statistics provided about 2016 only include data till August.

	A	B	C	Total		On/off	Safety	Control	Total
2014	18%	54%	29%	100%	**2014**	18%	60%	22%	100%
2015	14%	57%	29%	100%	**2015**	15%	66%	19%	100%
2016*	25%	46%	29%	100%	**2016***	13%	68%	18%	100%

The weekly demand pattern from January 2014 till August 2016 is also analyzed regarding the safety valves (Figure 12). As shown, the weekly demand is not growing or decreasing steadily. Instead, the weekly demand highly fluctuates from successive weeks. Based on interviews, it is known that these peaks are mainly caused by the occurrence of TARs. Since TARs are accepted by higher management, this demand type is given to the system and cannot be changed by the customer order acceptance function.

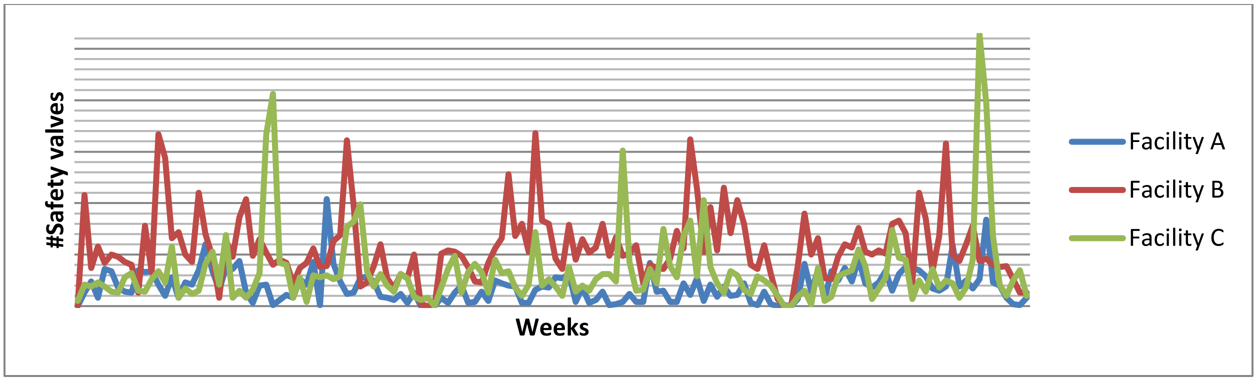

Figure 12: Weekly demand per facility for safety valves observed from January 2014 till August 2016

The last characteristic that is used to analyze the demand is in terms of the DN-size. As mentioned in Section 3.1, the DN-size is the main driver for the processing time. Table 4 visualizes the cumulative probabilities of the DN-sizes observed at Facility B regarding the product group safety valves and the expected total processing times involved with these DN-sizes.

Table 4: Cumulative distribution function regarding the valve sizes for safety valves at facility B and the total expected processing times expressed relatively against the biggest DN-size. Note that these values are fictitious due to confidential reasons.

DN-Size [mm]	Cumulative	Expected total processing time regarding a standard overhaul
DN ≤ 16	15%	100%
16 < DN ≤ 33	57%	110%
33 < DN ≤ 66	77%	120%
66 < DN ≤ 82	84%	130%
82 < DN ≤ 102	90%	140%
102 < DN ≤ 153	96%	150%
153 < DN ≤ 204	98%	160%
204 < DN ≤ 254	99%	170%
254 < DN	100%	180%

So far, the demand is analyzed based on data derived from the enterprise resource planning (ERP) system. Although many statistics can be analyzed, statistics such as (inter)arrival times between customer orders, the number of valves within a customer order (i.e. order size) and the total time available to overhaul a valve from an order (i.e. lead times) cannot be analyzed from this data. Since these statistics are input to the simulation model (see Section 5), data is collected and analyzed to obtain values regarding these statistics. The next section discusses the results of these demand characteristics.

3.1.2 Demand Characteristics

Since the data derived from the ERP system does not contain all demand statistics that are required for the simulation model, two other data sources are analyzed to gain the required insights. Although PLVS recognizes four demand types (i.e. TAR, TAL, standard and emergency), it was decided to collect data regarding a period in which no TAR was executed (henceforth called: regular demand data) and to collect data regarding a TAR explicitly (henceforth called: TAR demand data). The regular demand data can then be used to simulate a demand period in which no TAR is executed (henceforth called: regular demand period). On the other hand, the combination of both the regular demand data and TAR demand data can be used to simulate a demand period in which a TAR is executed (henceforth called: TAR demand period). Allowing regular demand during a TAR is a correct approach, since in practice customer orders are almost always accepted by PLVS' planners (Section 3.1).

The regular demand data is collected during a three week period in March 2017 (Appendix A). Data from one of the most extreme TARs (i.e. lots of valves are overhauled in a short time-frame) is analyzed to represent TARs in general. This TAR is selected, since for this TAR a tool was designed to track the state of the valves overhauled. The descriptive statistics regarding both datasets are described below. Furthermore, for validation purposes, two statistics are compared with the statistics derived from the ERP system's data.

Regular demand data

Table 5 contains the descriptive statistics regarding the regular demand period. In here, statistics are gathered per customer order arrival, since all jobs from one customer order consists of the same lead time. The sample sizes per statistic differ because of missing values.

Table 5: Descriptive statistics regarding the input parameters for regular demand

Descriptive statistic	Interarrival-time	Order size	Lead time (per order)
Sample Size	39	41	36
Minimum	0	1	150
Maximum	600	15	4440
Mean	147.59	2.171	1106.14
Median	110	1	603.50
Std. Deviation	143.687	2.635	999.60
Skewness	1.570	3.441	1.422
Kurtosis	2.464	17.082	5.097

TAR demand data

Table 6 contains the descriptive statistics regarding the regular demand period. Here, statistics regarding the interarrival-time and order size are gathered per customer order. The statistics regarding the lead time are analyzed per job, because within a customer order arrival jobs can have various planned lead times.

Table 6: Descriptive statistics regarding the input parameters for TAR demand

Descriptive statistic	Interarrival-time	Order size	Lead time
Sample Size	36	36	179
Minimum	0	1	480
Maximum	502	34	4800
Mean	187.69	4.806	1421.23
Median	146.33	3	1440.00
Std. Deviation	139.38	5.806	701.31
Skewness	0.825	3.880	2.043
Kurtosis	3.004	21.654	9.956

Validation descriptive statistics

As mentioned, the descriptive statistics are validated in terms of the average DN-size and the average jobs that arrive per day. These statistics are selected for two reasons. On the one hand, data from the EPR system can be used to determine the average DN-size and the average jobs per day. On the other hand, the workload in the system depends mainly on those two statistics. Table 7 provides the average statistics for both demand data's.

Table 7: Comparison of the mean DN-size and the mean job arrivals per day regarding the sample data and data from the ERP system

Descriptive statistic	Dataset	Sample average	ERP system's data
Mean DN-size	Regular demand data	42.4	50.9
Mean jobs/day	Regular demand data	7.1	8.5
Mean DN-size	TAR demand data	N.A.	54.7
Mean jobs/day	TAR demand data	12.3	24.8

In here, the sample averages for the mean jobs per day are determined using the formula: $E(jobs\ per\ day) = \frac{480}{E(interarrival-time)} * E(order\ size)$. Table 7 shows that the averages jobs per day obtained from the two data sources differ from the ERP system's data. Although the difference may influence the outcomes that will be obtained, it is decided to use this statistics for modeling purposes for two reasons. First, data from the ERP system can be erroneous. For example, the mean jobs per day regarding the TAR demand data equals 24.8 and is based on 25 TAR days a year. Management has confirmed that the number of TAR days a year is at least twice as much as the 25 TAR days obtained from the ERP system. Second, although we know that the exact outcome values will be affected by the input parameters, we do not expect that these input values affect the main conclusion of each research question. That is, if a certain model (e.g. EDD versus FCFS) outperforms another model, this conclusion will be similar when increasing the demand. We will come back to this in the limitations (Section 7.1).

3.2 Process Characteristics

Once a valve arrives at PLVS, the in shop valve overhaul process starts. Figure 13 contains the swimlane process diagram which visualizes the flow of valves through PLVS' facility. In here, the swimlanes represent the various machine types PLVS distinguishes and each color represents an operator skill level which indicates the minimum required skill level for operators to execute the process. PLVS recognizes 21 different processes from which 19 are executed by operators working for PLVS. Process 8 represents the mechanical machining activities which are outsourced internally or to an external company. Next, process 21 denotes the activity that materials have to be ordered due to unavailable spare parts, which is not performed by an operator.

The general processes to overhaul a valve at PLVS are in line with literature, which concludes that maintenance requires disassembling, cleaning, inspection, reassembling and testing (Kurilova-Palisaitiene & Sundin, 2014). However, the exact processes and accordingly the machine types involved with a valve overhaul highly vary per overhaul (Appendix B.3). Moreover, the required processes to overhaul a valve are unknown at the start, but can only be determined after inspection (process 7) is executed. Another characteristic of PLVS' valve overhaul process relates to the rework activities valves may be faced with. According to Hopp and Spearman (2011), rework activities are undesired since rework increases both the cycle time average and the cycle time variance. Although these processes are known, data regarding job's routing or percentage about processes executed are not available. As such, the data from the valve tracking procedure is used to gain insights about these input parameters. We refer to Section 5.1 for a detailed description of the results of the analysis provided in Appendix B.3.

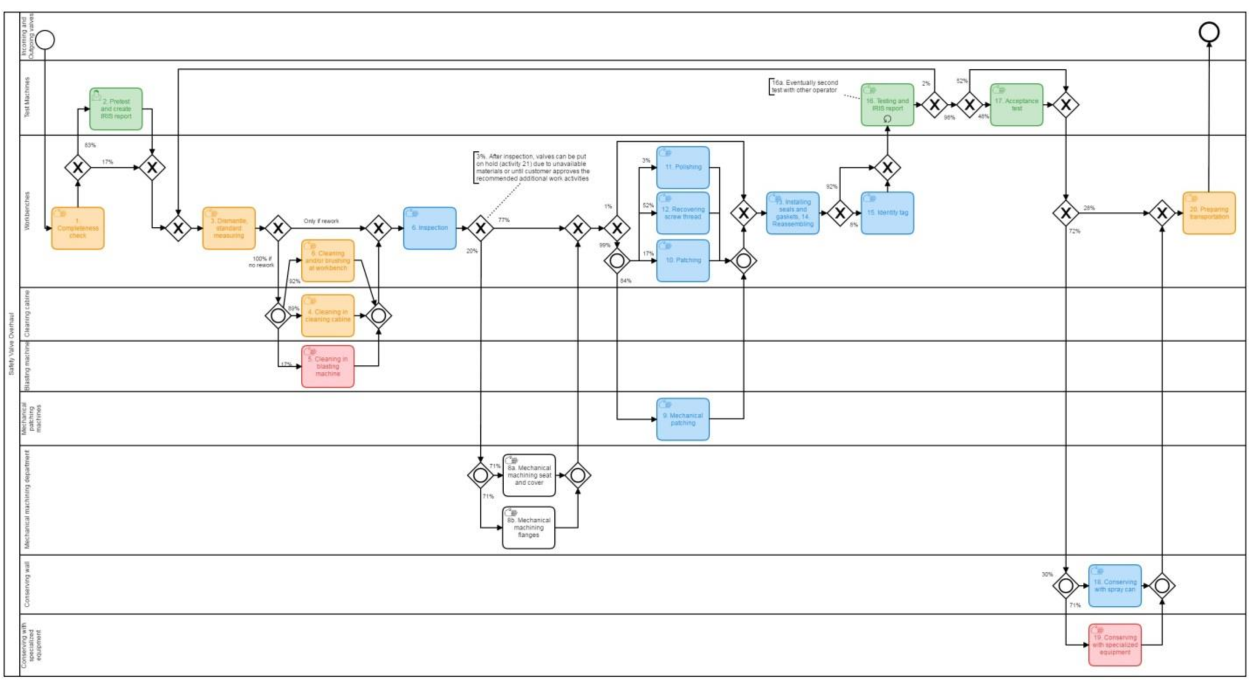

Figure 13: BPMN process model regarding the safety valve overhaul process. In here, each swimlane represents a machine type and each color denotes an operator competence level.

Equipment

Table 8 shows the relative number of machines for each machine type. Note that these numbers are changed for confidential reasons.

Table 8: Relative number of machines per machine type. Due to confidential reasons, these numbers are fictive.

Machine type	Number of machines
Work benches	46%
Test machines	15%
Cleaning cabins	12%
Blasting machines	8%
Lapping machines	12%
Conserving specialized equipment	4%
Conserving wall	4%
Total	100%

Workforce

Table 9 shows the relative number of operators for each operator type. Furthermore, the hourly costs involved with the current workforce level as well as the costs of hiring an operator from a particular operator competence level are shown. Again, these numbers are fictitious due to confidential reasons.

Table 9: Relative number of operators, workforce costs and hiring workforce cost per operator competence level. Due to confidential reasons, these numbers are fictive.

Operator competence level	Relative current workforce levels	Workforce costs [€/hour/operator]	Hiring workforce costs [€/hour/ operator]
Orange	20%	€50	€75
Blue	35%	€100	€100
Red	15%	€80	€100
Green	30%	€120	€100
Total	100%	N.A.	N.A.

3.3 Key Performance Indicators

Key performance indicators (KPIs) are used to evaluate system performances (Nahmias & Cheng, 1993). PLVS uses billability as the only KPI to measure how operational planning currently performs. Billability is denoted as the ratio between the charged hours and the total available hours (equation below). In here, the charged hours equals the expected total processing times for the activities fulfilled. Although we will not discuss billability in detail, PLVS management has mentioned that billability targets for operators are not met yet.

$$BBTY = \frac{charged\ hours}{charged\ hours + uncharged\ hours}$$

According to Keizers et al. (2001), due date reliability is an important KPI for maintenance depots, since an uncontrolled maintenance delivery performance results in an uncontrolled operational availability of the technical system. A measurement for due date reliability is called service level. In this study, service level is denoted as the percentage of jobs overhauled on or before their due date. It is remarkable that PLVS does not measure the service level. Moreover, the completion date of a valve overhaul is not recorded. As such, data from the valve tracking procedure (Appendix A.2) is analyzed which shows a current service level performance equal to 93.5% during regular demand periods. The service level is also determined for a TAR in which 181 safety valves were overhauled (Appendix D). For this TAR, the obtained service level equals 46.9%. Since the actual arrival date highly deviated from the planned arrival date, the service level is also determined in terms of the actual cycle time versus planned cycle time. Based on this analysis, the actual cycle times were in 45.8% lower than the planned cycle times. Since management targets a 98% service level performance, it is concluded that current service levels are extremely low.

3.4 Conclusion

Chapter 3 describes how the shop floor control is currently organized and how the valve overhaul process is characterized as observed at the maintenance depot under analysis. First, conclusions regarding the maintenance depot characteristics are provided. In line with literature, it is concluded that the maintenance depot contains complex characteristics. This complexity is caused by highly variable demand, uncertain arrival times, variable lead times and uncertainty about the total processing time since a job's content is unknown at the start of the overhaul process. The shop floor control structure is even more complicated since each process requires a specific machine type and an operator who is qualified to perform the particular process. Second, it is concluded that the throughput rate at which valves are overhauled is constrained by both the equipment level (i.e. number of machines) and the workforce level. As such, once WIP levels increases, the capacity planning decision function has to decide about both workforce and equipment levels in order to achieve the same cycle times.

Next, conclusions are provided about the current shop floor control structure. First of all, it is concluded that the current shop floor control structure does not perform well. Although PLVS does not use service level as a KPI, service level is the most important KPI based on literature (Keizers et al., 2001). Data analyses show that the obtained service levels are below management target for both regular demand as well as for the TAR analyzed. As mentioned in Chapter 2, service level depends on both a job's cycle time and a job's lead time. Since lead times are confirmed by the customer order acceptance function and cycle times are controlled by shop floor control management, it is expected that both decision functions cause the poor service level performance. Reasons for this are described in next paragraph.

First, the procedure how customer orders are accepted causes problems during regular demand periods. During these periods, planners accept customer orders (i.e. confirm start and completion dates) based on the available capacity in that period and the expected total processing times. These expected total processing times, however, do not consider variability. This is unrealistic since a job's total processing time is highly variable due to uncertainty about the job's content at the start of the overhaul process and the probability of rework. Furthermore, lead times (i.e. completion date minus start dates) are approved without performing a cycle time check. More specifically, planners expect that cycle times equal the expected total processing times. However, a job's cycle time is highly variable due to factors such as e.g. an unbalanced production line which may cause congestion, waiting times due to different operator skill classes, uncertainty about the required processes and the presence of other jobs. A third problem regarding the current customer order acceptance function is that operators are tried to be planned fully utilized. Since cycle times non-linearly increase with the utilization rate (Hopp & Spearman, 2011), this might cause due date reliability problems.

Second, the current shop floor control structure may also cause due date reliability problems. First of all, it is concluded that no upper bound on the WIP level is specified, since jobs are released immediately to the production area once they arrive at the facility. Second, foremen do not use a specific sequencing rule to decide in which order jobs are processed. Hence, it is reasonable to conclude that operators may be working on jobs which with less priority. Last, although the shop floor control structure is highly complicated, operators and machine types are not decomposed into multiple production units to reduce system's complexity. Taking all the above into account, it is expected that PLVS can benefit from simple mechanisms provided in literature.

4 Research Context

As mentioned in Section 1.5, the theoretical background (Chapter 2) aimed to gain insights about the control mechanisms provided in literature to design the shop floor control problem in general. Subsequently, the case study provided insights about the MD environment. Based on the information provided in these chapters, Chapter 0 discusses the research context in more detail. We formulate research questions to decompose the complexity of the main research question. Furthermore, the answers to the research questions together will provide the answer to the main research question. Next, this chapter furthermore describes the research approach (Section 4.2) and the research scope (Section 4.3).

4.1 Research Questions

As mentioned in Chapter 0, the main research question which is leading throughout this study is formulated as:

How to design a shop floor control system for a maintenance depot which minimizes costs, while meeting a 98% aggregate service level target?

The research approach applied in this study is called simulation (Section 4.2). Simulation can only be applied in case a simulation model can be build that represents the system analyzed (Law & Kelton, 2015). As such, the first research question aims to build a valid simulation model:

1. *How to design a simulation model which represents the current safety valve overhaul process?*

According to Hopp & Spearman (2011) and Bertrand et al. (1998), service level depends on both a job's cycle time and its lead time. As such, the proposed shop floor control system design should control both cycle times and lead times. Cycle time is a function of the WIP level divided by the throughput rate (Little, 1961). A control mechanism provided in literature to control WIP levels relates to sequencing rules (Bergamaschi et al., 1997). Since many different sequencing rules exist and the fact that PLVS is not familiar with general sequencing rules, research question 1 is established to determine which sequencing rule should be applied within the shop floor control system for a maintenance depot:

2. *Which sequencing rule results in the best service level performance given the workforce costs during regular demand periods?*

The sequencing rules that will be compared are First-Come First-Served (FCFS) and Earliest Due Date (EDD). These static sequencing rules, i.e. job sequence is time independent (Pinedo, 2005), are selected over the dynamic sequencing rules minimum slack (MS) and critical ratio (CR), because static sequencing rules are relatively easy to understand, use, and implement (Nahmias & Cheng, 1993). The static sequencing rule shortest processing time (SPT) is out of scope, because according to Baker and Bertrand (1982) EDD outperforms SPT for medium to high allowance factors. The allowence factor is the ratio between the flow allowence (i.e. time between a job's arrival time and its due date) divided by the expected total processing time (Baker & Bertrand, 1982). Since the aggregated mean allowance factors equal 6.1 and 7.9 regarding regular demand arrivals and TAR demand arrivals respectively, we assume that EDD outperforms SPT.

Next, research question three copes with controlling throughput times. As mentioned in Section 2.1.2, throughput rates can be bounded by capacity restrictions in terms of workforce or equipment. Since the ratio workforce divided by equipment equals 0.37 and the fact that during shop floor observations a machine bottleneck was not found, we assume that workforce limits the throughput rates. Nahmias and Cheng (1993) claim that near optimal throughput rates can already be achieved for low flexible workforce. Since processes within the valve overhaul process require various operator competence levels and the fact that operators within the MD under analysis are (partially) cross-trained, we expect that the way how workforce is allocated affects the service level performance. Moreover, as visualized in Table 9Table 9: Relative number of operators, workforce costs and hiring workforce cost per operator competence level. Due to confidential reasons, these numbers are fictive., various costs are associated with each operator competence level. Therefore, we expect that, from a cost perspective, a workforce allocation policy using full flexible operators will not always outperform other workforce allocation policies using less flexible operators. To verify our expectations, research question 3 is established to explore which workforce allocation policy results in the best service level performance for a certain cost factor:

3. *Which workforce allocation policy results in the best service level performance given the operational workforce costs?*

In this study, five different workforce allocation policies are modeled and analyzed (Table 10**Error! Reference source not found.**). The first three models differ from one another in terms of their workforce flexibility. Since systems with full flexible workforce outperform systems with less flexible workforce (Hopp & Spearman, 2011; Nahmias & Cheng, 1993), the fourth model is established to obtain insights about how current equipment levels limit the throughput rate. Last, model 5 is based on the Eindhoven Planning Framework, which decomposes the current system in production unit in order to reduce system complexity (Bertrand et al., 1998). In this model, cross-trained workers are allowed to perform activities of other competence levels (i.e. partially cross-trained). We refer to Section 5.2 in which a detailed description is provided about how these five workforce allocation policies are modeled.

Table 10: Workforce allocation policies and their characteristics

Workforce allocation policy	Workforce flexibility [cross-training]			Equipment flexibility		Overhaul process	
	No	Partial	Full	Current situation	Full	Current situation	3 production units
Policy 1 (NOCTW)	X			X		X	
Policy 2 (PACTW)		X		X		X	
Policy 3 (FUCTW)			X	X		X	
Policy 4 (FUCTWAE)			X		X	X	
Policy 5 (3PU)		X		X			X

Apart from the mechanisms provided to control the cycle time, the last research question is established to explore how lead times can be controlled such that a 98% service level target can be met. Since PLVS is able to discuss start and end dates for customer orders regarding the standard demand type, it is expected that there exists a lead time control rule that satisfies a 98% service level and decreases current average lead times. As such, research question 4 is established to design such a lead time control rule:

4. *How to design a lead time control rule that results in a 98% service level performance, while maintaining current average lead times?*

Research question 4 aims to determine a deterministic lead time control rule. This deterministic lead time control rule will be based on the approach introduced by Bertrand et al. (1998) and Hopp and Spearman (2011), which is described in Section 2.2.

4.2 Research Approach

According to Law and Kelton (2015), a system can be studied in various ways (Figure 14). In this study, simulation will be used to experiment how the various sequencing rules, operator allocation methods and lead time control rules perform. Simulation is selected, because of the low costs involved with designing a simulation model and the fact that literature is available to build a mathematical model (e.g. factory physics, Law and Kelton, Silver & Pyke). Furthermore, simulation is preferred over an analytical solution, because of the model complexity (Law & Kelton, 2015). This is in line with Nahmias and Cheng (1993), who claim that complex models has to be studied using simulation. In this study, simulation is defined as the numerical approach to assess how the inputs in question affect the output performance metrics (Law & Kelton, 2015).

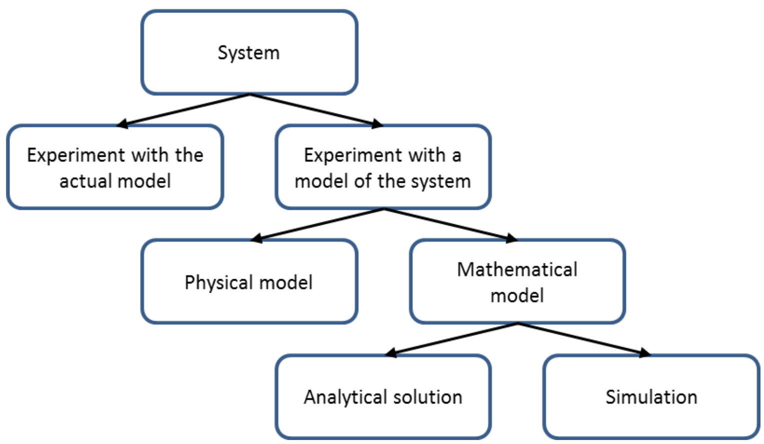

Figure 14: Ways to study a system according to Law and Kelton (2015, P.4)

According to Law and Kelton (2015), simulation models can be classified along three different dimensions. Without going into details, the simulation model build in this study is discrete, dynamic and stochastic and is denoted as discrete-event simulation. We refer to page 6 of Law and Kelton (2015) for a detailed description about discrete-event simulation models.

Simulation models

Now that simulation is chosen as the appropriate research approach, simulation models have to be designed for each proposed solution design individually. Furthermore, since data regarding a regular demand period and a TAR demand period is gathered (Section 3.1.2), we aimed to study the research questions for each demand period individually. This indicates that the total number of simulation models that will be designed equals at least 40 (i.e. two sequencing rules, five workforce allocation policies, at least two lead time control rules and two demand periods). Since 40 simulation models are inappropriate from a time perspective, we have limited the number of simulation models. The procedure how the number of simulation models are limited is described in the next paragraph.

The decisions made are mainly based on the results of previous research question. In short, we have designed ten different simulation models in which the two sequencing rules and the five workforce allocation policies were designed during a regular demand period using lead times derived from the regular demand case. Using these results (Figure 15), it is expected that EDD also outperforms FCFS during TAR demand periods. This is in line with literature, since EDD is aimed to reduce due date related objectives (Pinedo, 2005).

Next, simulation models SM11-SM15 are added to visualize how the workforce allocation policy affects the service levels during TAR demand periods. In here, the EDD sequencing rule is applied. Based on the results (Figure 16, Figure 17, Figure 18), it is shown that lead times regarding the regular demand arrivals cause problems in terms of the average service level. Moreover, a 98% service level target regarding the TAR demand arrivals can be achieved for most cost factors. As such, we have limited the number of simulation models by establishing a lead time control rule that results in a 98% service level performance and decreases the current average lead time. This lead time control rule is established for a model in which a partially cross-trained workforce policy (PACTW) is applied and jobs are scheduled according to the FCFS sequencing rule. A PACTW model is selected because it can be implemented directly (no other workforce types are required). The FCFS sequencing rule is selected, because this rule minimizes the average cycle time variance (Nahmias & Cheng, 1993). Table 11 provides an overview of all 17 simulation models designed in this study.

Table 11: Overview of all simulation models involved

Sequencing rule		FCFS					EDD				
Workforce flexibility											
Lead Time	**Demand period**	**NOCTW**	**PACTW**	**FUCTW**	**FUCTWAE**	**3PU**	**NOCTW**	**PACTW**	**FUCTW**	**FUCTWAE**	**3PU**
From data	**Regular**	SM1	SM2	SM3	SM4	SM5	SM6	SM7	SM8	SM9	SM10
From data	**TAR**						SM11	SM12	SM13	SM14	SM15
Decision variable	**Regular**		SM16 & SM17								
Decision variable	**TAR**										

4.3 Simulation Scope

Section 4.3 discusses 5 aspects to specify the research boundaries.

The first boundary relates to the facility that will be analyzed. Since shop floor control systems deal with the control of one operation, it is expected that the shop floor control system can be designed for one of the facilities within PLVS and that the provided recommendations can serve as a starting point for the shop floor control design of other MDs. Table 3 shows the average monthly demand for each facility based on data from 1 January 2014 till August 2016. Since Facility B consists of the highest sales, it is expected that changing the shop floor control system for this facility will be most beneficial for PLVS. As such, data regarding Facility B will be used to design the operations planning and control system for PLVS.

Since all three operations are managed without concerning input about the shop floor control problem of other facilities, it is expected that the shop floor control system can be designed for one facility and that the provided recommendations can serve as a starting point for the design of other shop floor control systems within a MD. Table 3 contains the average monthly demand for each facility based on data from 1 January 2014 till August 2016. The product group safety valves is selected for two reasons. First, as visualized in Table 3, the sales volumes regarding the safety valves are significantly higher than the other product groups. Second, as explained in Appendix A.2, sufficient additional data is only collected for the product group safety valves. This data is required to design a simulation model. As such, the other two product groups cannot be analyzed by a simulation approach using the current data.

Third, the research is further scoped regarding the specific product types. As mentioned in Section 3.2, PLVS does not record data about process characteristics such as processing time or routings. This indicates that data needs to be gathered first. Since PLVS distinguishes over 30 different safety valve types (SABIC Europe, 2009), a selection is made based on the valve sizes (i.e. DN-size). As explained in Section 3.1, a valve's DN-size is the main factor which influences the processing times. In consultation with PLVS management and based on data analysis, it is chosen to gather data regarding the product types DN-25, DN-50 and DN-80, since these valve sizes cumulatively account for 84% of the total sales volume (Table 4).

We furthermore differentiate between periods in which TARs are executed and regular demand periods. As such, regular demand periods incorporate TALs, emergency orders and service contract demands. This is valid by assuming that high order sizes in the regular demand model represent the TALs and small order sizes with short lead times relate to emergency orders.

Finally, we only consider the shop floor control problem. This indicates that the order acceptance function as executed by planners is out of scope. The lead time control rule which is discussed in research question 4 is meant to specify a lead time at the moment a customer order arrives at the PLVS facility.

5 Models and Cases

In this Section, models are described that are used in this study to evaluate how workload can be managed in the MD. First, Section 5.1 describes the general model logic used within each alternative model. Next, Section 5.2 describes the five alternative models that are established based on literature. Last, Section 5.3 introduces the cases that will be analyzed.

5.1 Basic Simulation Model

This section explains how the MD is designed in the simulation model and is used as the foundation within each of the alternative models. In here, the general system variables, model description, model assumptions, control mechanisms are described. Finally, the model is verified and validated to assess how representative the model is. We refer to Appendix E.1 in which all variables are explained for this study.

5.1.1 Model description

The valve overhaul production system consists of a network of 20 different processes, $pr = \{1,2, \dots ,20\}$, through which jobs are processed. A job, $j \in J$, always starts at process 1 and is successfully overhauled as soon as the job finishes process 20. Each job is of job type $d = \{1,2,3\}$ with probabilities 0.681, 0.203 and 0.116 (Appendix B.1). These job types represent the job types DN-25, DN-50, and DN-80, respectively.

A job is in the system at the moment a customer order $co \in CO$ arrives at the system. Customer orders arrive with interarrival times $\tau^{dt}_{co,co+1}$ and consist of an order size Q^{dt}_{co} which distributions depend on the demand type $dt = \{1,2\}$. Moreover, for each job that arrives within customer order co, $j \in J_{co}$, a lead time LT^{dt}_{j} is sampled from a distribution which also depends on its demand type dt. We refer to Section 5.3 in which the demand types are explained.

Once a job arrives at the system, it starts its overhaul process at process one and continuous the overhaul process by moving from one process to another until the job departs the system as soon as process 20 is finished. Based on process mining (Appendix B.3), it is known that jobs are not faced with fixed routings. As such, an algorithm is developed to determine a jobs next process (Appendix E.4).

In general, a job moves from process $pr \in PR$ to process $pr + 1$ at rate r_{pr+1}. As such, the relative number of jobs that are served at a particular process, $\bar{X}_{pr}$, approaches r_{pr}. However, two main exceptions have to be addressed. First, inspection (process 7) may conclude that spare parts have to be ordered before the job can be further processed. Therefore the job is put on hold with rate r_{OH}. Second, after the job is tested (process 16), jobs may be sent back for rework activities with probability r_{Rew}. Jobs that are faced with rework activities always first follow the same sequence of processes $pr \in PR_{Rew}$, after which the job returns to the normal procedure again. Table 12 shows the rates and the associated confidence interval that are included in the model. Appendix B.3 explains the procedure about how these rates are obtained.

Table 12: Processing rates and confidence intervals for each of the 20 processes involved in the valve overhaul production process and the relative probability that rework occurs or jobs are put on hold.

pr	**Sample size n_{pr}**	r_{pr}	**Normally approached?**	$r_{pr} \pm 1.96\sqrt{\frac{r_{pr}(1-r_{pr})}{n_{pr}}}$
1	87	1.00	No	N.A.
2	87	0.83	Yes	0.83±0.08
3	87	1.00	No	N.A.
4	87	0.89	Yes	0.89±0.08
5	87	0.17	Yes	0.17±0.08
6	87	0.92	Yes	0.92±0.06
7	87	1.00	No	N.A.
8	87	0.20	Yes	0.20±0.08
9	65.8	0.82	Yes	0.82±0.09
10	65.8	0.17	Yes	0.17±0.09
11	87	0.03	No	N.A.
12	87	0.52	Yes	0.52±0.11
13	87	1.00	No	N.A.
14	87	1.00	No	N.A.
15	87	0.08	Yes	0.08±0.06
16	87	1.00	No	N.A.
17	87	0.48	Yes	0.048±0.11
18	87	0.22	Yes	0.22±0.09
19	87	0.52	Yes	0.52±0.11
20	87	1.00	No	N.A.
On hold	N.A.	$r_{OH} = 0.03$	N.A.	N.A.
Rework	87	$r_{Rew} = 0.02$	No	N.A.

Each process $pr \in PR_{sk}$ requires an operator $o \in O_{sk}$ who is skilled to execute the process, and a corresponding machine $ma \in MA_k$. The model recognizes 7 different machine types $k = \{1,2,\dots,7\}$, which are related to workbenches, test machines, cleaning cabins, blasting machines, patching machines, the conserving installation and the conserving wall, respectively. Each machine type MA_k has a finite number of machines. Besides the machines, the system distinguishes 4 operator competence levels. These competence levels are A, B, C and D and mathematically denoted by $sk = \{A, B, C, D\}$. Additionally, the processes $pr \in PR$ are also divided into subsets using these four competence levels, such that $P(pr \in PR | pr \in PR_{sk}) = 1$. Which operator type is allowed to execute a particular process type depends on the model considered. Whenever an operator type is selected, we assume that idle operators from this particular operator type are scheduled according to a FCFS policy. This sequencing rule balances the utilization rate between operators of a particular operator type. Note that none of the operators in the system is allowed to execute process 8, which means that process 8 is executed through a different department within the company under analysis.

If a job arrives at process $pr \in PR$ and a competent operator is free and a machine idle, the job is processed. The required processing time $pt_{j,d,pr}$ is a BetaPERT IID random variable with input parameters $a_{d,pr}, ml_{d,pr}, b_{d,pr}$ for the minimum, most-likely and the maximum processing times, respectively (see Appendix B.2 how this theoretical distribution is determined). Table 13 shows the mean and standard deviation for each process pr and job type d, which are independent from whether or not a job is faced with rework. If no competent operator is free, the job joins the list of jobs waiting for this operator type. On the other hand, in case an operator is free but no machine is idle, the job and the operator together joins the queue of the particular process.

Table 13: Mean and standard deviation for the input parameters regarding the processing times per process pr and job type d.

	Job type $d = 1$		Job type $d = 2$		Job type $d = 3$	
pr	$\mu_{1,pr}$	$\sigma_{1,pr}$	$\mu_{2,pr}$	$\sigma_{2,pr}$	$\mu_{3,pr}$	$\sigma_{3,pr}$
1	3.00	0.00	3.00	0.00	3.00	0.00
2	10.34	1.77	12.46	2.13	14.54	2.08
3	15.83	2.14	19.39	2.42	22.24	2.63
4	13.75	2.29	19.17	3.06	21.67	2.14
5	9.17	0.83	9.17	0.83	9.17	0.83
6	13.79	1.83	17.67	2.00	17.02	1.79
7	10.19	1.76	11.72	1.86	11.97	1.72
8	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
9	13.02	2.40	13.75	2.36	15.48	2.38
10	18.71	2.29	18.60	1.67	17.78	1.67
11	18.71	2.29	18.60	1.67	17.78	1.67
12	11.67	2.08	15.58	2.62	13.92	2.26
13	8.69	1.31	8.27	1.17	9.05	1.17
14	15.50	2.12	19.33	1.94	24.04	2.37
15	8.21	1.17	8.21	1.17	8.21	1.17
16	18.27	2.33	21.27	2.33	22.33	2.33
17	10.72	1.72	11.53	2.00	13.67	1.93
18	15.33	1.75	17.50	1.67	16.00	1.67
19	14.17	0.83	14.17	0.83	19.17	0.83
20	9.62	1.38	10.65	1.27	11.89	1.48

Sometimes, a job is not sent to a process $pr \in PR_D$. That is, a job requires process 8 or is put on hold due to the absence of materials. In both cases, the processing times pt_j^{MM}, pt_j^{OH} for process 8 (i.e. mechanical machining) and on hold equal exactly 1 day (i.e. 480 minutes).

5.1.2 Assumptions

Table 14 describes the general assumptions that are used in each model. The assumptions are divided into 4 categories, which are jobs, operators, processes and machines.

Table 14: Overview of the assumptions made in the simulation model. These assumption are decomposed into four categories, which are jobs, operator, processes and machines.

Notation	Assumption
J1	Jobs always finish the overhaul process. As such, no escalation procedure exists.
J2	All incoming customer orders are accepted.
O1	A job can be processed only by one operator at the same time.
O2	An operator is 100% effective, which means an operator is never sick, in meetings, etc.
O3	We assume no processing time loss if processes are unfinished due to breaks or end of working days
O4	All operators contain the same work pace, i.e. processing times are independent from the operators.
O5	1 operator accounts for 1 FTE.
O6	Operators work 8 hours a day, 5 days a week during weekdays. As such, no overtime or weekend time is included in the model.
O7	Operators within each operator competence level are scheduled according to a FCFS policy
P1	The processing time for mechanical machining activities (process 8) is deterministic and equals 8 hours.
P2	The time a job is put on hold due to the absence of spare parts is deterministic and equals 8 hours.
P3	Transportation times between processes are not modeled and are assumed to be included in the processing times.
P4	A job is faced with rework activities only once per overhaul.
P5	When a job requires rework, the processes and the routing in which the processes are executed are fixed.
P6	If a job needs to be checked by a contractor through an acceptance test (process 16), this test will be executed immediately after testing (process 15) is performed. As such, we assume that the contractor is at the facility and we expect no cycle time loss.
M1	Machines are 100% effective, which means no break downs occur.
M2	Machines only process jobs that are included in the scope. As such, no capacity is reserved to process jobs from other product types.

5.1.3 Control Mechanisms

This section describes the control mechanisms that are incorporated within each model. The control mechanisms that are designed for each model specifically are explained in Section 5.2.

Release method: customer order arrival

All jobs from a customer order arrival are always immediately released to the production area. The order in which jobs are processed depends on the sequencing rule, which is an input parameter to the model. A job is processed in case an operator who is competent and allowed to start the overhaul process is free. Whether an operator is allowed to start the valve overhaul process depends on the model type. If no operator who is allowed to start the valve overhaul process is free, the job joins the queue of jobs waiting to start the overhaul process. For simplicity, this queue is henceforth called the start queue $Queue_{start}$.

Release method: spare parts arrived or mechanical machining activities are successfully performed

Jobs that were put on hold due to the unavailability of spare parts or have left the production department for mechanical machining activities immediately return into the production system as soon as the spare parts are delivered or the mechanical machining activities have been completed successfully. If an operator is free who is allowed to fulfill the job's next process, the job is allocated to this operator. On the other hand, if no operator is free to execute the next process, the job joins the queue of the operator competence level $Queue_{sk}$ that belongs to the minimum operator competence level class of process $pr \in PR_{sk}$.

Control rule: next job scheduled from waiting for a machine queue

A job which moves from process $pr = \{1,2, \dots, \widetilde{pr} - 1\}$ to a next process, $pr + i \in PR$ for $pr + i \neq pr$, may be executed on the same machine type, i.e. $pr \in PR_k \wedge pr + i \in PR_k$. If an operator is available to execute this next process $pr + i$, the job is processed on the same machine. On the contrary, if a job's next process is executed on a different machine type or no operator is available to execute the next process, the machine becomes idle. Then, the following algorithm is applied:

1. IF $Queue_k > 0$, for $k = \{1,2, \dots, \tilde{k}\}$ THEN machine starts processing the next job in line. Which job is scheduled next depends on the sequencing rule applied in the model.
2. ELSE machine becomes idle.

5.1.4 Model Validation

The most definitive test of a simulation model's validity is to establish that the outputs obtained closely resemble the outcomes that would be expected from the actual system (Law & Kelton, 2015). As such, the model is validated which is done through hypothesis tests on the mean total processing times per job type d. This statistical test is chosen since the expected mean total processing times per job type are the only parameters which are known by PLVS. These parameter values contain the total processing times for all processes except pretesting (process 2), mechanical machining (process 8) and constructing an identity tag (process 15) (SABIC Europe, 2009). Furthermore, these mean total processing times are calculated without concerning about time losses due to e.g. queue time. As such, the simulation model is designed concerning infinity many resources and operators to be fully cross-trained. In addition, the time required for process 2, 8, 15 and waiting times due to spare parts that are out of scope were removed from the model.

The hypotheses test on the mean is constructed as follows. For each job type d, 25 replications ($n = 25$) are simulated in which m jobs ($m \approx 7{,}750$) per replication are processed. Then, for each replication $repl = \{1,2, \dots, n\}$, the mean total processing time $X_{repl,d}$ is calculated for each job type d. These mean total processing time outcomes are IID observations and can be assumed to be normally distributed (Law & Kelton, 2015). The obtained values are then used to calculate the sample mean total processing time $\bar{X}_d(n)$, the sample variance $S_d^2(n)$ and the test statistic t_n^d, which are calculated according to the formulas provided in Law and Kelton (2015). These parameters are used to test the hypothesis on the mean, which is defined as:

$$\begin{cases} If\ |t_n^d| > t_{n-1,1-\alpha/2}, reject\ H_0: \mu^d = \mu_0^d \\ If\ |t_n^d| > t_{n-1,1-\alpha/2}, fail\ to\ reject\ H_0: \mu^d = \mu_0^d \end{cases}$$

Where all μ_0^d are fixed, obtained from PLVS and hypothesized values for the μ^ds. The μ^ds are estimated and replaced by the unbiased estimators $\bar{X}_d(n)$ (Law & Kelton, 2015).

Table 15 shows the results of the hypothesis tests. Since for all $d \in D$ the test statics $\left|t_n^d\right|$ exceeds the cutoff score $t_{n-1,1-\alpha/2} = 2.064$, we have to reject all null hypotheses. Rejecting the null hypotheses indicate that the proposed simulation model does not represent the reality for each of the job types. Therefore, one normally has to design a different simulation model. However, the proposed simulation model design is still used as a basis to analyze alternative models, because of three reasons. First, the mean total processing times are based on time studies which are executed before 2010. It is expected that some of the process times measured are outdated due to investments in new machine types and/or changes in the procedures which are for example caused by new technologies (e.g. test reports are constructed digitally instead of manually). Second, as mentioned in Section 3.1, the mean total processing times available for operators contain only a proportion of the total processing times measured by the time motion study from SABIC Europe (2009), which is aimed to stimulate operator's work pace. It is expected that these proportions do not necessarily represent reality. Last, since the absolute time difference between the $\bar{X}_d(n)$ and μ_0^d for all $d \in D$ are small and the fact that processing times per process individually were not available from data, PLVS' management is satisfied with the mean total processing times obtained from the simulation model. Based on these reasons, it is decided to use the simulation model as a basis to compare alternative models with.

Table 15: Results of the hypothesis tests on the mean total processing times with the null-hypothesis: $\boldsymbol{H_0}: \boldsymbol{\mu^d} = \boldsymbol{\mu_0^d}$

Job type d	$\boldsymbol{\mu_0^d}$	$\boldsymbol{\bar{X}_d(n)}$	$\boldsymbol{S_d^2(n)}$	$\boldsymbol{t_n^d}$	$\boldsymbol{t_{n-1,1-\alpha/2}}$
1	151.2	145.9	0.042	129.6	2.064
2	159.6	170.5	0.050	243.8	2.064
3	180.6	186.9	0.052	139.0	2.064

5.2 Alternative Models

As mentioned in Section 3.1.1, MD's demand pattern highly fluctuates due to the maintenance strategies applied by customers in the Gas and Oil industry. Since we cannot control the customer's strategy, models have to be developed that account for these demand fluctuations. Literature has shown that one who wants to stabilize cycle times have to keep the throughput rate proportionally to the WIP levels (Little, 1961). The effective throughput rate, however, is often constrained by capacity restriction in terms of equipment or workforce (Hopp & Spearman, 2011). Since the MD under analysis contains much more equipment than workforce, it is expected that workforce limits the effective throughput rate. In such systems, cross-trained workers can significantly increase the effective throughput rates without increasing equipment or workforce levels (Nahmias & Cheng, 1993). Hence, three models are established which are used to evaluate the impact of cross-trained workers in the current situation. In order to be able to verify whether equipment constraints the performance output, a fourth model is developed which includes full flexibility regarding the equipment. Lastly, a fifth model is developed which relies on the principles of the EPF. According to Bertrand et al. (1991), one can deal with complexity by decomposing a complicated production system into smaller less complicated production units. As such, the fifth model consists of three production units, in which two production units are within the scope. These five models are successively explained in the sections below.

5.2.1 Workforce Allocation Policy 1: No Cross-Trained Workforce

Workforce allocation policy 1 is called the no cross-trained workforce (NOCTW) allocation policy. This workforce allocation policy allocates operators only to those jobs that need to be processed at a process of their competence level (Table 16). Furthermore, the number of machines used in this workforce allocation policy equals the number of machines available at the MD under analysis. As such, this model is characterized as the least flexible workforce allocation policy of all workforce allocation policies considered. The control rules included in this policy are explained below.

Table 16: Cross diagram regarding the operator competence levels $\boldsymbol{O_{sk}} \forall \boldsymbol{sk}$ and the process subsets $\boldsymbol{pr_{sk}} \forall \boldsymbol{sk}$ for model 1: NOCTW.

	$\boldsymbol{pr \in PR_A}$	$\boldsymbol{pr \in PR_B}$	$\boldsymbol{pr \in PR_C}$	$\boldsymbol{pr \in PR_D}$
$\boldsymbol{o \in O_A}$	X			
$\boldsymbol{o \in O_B}$		X		
$\boldsymbol{o \in O_C}$			X	
$\boldsymbol{o \in O_D}$				X

Control rule: operator's next task

Once an operator finishes a job at process pr, the job moves to the next process $pr + i$ for $i = \{1,2, \dots, pr - i\}$. If pr and $pr + i$ relate to the same competence level class sk, that is $pr \in PR_{sk} \wedge pr + i \in PR_{sk}$, the same operator executes the job's next process. On the other hand, an operator who executes process pr may become free if the next process $pr + i$ is executed at a different competence level class. Then, the algorithm below is used to determine the operator's next task. This algorithm is furthermore used in case an operator finishes the last overhaul process $\widetilde{pr}$.

1. IF operator $o \in O_{sk}$ AND $Queue_{sk} > 0$, for $sk = \{A, B, C, D\}$ THEN operator moves to the next job. Which job is picked depends on the sequencing rule that is applied in the policy.
2. ELSEIF operator $o \in O_A$ AND $Queue_{CW} > 0$ THEN operator moves to a job which has to start the overhaul process from the beginning. Which job is picked depends on the sequencing rule that is applied in the policy.
3. ELSE operator becomes free.

5.2.2 Workforce Allocation Policy 2: Partially Cross-Trained Workforce

According to Nahmias and Cheng (1993), partially cross-trained workers can significantly increase the effective throughput rates without increasing equipment or workforce levels. As such, workforce allocation policy 2: partially cross-trained workforce (PACTW) is established in which workforce is allowed to fulfill processes of a different operator competence level. Table 17 visualizes which operator competence level is allowed to execute which process subsets. The operator control rules are explained below.

Table 17: Cross diagram regarding the operator competence level $\boldsymbol{O_{sk}} \forall \boldsymbol{sk}$ and the process subsets $\boldsymbol{PR_{sk}} \forall \boldsymbol{sk}$ for model 2: PACTW.

	$\boldsymbol{pr \in PR_A}$	$\boldsymbol{pr \in PR_B}$	$\boldsymbol{pr \in PR_C}$	$\boldsymbol{pr \in PR_D}$

$\boldsymbol{o \in O_A}$	X			
$\boldsymbol{o \in O_B}$	X	X		
$\boldsymbol{o \in O_C}$	X	X	X	
$\boldsymbol{o \in O_D}$	X			X

Control rule: Customer order arrival

As mentioned in Section 3.1, each job from a customer order arrival is released immediately to the production area. In workforce allocation policy 2, which operator is allocated to the job depends on the following algorithm:

1. IF $OBUSY_A(t) < \#O_A$ THEN an operator $o \in O_A$starts processing the first activity of this job
2. ELSEIF $OBUSY_B(t) < \#O_B$ THEN an operator $o \in O_B$ starts processing the first activity of this job.
3. ELSEIF $OBUSY_D(t) < \#O_D$ THEN an operator $o \in O_D$starts processing the first activity of this job.
4. ELSEIF $OBUSY_C(t) < \#O_C$ THEN an operator $o \in O_C$ starts processing the first activity of this job.
5. ELSE all operators are busy and the job joins the queue of jobs waiting to start the overhaul process, $Queue_{CW}$.

Control rule: operator priority change

Since processes regarding a particular competence level are spread throughout the entire valve overhaul process, a control rule is specified to evaluate whether an operator should change to a different job. This function is invoked in case an operator has executed a process which does not relate to its own competence level. Furthermore, in case the next process $pr + i$ is of a lower competence level, an algorithm is developed which first checks whether a job is waiting in the queue for the particular competence level of the operator. Below the algorithms are introduced for both the priority evaluation after a process is finished and after the next process is determined for the job.

Algorithm to evaluate an operator's priority after a job has finished process pr.

1. IF $o \in O_{sk}$ AND $pr \notin PR_{sk}$ THEN
   - IF $Queue_{sk} > 0$ THEN the operator start processing the next job waiting in $Queue_{sk}$.
   - ELSEIF $o \in O_D$ AND $Queue_A > 0$ THEN the operator starts processing the next job waiting in $Queue_A$.
   - ELSEIF $o \in O_C$ AND $pr \in PR_A$ AND $Queue_B > 0$ THEN the operator starts processing the next job waiting in $Queue_B$.
2. Else the operator remain at the job until the job's next activity $pr + i$ is determined.

Algorithm to evaluate an operator's priority after a job's next process $pr + i$ is determined.

1. IF $pr + i \in PR_A$ AND $o \in O_D$ AND $Queue_D > 0$ THEN operator starts processing a job waiting in $Queue_D > 0$.
2. ELSEIF $pr + i \in PR_A$ AND $o \in O_B$ AND $Queue_B > 0$ THEN the operator starts processing a job waiting in $Queue_B > 0$.
3. ELSEIF $pr + i \in PR_B$ AND $o \in O_C$ AND $Queue_C > 0$ THEN the operator starts processing a job waiting in $Queue_C > 0$.
4. ELSEIF $pr + i \in PR_A$ AND $o \in O_C$ AND $Queue_C > 0$ THEN the operator starts processing a job waiting in $Queue_C > 0$.
5. ELSE the current operator executes the next process $pr + i$

Control rule: operator's next task

In case an operator is not allowed to execute a job's next process or the job has successfully finished the overhaul process, the operator is freed in case no jobs are available that can be processed by this operator. The algorithm to determine whether an operator becomes free is explained as follows:

1. IF operator $o \in O_{sk}$ AND $Queue_{sk} > 0$, for $sk = \{A, B, C, D\}$ THEN the operator is allocated to a job waiting in $Queue_{sk}$. Which job is picked depends on the sequencing rule that is applied in the model.
2. ELSEIF operator $o \in O_C$ OR $o \in O_B$ AND $Queue_{sk-1} > 0$ THEN the operator is allocated to a job waiting in $Queue_{sk-1}$. Which job is picked depends on the sequencing rule that is applied in the model.
3. ELSEIF operator $o \in O_C$ AND $Queue_A > 0$ THEN the operator is allocated to a job waiting in $Queue_A$. Which job is picked depends on the sequencing rule that is applied in the model.
4. ELSEIF operator $o \in O_D$ AND $Queue_A > 0$ THEN the operator is allocated to a job waiting in $Queue_A$.
5. ELSEIF $Queue_{start} > 0$ THEN the operator is allocated to a job waiting in $Queue_{start}$.
6. ELSE operator becomes free.

5.2.3 Workforce Allocation Policy 3: Fully Cross-Trained Workforce

Although partially cross-trained workforce may already result in near optimal throughput rates, according to literature, fully cross-trained workforce (FUCTW) will outperform less cross-trained workforce (Nahmias & Cheng, 1993). As such, workforce allocation policy 3 evaluates the system's performance based on operators who are fully cross-trained. In this policy, only one operator type is defined who executes all processes from start to finish. Since PLVS' current workforce level has not yet incorporated operators who are fully competent, the current workforce level need to be modified when applying this workforce allocation policy. For this reason, the operator skill class O_E is introduced such that each operator $o \in O_E$ is allowed to execute all processes $pr \in PR_E = PR_A \cup PR_B \cup PR_C \cup PR_D$. Only one control rule is determined to specify the prioritization of an operator's next job once he completes his previous job.

Control rule: operator's next task

1. IF operator $o \in O_E$ AND $Queue_E > 0$ THEN the operator is allocated to a job waiting in $Queue_E$. That is, a job returns from mechanical machining department or spare parts are successfully ordered.
2. ELSEIF $Queue_{start} > 0$ THEN the operator is allocated to a job waiting in $Queue_{start}$ to start the overhaul process from the beginning.
3. ELSE operator becomes free.

5.2.4 Workforce Allocation Policy 4: Fully Cross-Trained Workforce and Ample Equipment

Throughput rates can be constraint by capacity in terms of workforce and equipment (Hopp & Spearman, 2011). So far, workforce allocation policies 1 to 3 only evaluate the impact of workforce flexibility. Workforce allocation policy 4, on the contrary, is similar to workforce allocation policy 3, but includes besides fully cross-trained workforce also ample equipment (FUCTWAE). That is, the number of machines $\#MA_k$ for all $k \in K$ equals the number of operators in the system. As such, jobs and operators will never be blocked due to machines that are fully utilized at a particular moment in time. The same control rule is used as in workforce allocation policy 3 in case an operator has finished a previous job.

5.2.5 Workforce Allocation Policy 5: 3 Production Units

In contrast to the previous workforce allocation policies, workforce allocation policy 5, henceforth called the 3PU policy, decomposes the production system into production units (PUs). This policy is proposed, because MD's production complexity can be reduced through decomposing the system into separated production units (Bertrand et al., 1998). Bertrand et al. (2016) have identified four reasons to decouple processes into production units. When applying these reasons, almost every process has to be decoupled into PUs because successive processes are not often not synchronized in either speed, setup or uncertainty. Since it is not useful to consider each process separately (Bertrand et al., 2016), it is decided to decompose the production system into three PUs. Three PUs are proposed because of the following reasoning. First, a production unit is designed for the mechanical machining activities (process 8), since these activities are already executed by a different department. Second, in practice and stated in literature as well, the overhaul processes can be grouped into cleaning, inspection, reassembling and testing activities. Since a job's content is only known after the inspection activity is executed, it is expected that a PU that includes the activities until inspection and a PU which starts their activities after the inspection activity can be implemented in practice. As such, the processes within each PU, $pr \in PR_{pu}$ for $pu = \{1,2,3\}$, is mathematically expressed as follows. PU1 contains the processes $PR_1 = \{1,2, \dots ,7\}$, PU2 only contains process 8; $PR_2 = \{8\}$. Last, PU3 consists of the processes $PR_1 = \{9,10, \dots ,20\}$.

According to Bertrand et al. (1998), PUs are black boxes that transform input materials into output PU-end items without using any information about how the design problem of other PUs is solved (Bertrand et al., 2016; de Kok & Fransoo, 2003). As such, applying the EPF (i.e. decomposing the production system into PUs) results in a specific allocation of available resources. Although the decision variables in this study relate to the number of operators per operator type, we still have to adjust the current workforce levels. Namely, both production units require at least one operator of competence level D, which is more than the one operator currently included in the workforce level. Next, machines are divided over the production units as follows. All cleaning cabines and blasting machines are allocated to PU1, since none of these machine types are required in PU3. Similarly, the lapping machines and conservation equipment are allocated to PU3. The test machines and workbenches are divided in the way how operators are divided over the PUs. For example, in case the number of operators who are allowed to use the testing machines equals 1 and 2 for PU1 and PU3 respectively, then, the testing machines are allocated accordingly. In case the number of operators who are able to use the test machines and workbenches exceeds the number of available machines in the system, the machines are divided proportionally.

The control rules applied in the 3PU policy are similar to the control rules applied in the PACTW policy. One exception is made, operators can only execute processes in the PU they are assigned to.

5.3 Cases

Data from Section 3.1.2 is used to establish the input distributions regarding the interarrival times, lead times and customer order sizes for both the regular demand data as well as for the TAR demand data (Table 18 and Table 19). We refer to Appendix C and Appendix B how these distributions are obtained. Note that some distributions are truncated to ensure that observations will not result in an impossible value. That is, the minimum and maximum values are finite instead of infinity to ensure that undesired values are obtained from the model. Although truncating models will influence the mean and variance of the distribution, we mention that the impact regarding the mean is not significant.

Table 18: Input distributions regarding the regular demand data

	Sample size n	Mean(n)	Best fitted distribution	P1	P2	P3	Domain	Mean
Inter-arrival times	39	147.59	Exponential	λ=147.59			[0,960]	±145
Lead times	36	1106.14	Log-Logistic	α=1.3833	β=531.36 56	ϒ = 0.3986	[0,4800]	±950
Order size	41	2.171	Negative-Binominal	s=1	p=0.4606 7	ϒ = -1	[0,Inf]	2.171

Table 19: Input distributions regarding the TAR demand data

	Sample size n	Mean(n)	Best fitted distribution	P1	P2	P3	Domain	Mean
Inter-arrival times	36	187.69	Weibull	α =1.3597	β =211.38	ϒ = -6.7627	[0,502]	±172
Lead times	181	1421.23	Empirical distribution				[0,4800]	1421.23
Order size	36	2.171	Negative-Binominal	s=1	p=0.20809	ϒ = -1	[0,Inf]	2.171

These distributions will be used for the two cases that will be analyzed. Case 1: Regular demand case, contains only the distributions provided in Table 18. On the other hand, in the TAR demand case the distributions from both datasets are implemented in the simulation models.

6 Results

In Chapter 6, the results regarding research questions 2, 3 and 4 are provided. Research question 1 is not included in this section, since the answer to this research question is already provided in Section 5.1.4. This section starts with a description about the simulation design (Section 6.1). Subsequently, the results regarding the research questions are provided in succession.

6.1 Simulation Design

The alternative workforce allocation policies proposed in Section 5.2 are built into the simulation model described in Section 5.1. Using these models, simulation experiments are performed to gather results. These simulation experiments are based on the guidelines provided in Law and Kelton (2015) and briefly described below.

For each of the replications performed, a warm-up period and simulation length are determined which are constructed using Welch's approach (Law & Kelton, 2015). According to this approach, the warmup period regarding the regular demand period is set to 175,200 time units (i.e. 1 year) and 87,600 time units for TAR demand periods. Each replication ends at respectively 1,401,600 and 700,800 time units, after which the statistics are recorded. We have selected the metric operator's utilization level to determine whether the initial transient period is smoothed out. This metric was chosen over the KPI service level, since service level is discrete time statistic which changes each time a job finishes his overhaul. On the other hand, operator utilization level is continuous over time.

Within each simulation experiment, we performed at least 25 replications. A simulation experiment incorporated two stopping criteria. First, and most often used, a simulation experiment ended we reached an absolute precision for both the average service level and the operator utilization rates less than ±0.002 with 95% confidence. Second, a maximum number of replications was built in due to memory issues of the computer used for the simulation runs. These maximum replication numbers are 65 and 73 for respectively the TAR demand periods and the regular demand periods. When all simulation experiments are considered, the maximum absolute precision error observed at the 95% confidence level equals ±0.003.

Last, we want to mention that we have applied common random numbers (CRN) as a variance reduction technique. This technique is chosen for two reasons. First, the technique is especially useful when comparing two or more models (Law & Kelton, 2015). Second, according to Law and Kelton (2015), CRN is the most useful variance reduction technique. However, due to this variance reduction technique, the models in Section 6.2 are compared according to the sample-t test statistic since this test statistic allow for dependence between observations where other tests do not (Law & Kelton, 2015).

6.2 Results Research Question 2

Section 6.2 provides the results regarding research question 2: *Which sequencing rule results in the best service level performance during regular demand periods?* The results regarding the sequencing rules are displayed in Figure 15 (a,b,c,d,e) for each of the five models separately. For each sequencing rule, the average tardiness, which equals $1 - average\ service\ level$, is plotted against the relative costs. The relative costs are calculated for each individual experiment by dividing the total hourly costs by the current hourly costs. This current hourly cost factor is based on the workforce level currently on the payroll.

Since all graphs show that the average tardiness level flattens out as the cost increases, the results are only displayed for a particular subset. The domain of these subsets are determined as follow. The minimum cost factors are those where the average tardiness level is below 20%, that is, the average service level is higher than 80%. The maximum cost factors are those for which the difference between the average tardiness of two subsequent cost factors are less than 0.02%. Appendix E.5 contains the results of all simulation experiments are displayed including their input variables.

As displayed in Figure 15 (a,b,c,d,e), the sequencing rule EDD outperforms FCFS for average tardiness levels below 20%. This outcome is additionally confirmed by the paired-t 95% confidence interval test statistic (Appendix E.4), which allows us to state with 95% reliability that EDD outperforms FCFS for each cost factor with average tardiness levels below 20%.

The results furthermore show that only model 4 can achieve the service level target of 98% (Figure 15d). When the fully cross-trained workforce and ample equipment strategy is applied, a minimum relative hourly costs of 146.1% will result in an average service level equal to 98.03%. Note that the average operator utilization rate regarding this strategy equals 20.55%± 0.10% with 95% confidence interval (Appendix E.5).

Last, model M2 shows that, independent from which sequencing rule applied, which operator type need to be hired should be evaluated cautiously. This, because hiring a higher qualified operator (e.g. competence level C instead of A) will not automatically result in lower average tardiness levels. Although the differences are small, the average tardiness level regarding the associated cost factors 107.4% and 112.2% are 2.447% and 2.455%, respectively (Appendix E.5).

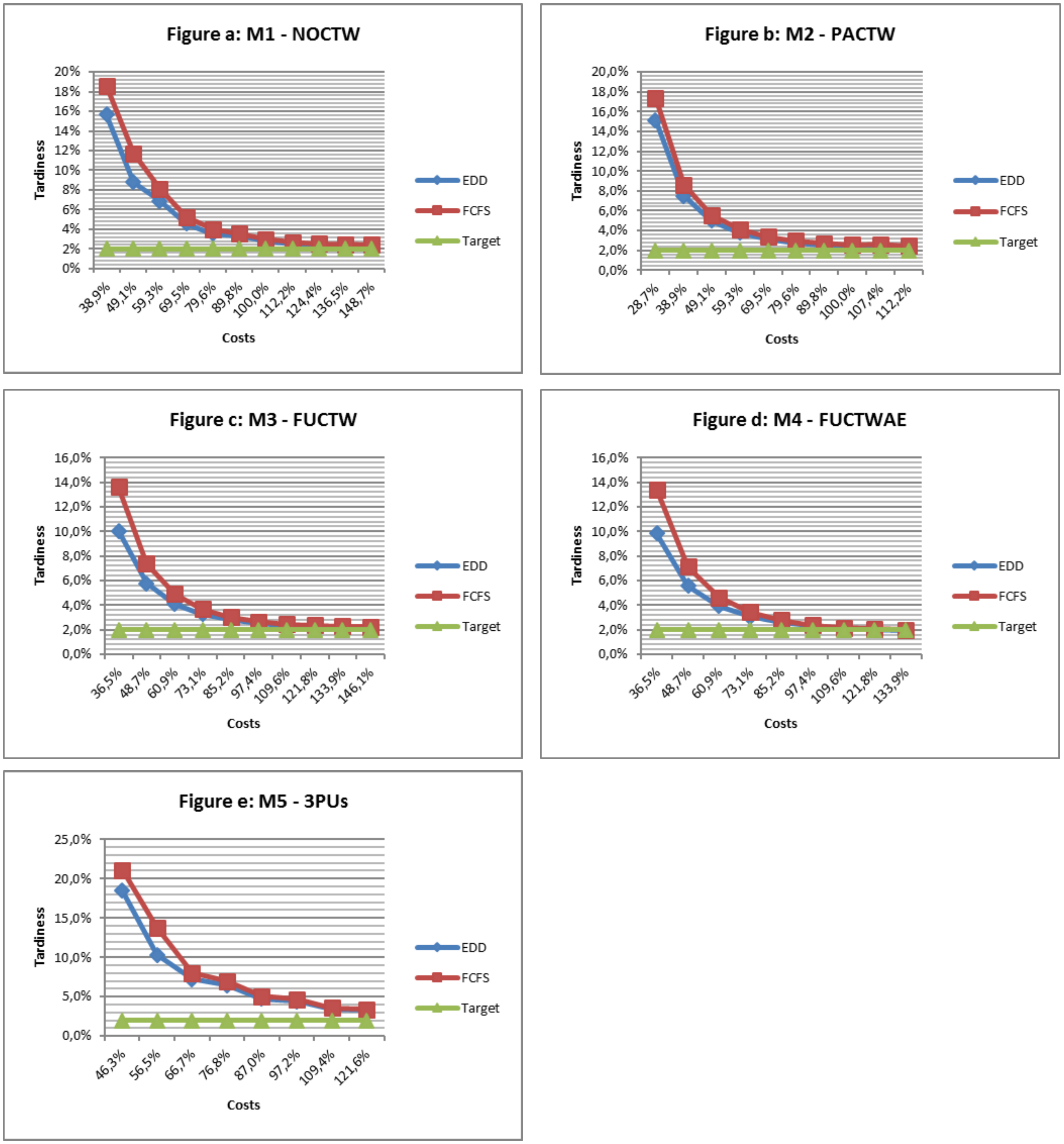

Figure 15a,b,c,d,e: Results regarding the sequencing rules for each of the five models. In here, the average tardiness is plotted against the relative costs.

6.3 Results Research Question 3

Section 6.3 provides the results regarding research question 3, which is about the model design best applicable for the MD under analysis sensitive to the demand type period. The results regarding the regular demand period are described in Section 6.3.1. Subsequently, Section 6.3.2 provides the results with regard to the period in which a TAR is scheduled next to the regular demand.

6.3.1 Model evaluation - regular demand period

Figure 16 plots the tardiness against the relative cost factors for the five models using their sequencing rule which results in the lowest average tardiness levels. Since the models do not provide results for similar cost factors, it is hard to state which model is best based on statistics. However, models SM6 and SM7 and models SM8 and SM9 provide results for similar cost factors. As such, for these models, a paired-t 95% confidence interval test statistic is used to examine if one of these models outperform the other one. According to Law and Kelton (2015), the paired-t 95% confidence interval test statistic is used to construct a confidence interval, $\zeta = \mu_1 - \mu_2$, to test whether one variable differs from the other variable with 95% confidence. Table 20 and Table 21 show that with 95% confidence model SM6 is outperformed by model SM7 and model SM9 outperforms model SM8 for similar cost factors in terms of average service levels, respectively. Furthermore, a different pattern is observed between the two model comparison tests. Namely, the observed difference between models SM7 and SM6 is a declining function as the costs increases, whereas the observed difference between models SM9 and SM8 seems to be a parabolic function. This parabolic pattern might be explained by the fact that the available equipment constraint the workforce relatively more for higher costs levels than for lower costs levels. The declining function in Table 20 is an argument that the advantages from partially cross-trained workforce decreases as the costs increases. Or in different words, as the utilization rate decreases, the advantages in terms of service levels from partially cross-trained workforce decreases. Note however that the maximum cost factor in Table 20 is lower than in Table 21, which might explain why the pattern in between models SM9 and SM8 is not observed between models SM7 and SM6.

Table 20: Results of the paired-t 95% confidence interval test statistic to test whether model 6 or model 2 is superior for certain cost factors.

Costs	$\overline{SL}^6$	$\overline{SL}^7$	95% CI for $\zeta = \overline{SL}^7 - \overline{SL}^6$	Best Model
49%	84.3%	92.5%	[0.5313, 0.5553]	SM7*
59%	91.2%	95.0%	[0.1045, 0.1087]	SM7*
69%	93.1%	96.2%	[0.0486, 0.0512]	SM7*
80%	95.4%	96.9%	[0.0365, 0.0384]	SM7*
90%	96.5%	97.2%	[0.0171, 0.0185]	SM7*
100%	96.7%	97.4%	[0.0092, 0.0106]	SM7*
112%	97.5%	97.5%	[0.0067, 0.0077]	SM7*

Table 21: Results of the paired-t 95% confidence interval test statistic to test whether model 8 or model 9 is superior for certain cost factors.

Relative Costs	$\overline{SL}^8$	$\overline{SL}^9$	95% CI for $\zeta = \overline{SL}^9 - \overline{SL}^8$	Best Model
37%	68.3%	68.8%	[0.0042, 0.0057]	SM9*
49%	90.0%	90.1%	[0.0015, 0.0022]	SM9*
61%	94.2%	94.4%	[0.0016, 0.0022]	SM9*
73%	95.9%	96.1%	[0.0015, 0.0022]	SM9*
85%	96.7%	97.0%	[0.0017, 0.0024]	SM9*
97%	97.2%	97.4%	[0.002, 0.0026]	SM9*
110%	97.5%	97.7%	[0.0019, 0.0025]	SM9*
122%	97.6%	97.9%	[0.0022, 0.0029]	SM9*
134%	97.7%	98.0%	[0.0022, 0.0027]	SM9*
146%	97.8%	98.0%	[0.0023, 0.0028]	SM9*

In Figure 16, the tardiness patterns of each model individually are equivalent to the patterns displayed in Figure 15 (a,b,c,d,e), since the graph uses the same data. The results, however, are only displayed for tardiness levels below 10%. Figure 16 shows that no particular model performs best in terms of the tardiness level for all costs factors. The cut-off point is at 107.4%. For cost factors below 107.4%, the PACTW model (SM2) performs best, whereas the FUCTWAE model (SM4) outperforms all other models after this cost factor. Although we state that only two models are favorable, note that some costs factors can only be obtained by one model. For example, if one wants to apply a model structure which includes 97.4% relative costs, the 3PU model (SM10) has to be selected. However, the graph shows that the 3PU model is outperformed by all models for tardiness levels below the 5%. That is, for each tardiness level in the 3PU model there exists a cost factor in all other models which is lower and results in even lower tardiness levels.

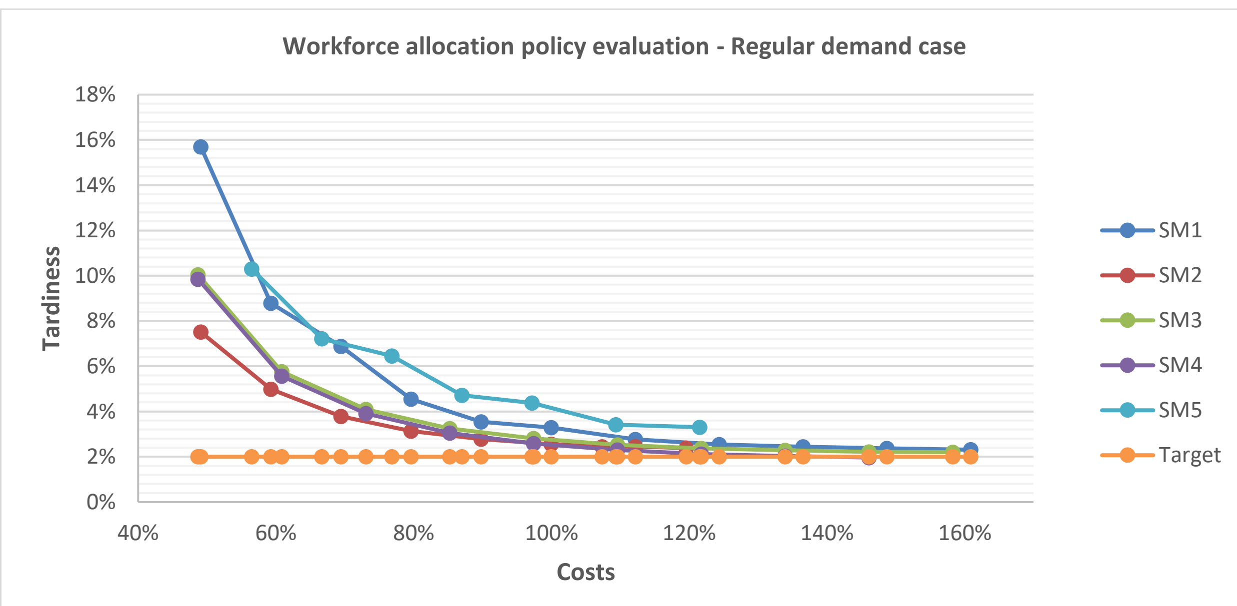

Figure 16: Workforce allocation policy evaluation regarding in the Regular demand case. In here, the models are plotted using the EDD sequencing rule.

6.3.2 Model evaluation – regular demand and TAR period

The results regarding the tardiness performance levels during a period in which a TAR is planned while regular demand arrives as well are plotted in Figure 17 and Figure 18 concerning TAR demand arrivals and the regular demand arrivals respectively. In these figures, the tardiness performance levels are displayed against the relative cost factors for all five models. Furthermore, the targeted service level performance is included in the figures as well. Figure 17 shows that the tardiness levels are a declining function as the costs increase. In addition, at some cost factor, all models achieve a 100% service level performance, i.e. 0% tardiness. As such, the maximum tardiness performance target (2%) can be achieved for all model types. The associated cost factors at which the model types first achieve the target performance level, however, differ per model type. These cost factors are 109.2%, 89.2%, 109.6%, 109.6% and 97.2% for models SM11, SM12, SM13, SM14 and SM15 respectively.

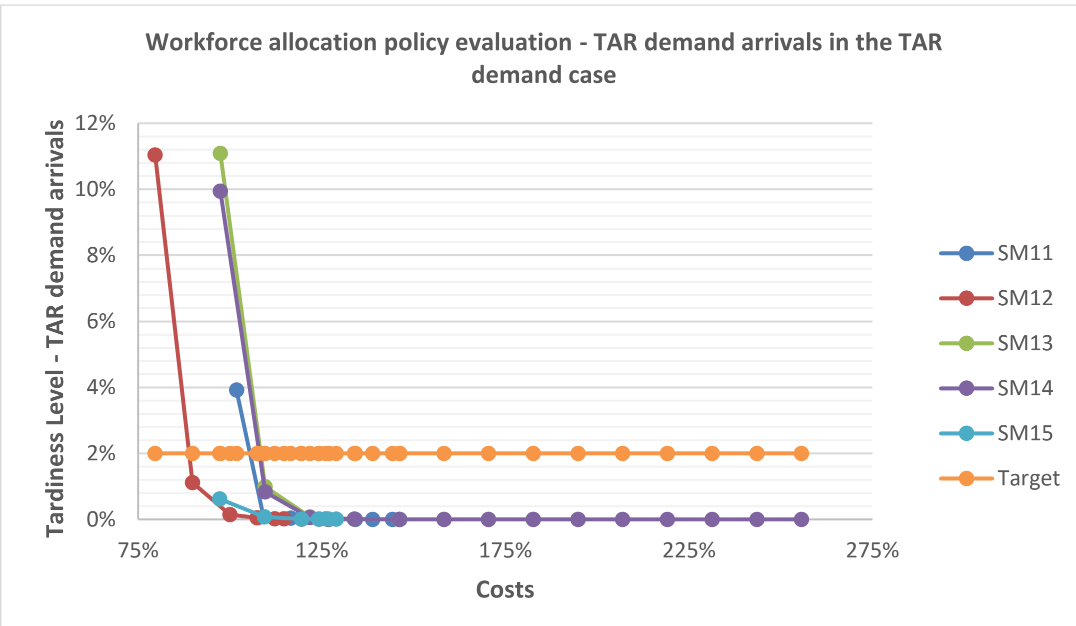

Figure 17: Workforce allocation policy evaluation regarding TAR demand arrivals in the TAR demand case. In here, the models are plotted using the EDD sequencing rule.

Next, Figure 17 shows the results of the tardiness performance levels for the regular demand arrivals during a TAR demand period. As visualized, the tardiness performance levels are a declining function over the costs with some exceptions in between regarding the models SM11 and SM15. In these models, the decision which operator type is hired should be made cautiously, since hiring a more expensive operator type may not necessarily result in a lower tardiness performance level.

The Figure furthermore visualizes that only the FUCTWAE model (SM12) achieves the tardiness performance level target. SM14 achieves this tardiness performance level target when the hourly wages are at least 244% of the current hourly costs.

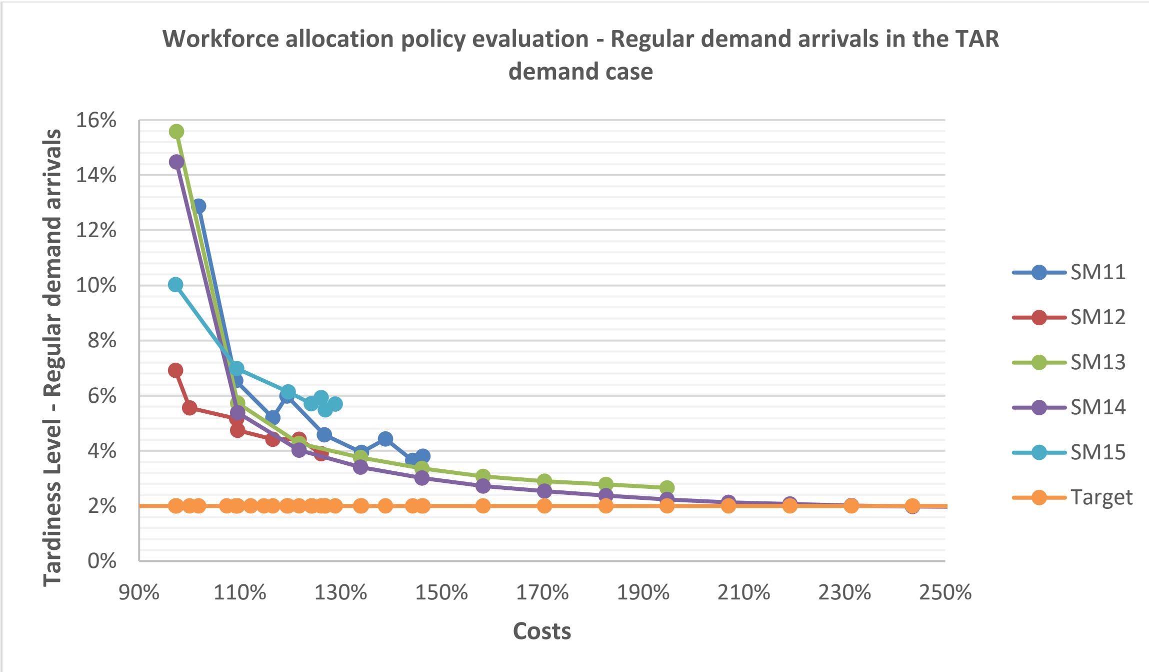

Figure 18: Workforce allocation policy evaluation regarding the regular demand arrivals in the TAR demand case. In here, the models are plotted using the EDD sequencing rule.

When comparing Figure 17 and Figure 18, the following conclusions are drawn. First, for each cost factor and for each model type, it is concluded that the average tardiness levels are lower regarding the TAR demand arrivals compared to the regular demand arrivals. This might be due to the lower allowance factor used for regular demand arrivals than for TAR demand arrivals. Second, the policy which results in the lowest average tardiness level for the current cost factor relates to the PACTW model (SM12). The PACTW model results in the lowest average tardiness levels for both regular demand arrivals as for TAR demand arrivals. Third, based on the models analyzed, no model exists that achieves the tardiness performance level target during a TAR demand period for both demand types individually without making any equipment investment. This is concluded since only model M5 (FUCTWAE) achieves the service level targets for both demand types.

6.3.3 Discussion regarding demand type sensitivity

Section 6.3.1 and Section 6.3.2 discussed the results regarding a regular demand period and a TAR demand period respectively. The graphs included in these sections show similar declining patterns for each model type regarding the tardiness performance level for increasing cost factors. Furthermore, only model M5 (FUCTWAE) achieves the tardiness performance level target (2%) during both demand periods. As such, management is recommended to use the workforce allocation strategy applied in M4. Then, the minimum hourly cost factor increases by at least 46% during regular demand periods and by at least 144% TAR demand periods. Although these investments in hourly wages are required to ensure the tardiness level performance is achieved, the operator utilization rates associated with these cost investments are relatively low (20.6% and 35.4%, respectively). This implies that the proposed due dates (i.e. arrival time + throughput time) are hard to achieve for higher utilization rates. Since operator utilization rates are often around 80%

in production and maintenance industries (Silver et al., 1998), next Section provides results on the lead time control rule.

6.4 Results Research Question 4

According to Hopp and Spearman (2011, P.332), the lead time control rule that satisfies a particular service level is a function of both the mean and standard deviation of the cycle time. If those cycle times (CT) are normally distributed, then for a service level (SL) the minimum lead time (LT) equals (Hopp & Spearman, 2011; Bertrand et al., 1998):

$$LT = CT + z_{SL} * \sigma_{CT}$$

In here, z_{SL} equals the value in the standard normal table for which $\Phi(z_{SL}) = SL$. The term $z_{SL} * \sigma_{CT}$ is called the safety lead time (Hopp & Spearman, 2011). Note that this formula assumes cycle times to be normally distributed. Therefore, a K-S goodness of fit test is used to establish whether this assumption is valid. As explained in Appendix E.5, based on the K-S test statistic the null-hypothesis: *cycle times are normally distributed*, is rejected (1.242>1.035, at the $\alpha = 0.01$ confidence level). This conclusion remained intact after log-normalizing the cycle times. As such, the cycle times are analyzed using its empirical distribution.

Figure 19 depicts the cumulative distribution function (CDF) regarding the cycle times respectively for both operator utilization levels 62% and 83% using the PACTW workforce allocation policy (SM16) and a FCFS sequencing rule. A FCFS sequencing rule is applied, since this rule minimizes cycle time variances (Nahmias & Cheng, 1993). The PACTW workforce allocation policy is selected instead of the NOCTW policy and 3PU policy, since this policy requires a minimum number of operators that result in already medium operator utilization rates. On the other hand, the PACTW workforce allocation policy is privileged over the FUCTW policies, because the operational costs embedded with the PATCW are lower. The cycle times observed stems off from 1 simulation run in which 25,000 jobs were overhauled.

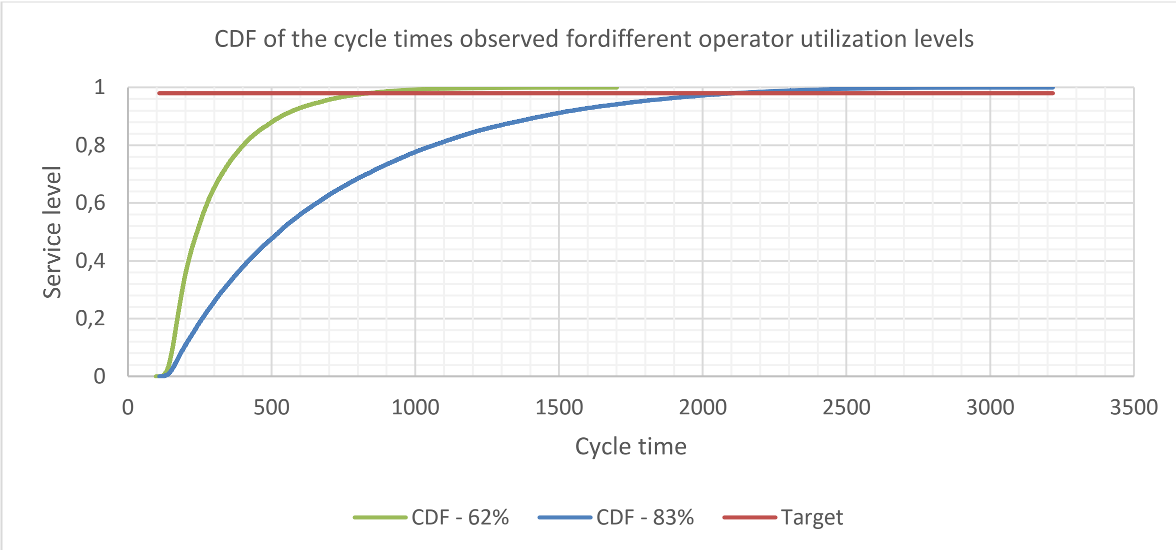

Figure 19: Empirical CDFs of the cycle times observed for operator utilization levels equal to 62% and 83%. The empirical CDFs are based on 25,000 jobs.

As shown, the minimum values which guarantee a 98% service level target correspond to 833.7 and 2105.4 minutes respectively for utilization rate levels 62% and 83%. Since these results are obtained from only one simulation run, we have validated the results by simulating 73 replications and constructed a 95% CI t-test statistic on the mean service level when including a lead time equal to 840 minutes. Then the observed average service level is higher than the 98% service level target with approximately 95% confidence, since the 95% CI does not contain zero (Appendix E.5). As such with approximately 95% confidence, we conclude that PLVS can apply a deterministic lead time control rule approach during regular demand periods which reduces the average lead times ($840 < 1106.14$), increases the operator utilization rates up to a maximum of 62% while at the same time a 98% service level target is met.

7 Conclusions and Recommendations

In this section, we answer the main research question which was formulated as follows:

How to design a shop floor control system for a maintenance depot which minimizes costs, while meeting a 98% aggregate service level target?

The main research question can only be answered by first providing the conclusions regarding the four research questions individually. These conclusions are discussed in the four sections below, which finally result in a recommendation for MD's management. The research questions were formulated as follows:

1. *How to design a simulation model which represents the current safety valve overhaul process?*
2. *Which sequencing rule results in the best service level performance given the workforce costs during regular demand periods?*
3. *Which workforce allocation policy results in the best service level performance given the operational workforce costs?*
4. *How to design a lead time control rule that results in a 98% service level performance, while maintaining current average lead times?*

Simulation model

The simulation model which is designed to reflect the safety valve overhaul process is based on the fundamentals of a job shop. As such, we have used the guidelines provided in Law and Kelton (2015) to build a discrete event simulation model while using input parameters estimated from practical data. For generality, we have applied theoretical input distributions in our simulation models for those input distributions which fitted well on the available data. For example when considering the regular demand case study, we have applied a negative binominal distribution for the order size and an exponential distribution for the interarrival times such that a compound poisson arrival process is modeled. A compound poisson arrival process is often observed in practice when orders arrive in batches (Law & Kelton, 2015).

The simulation model is validated in Section 5.1.4. Although the KS-test statistic results in rejecting the null hypothesis that the simulation model fits well with the total planned processing times used by PLVS, the model fits satisfactory well according to management.

Sequencing rules

As shown in Figure 15 (a,b,c,d,e), the sequencing rule EDD results in higher service level performances as compared to FCFS during regular demand periods. In addition, EDD significantly outperforms FCFS independent from which workforce allocation policy is applied. This result is in line with literature, which states that EDD performs better than FCFS regarding due date related objectives for medium to high allowance factors (Baker & Bertrand, 1982). Based on these findings, our first recommendation to MD's management is:

R1: Apply the EDD sequencing rule in the production area. This affects two decisions in the current shop floor control management. First, whenever an operator becomes idle and jobs are waiting to start the overhaul process, then, the operator should pick the job containing the earliest due date next. Second, in case a machine type is busy and operators are waiting in queue, whenever such a machine becomes idle the job (and operator) which start processing next is the one with the job containing the earliest due date.

Workforce allocation policy

The results in Section 6.3 demonstrate that the only workforce allocation policy which achieves the 98% service level target is the FUCTWAE policy. This 98% service level target is first met for associated workforce costs levels 146.1% and 243.5% regarding regular demand periods and TAR demand periods, respectively. As such, it is concluded that PLVS can only obtain its 98% service level target when investments are made in both workforce and equipment. Note however that it might not be necessary to invest in an ample equipment production area, i.e. the number of machines per machine type equals the number of operators available in the system, to observe the same results as the FUCTWAE model presents. It is expected that the maximum number of machines busy for a machine type concerned with low utilization rates may not be equal to the number of operators in the system. For example, when implementing this workforce allocation policy, management may not have to invest in blasting machines up to the number of operators in the system.

Although this policy is recommended from a service level target point of view, we do not advise management to implement the FUCTWAE model into practice. On the one hand, because the implementation costs regarding workforce and equipment are expensive. Workforce investments are required to have fully cross-trained workforce. This can be obtained by either contracting new fully cross-trained operators or by training the current workforce level (Hopp & Spearman, 2011). Additionally, when considering the case in which the current workforce level is trained towards fully cross-trained operators, we do not recommend this FUCTWAE model because of the willingness of operators. Often in practice, the best system will not be implemented, but instead a system is implemented that achieves employee's collaboration (Maskin & Sjöström, 2002). As such, from a practical point of view, we recommend management to implement a PACTW model (M2), since this model performs best when leaving out of picture the models with fully cross-trained workforce. Accordingly, management is advised to reconsider the current performance level target, because it is impossible to achieve a 98% service level target based on the models provided and the case studies analyzed.

R2: Apply a PACTW model. That is, do not allocate operators to specific jobs (FUCTW), but allocate operators to tasks they are competent for. In addition, allow operators to execute tasks from other operator competent levels whenever they are idled. Note that, this model can only be applied in combination with recommendations 4 and 5.

R3a: Reconsider the desired service level target.

Lead time control rule

The results in Section 6.4 show that a deterministic lead time control rule can be specified during regular demand periods which decreases the average lead time experienced by customers by 24.1%, while at the same time a 98% service target is met. Moreover, the operator utilization level can be increased from 24% to 62%. This indicates that operational workforce costs can be reduced by 61.1% during regular demand periods. Note however that reducing the operational workforce level will increase the costs of hiring operators during TAR demand periods.

Although the results are validated, we highly recommend to interpret these results with caution. This, because the results are obtained within the parameter settings as provided in case study 1. Since the constructed lead time control rule is deterministic, it is not sustainable and robust for environmental changes. Although the annual sales volumes are quite stable (Figure 12), a control rule which is not robust for future demand changes is undesired (Bertrand et al., 2016). Fortunately, many researchers have already studied lead time control rules (e.g. Hopp & Spearman, 2011). We refer to their work if management decides to start researching a sustainable control rule. At this moment, we showed that there exist a lead time control rule that decreases the average lead time while increasing operator utilization levels. We furthermore expect, that the techniques offered by researchers can even further improve the lead time control rule proposed. This all considered, the following recommendation is made to MD's management:

> *R3b: Renegotiate with customers the minimum lead time required to overhaul a valve. When considering the current workforce level, the minimum lead time required to overhaul a valve should at least be equal to 14 hours (i.e. 840 minutes).*

Shop floor control structure design

Considering the answers to the four research questions, we conclude that general control mechanisms proven in theory can be well applied within a MD. As such, we recommend to apply an EDD sequencing rule each time a decision has to be made regarding a queue. Furthermore, PACTW policy provides higher average service level performances as compared to NOCTW policy and the 3PU model including PACTW. Since the PACTW does not require investments in workforce's competences, the recommended shop floor control structure design applies an EDD sequencing rule and benefits from the advantages of cross-trained workforce by applying a partially cross-trained workforce policy.

7.1 Limitations

Section 7.1 describes the research limitations, which are divided into three categories. The first category contains the limitations about the control mechanisms applied (Section 7.1.1). Subsequently, limitations regarding the research scope are provided in Section 7.1.2. Last, Section 7.1.3 discusses limitations regarding the assumptions made in the simulation model.

7.1.1 Control Mechanisms

In this section, four topics regarding the control mechanisms are discussed.

Sequencing rules

In this research, we have examined whether theory about sequencing rules and cross-trained workforce can be applied within a MD environment. The sequencing rules evaluated in this study are EDD and FCFS. EDD and FCFS are selected, since these rules are static (Pinedo, 2005) and are therefore relatively easy to understand and implement in practice (Nahmias & Cheng, 1993). However, researchers have established many other sequencing rules (cf. Nahmias & Cheng, 1993; Thomas et al., 1997; Silver et al., 1998; Pinedo, 2008; Hopp & Spearman, 2011). Literature have indicated that EDD is especially useful for due date related objectives (e.g. Pinedo, 2005). Other sequencing rules that optimize due date related objects are for example minimum slack (MS) and critical ratio (CR) (Pinedo, 2005; Stockton et al., 2008). Moreover, Stockton et al. (2008) claim that CR is often used in a MTO production environment. That all considered, it is expected that we have not included the sequencing rule which results in the best performances yet.

Priority control rules.

When considering the simulation model, many decisions had to be made about prioritizations. Especially in the PACTW model (M4), lots of decisions had to be made. We illustrate five of these decisions in the bullet points below.

- Whenever a valve arrives, which operator competence type starts this job?
- When an operator finishes a job, which job will he process next? A job that is waiting to start the valve overhaul process? A job that is waiting after it returned from the mechanical machining department? Or another job?
- If all machines of a particular machine type are busy, does the job and the operator wait in the line or does only the job waits in line? Then, what will be the operator’s next job? Furthermore, who will process the job as soon as a machine becomes idle?
- When a job returns from the mechanical machining department, will the same operator continue the valve overhaul process?
- When a job is waiting for a particular operator who executes a process which belongs to a different operator competence level, will he finish or quit the overhaul process regarding his current job?

Such decisions are extensively researched in the operator allocation field (Hopp & Spearman, 2011). According to these authors, chaining and bucket brigade are general research topics that can be consulted which deal with operator allocation decisions.

Although lots of research is provided in literature, our simulation model is limited by including only the basic priority control mechanisms. In general, the following two principles are included in the model. First, since high WIP levels reduce system’s throughput rates, we have modeled that operators who complete a job overhaul always first continue working on a job which is waiting in the system, before start processing a job waiting at the beginning of the valve overhaul process. Second, we have modeled that operators always process jobs from their own competence level first before working on jobs or other competence levels. As such, it may happen that operators are interrupted from their job between two successive processes to start working on a different job. Note that this only happens in the PACTW model (M2) and the 3PU model (M5).

Next, in our simulation models we have designed that whenever a job is waiting for a machine to become idle, the operator is waiting as well. We expect that modeling operators according to a bucket brigade policy will result in higher average service levels.

R4: Allocate operators first to jobs that require their competence level. An idle operator is allowed to start processing a job which does not require his specific competence level, i.e. the operator can be subjected to jobs that require a lower competence level, until a job is waiting to be processed at the operator's specific competence level. If multiple jobs are waiting for an operator to be processed, then the job is selected that is waiting at the highest competence level he is allowed to work on.

CONWIP

CONWIP is a control mechanisms that aims to keep the WIP level at a predetermined constant level. In systems that apply a CONWIP rule, a next job is started as soon as a job departs from the system (Silver et al., 1998). This rule is aimed to control system's cycle times. Since cycle time is a function of the WIP level divided by the throughput rate (Little, 1961), limiting the WIP levels result in an upper bound on the cycle time when considering a particular throughput rate. The CONWIP rule is especially applicable in MTO process line environments (Silver et al., 1998).

Since the MD production area can be seen as a job shop (Bertrand et al., 1991), the optimal WIP level may not be necessarily equal to the number of operators in the system. Hopp and Spearman (2011) claim that production systems keep their operators busy instead of idled to achieve the best performances. However, literature has indicated that cycle times, and accordingly average service level performance, depends on the maximum WIP level the system achieve (Hopp & Spearman, 2011). Since all processes are executed in batch sizes equal to 1, it is expected that the average service level performance is a function over the maximum WIP level allowed which first remains constant and after a particular cutoff point decreases as the maximum WIP level increases. Whether our simulation models exceed this cutoff point is unknown. As such, our simulation models are limited by not incorporating a CONWIP rule. However, note that we use a control rule that assigns operators first to jobs that are waiting in the system before starting a new job from the beginning. This control rule is included to prevent for high WIP levels. Therefore, we advise MD's management to apply such a rule.

R5: Apply a CONWIP rule or assign operators to jobs waiting in the system before starting a new job overhaul process.

Lead time control rule

The lead time control rule provided in Section 6.4 is deterministic, i.e. for all jobs the same. However, according to Little (1961), the time required to process a job also depends on the WIP (workload available) and the throughput rates (i.e. number of operators and equipment in the system). As such, applying a deterministic processing rule may not be sustainable when shop floor management change the parameter settings. Since many researchers have studied the lead time control rule topic (e.g. Hopp & Spearman, 2011), we expect that the results provided in this study may be outperformed by other more sophisticated techniques.

7.1.2 Research Scope

In Section 7.1.2, we discuss our research scope and how this limits our research. As mentioned in Section 4.3, our research is scoped by the number of operations analyzed. Since all operations can operate independent from one another, we expect that the main empirical findings regarding the sequencing rules, operation allocation model and the lead time control rule can be implemented within the other operations as well. However, since they may be faced with different input parameters (e.g. lead times, interarrival times, order sizes, number of operators per operator type available, number of machines), the explicit results can only be applied to Facility B.

Next, the research is also scoped regarding the product groups analyzed. Although it is known that the safety valve overhaul process differs from the product groups on-off valves and control valves in terms of e.g. the processes and machines involved, we emphasize that the main findings can still be applied within the other product groups.

Last, our research is limited by including only the product types up to a DN-size equal to 80, which equals 84% of all safety valves overhauled (Table 4). Furthermore, we have generalized the job types into three categories: DN-25, DN-50 and DN-80, such that we have only included three job types in the simulation models. This decision limits our research, since the processing times are mostly a function of the valve size. Moreover, including more valve sizes in the analysis gives rise to investigate whether the shortest processing time (SPT) sequencing rule may result in better service level performance targets. Baker and Bertrand (1982) showed that applying a sequencing rule which combines the advantages of EDD and SPT result in better performances for situations in which the proportion total processing time divided by the time available are high.

7.1.3 Assumptions

In this study, several assumptions are made to cover the issues as observed when designing the general simulation model. These assumptions limit the rigorousness of the model. In this section, we will not discuss all of these assumptions, but we want to emphasize the assumptions in aggregate terms.

Input parameters

The general simulation model consists of many input parameters that are fundamental for our results. Most of these input parameters are estimated based on very low sample sizes. Especially the ratios at which processes are executed can highly deviate from the ratios applied in our simulation models. In addition, the ratios are determined based on safety valves overhauled during a regular demand period. It might be reasonable to assume that jobs during TAR demand periods are faced with other ratios, since those jobs are often heavily loaded as they are located in customer's main production areas.

Next, the assumption is made that whenever jobs are sent to the mechanical machining department (process 8) or put on hold due to the absence of spare parts, they always return after a deterministic amount of time units equal to 480 minutes. This however can be either lower or higher in practice. We furthermore have assumed that the approved due date extends similarly. This assumption, according to PLVS' management, is valid regarding the regular demand periods, but may not be always valid for TAR demand periods. As such, the obtained service level performances have to be interpreted cautiously.

Furthermore, we want to emphasize that the average rework level does not increase when additional workforce capacity is hired. However, we expect that operators who are less familiar with the quality levels of PLVS result in a higher rework ratio (Maskin & Sjöström, 2002). According to Silver et al. (1998), rework significantly affects cycle time's mean and variance.

Last, we have assumed that all capacity available in the simulation model is reserved to process jobs that arrive in the system. However, it is known that some machines and operators also process jobs from other product groups. As such, their availability is lower than what is used in the simulation models.

This all considered, the results have to be interpreted with caution. Furthermore, management is advised to gather data regarding the production processes. On the one hand, they can verify the results provided in this study. On the other hand, they are able to start operational excellence improvement projects.

R6: Collect data on a daily basis regarding the routings and processing times.

Case studies

Two case studies are used to examine if and how control mechanisms can be applied within a MD environment. It is assumed that these case studies represent a regular demand period and a TAR. However, the average number of jobs that arrive during the regular demand period is 17.4% lower compared to the average jobs per day from what is observed in the data between January 2014 and August 2016 (7.1 jobs/day versus 8.6 jobs/day). On the other hand, data from one of the most extreme TARs is selected to simulate the demand pattern during a TAR demand period (in combination with regular demand period).

7.2 Future Research

When considering the limitations, assumptions and conclusions to the research questions, we have established 2 areas in which projects are specified for future research.

1. Synergy

The first recommended future research relates to synergy. Synergy is defined as: *"the interaction or cooperation of two or more organizations, substances, or other agents to produce a combined effect greater than the sum of their separate effects"* (thefreedictionary, 2017). It is expected that PLVS can benefit from synergy in various ways. Below, we consider future research topics regarding synergy within PLVS, within the company and synergy benefits obtained from collaboration with competitors and customers. Note that all proposed future research regarding synergy are meant to investigate whether generalization result in a decrease in system's variability. In production environments, it yields that a reduction in system's variability results in lower flexibility levels to maintain the same performance targets (Bertrand et al., 1998; Hopp & Spearman, 2011). Since flexibility comes with a costs, it is expected that PLVS can reduce costs through applying synergy.

Synergy within PLVS

We expect PLVS can benefit from synergy within the production line in two ways. First, when PLVS decides to collect data about routings, processes and arrival times for all product groups, they are able to establish whether synergy between production groups can result in lower annual average workforce levels. Second, when this data is also gathered at each of the facilities, PLVS can examine whether outsourcing of jobs between facilities is possible. If outsourcing of jobs is possible, then PLVS is able to reduce demand variabilities by themselves.

Synergy within the company

Synergy within the company can be obtained in two ways. First, nowadays the mechanical machining activities are outsourced to a different department. According to Bertrand et al. (2016), the time required to execute a customer order increases as the number of production departments increases. As such, PLVS can investigate whether performing the mechanical machining activities by themselves will result in higher performance levels in terms of lower average cycle times, higher average service levels or lower workforce levels due to a higher average proportion of slack per job.

Second, as visualized in Figure 10, a job's actual arrival time highly deviate from its planned arrival time during TARs. Since this deviation unnecessarily results in jobs that become urgent, it is expected that PLVS can benefit from a better coordination with the company's operators working on-site during TAR periods.

Synergy with customers

As mentioned, customers in the chemical and Gas & Oil industry apply maintenance programs for their assets. These maintenance programs contain preventive maintenance policies. The decision in which period a job's preventive maintenance is executed is made by the customer's maintenance department in coordination with production management. It is expected that when PLVS can participate in this decision making process, the jobs labeled for preventive maintenance can be planned in periods that demand is low such that demand is less peaked and demand variance is reduced.

2. Evaluate annual workforce cost levels

As visualized in the results from the simulation experiments in Appendix E.5, current workforce utilization levels are low during regular demand periods. Based on the result of the simulation experiments provided in Appendix E.5, it is concluded that workforce utilization levels can be significantly improved if the lead time control rule can be reevaluated with contractors. Then, the current workforce level can be reduced while the same service level target is maintained.

Although a reduction in the current workforce level will reduce operational costs during regular demand periods, the workforce costs during TAR demand periods will increase. This, because more operators need to be hired as compared to the current situation. From a cost perspective, it might be interesting to examine which workforce level PLVS should apply to minimize annual workforce cost levels.

7.3 Academic Contribution

This research contribute to the existing literature in various ways. First, since most literature conducted in the maintenance spare parts supply chain field relate to the spare parts inventory control problem (cf. Guide & Srivastava, 1997b; Kennedy et al., 2002; Sherbrooke, 2006; Basten & van Houtum, 2014; Van Houtum & Kranenburg, 2015) and the repair shop control problem (Cf. Guide Jr & Srivastava, 2000; Keizers et al., 2001; Vernooij, 2011), a literature gap was found regarding the maintenance depot control problem. More specifically, earlier research has mentioned the existence of maintenance depots (cf. Vernooij, 2011; Driessen et al., 2015), but no literature is available on the maintenance depot control problem explicitly. As such, the results provided in this study complement the literature since we have bridged the gap between existing theory about shop floor control and a maintenance depot environment.

Next, we furthermore contribute to the literature, since MDs were only mentioned as being part of the asset holder's company (c.f. Vernooij, 2011; Driessen et al., 2015). Since the MD under analysis have many competitors, examining the MD control problem as a separate entity is interesting from a industrial point of view. The simulation models provided in this study can then be used as a starting point for further analysis.

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Appendix A - Data collection methods

Since limited data was available at PLVS, data is gathered by the researcher during the project. The data collection methods applied related to surveys to establish processing times. Furthermore, valves were tracked during a three week data collection period in order to obtain insights regarding input parameters such as routings, inter-arrival times, order sizes, etc. This section describes how these methods are constructed.

A.1 Surveys

Surveys are designed to determine the processing times for each activity for a particular valve. As will be explained in detail in Appendix A.1, operators are asked to specify a minimum, mode and maximum processing time required to fulfill a particular activity. These values are then used to establish a Perth-Beta distribution for each process individually. Again, we refer to Appendix B.2 for a more detailed explanation.

The valves that are included in the survey are displayed in Table 22. These valves are chosen in cooperation with PLVS management. The activities included in the survey are based on the processes involved in the valve overhaul process. Since the activities are different within the three product groups, a survey is compiled for each product group individually. Moreover, the surveys are designed differently for the three facilities, because of two reasons. First, the overhaul steps differ between facility C and facilities A and B (i.e. Valves are coated after cleaning at facility C). Second, the terminology that is used to describe a certain task also differs per facility. As a result, multiple surveys are designed to prevent for ambiguities. An example of a survey designed for facility B regarding the product group safety valves is visualized at the end of this Section.

Table 22: Valve types included in the surveys

V	Product group	DN-size	PN-size [Bar]	Manufacturer
C1	Control	25	40	Samson
C2	Control	50	40	Samson
C3	Control	150	40	Gulde
O1	On/Off	25	320	Sempell
O2	On/Off	50	320	Sempell
O3	On/Off	150	40	KSB
S1	Safety	25	N.A.	Leser
S2	Safety	25	N.A.	Sempell
S3	Safety	50	N.A.	Crosby
S4	Safety	80	N.A.	Sempell

Table 23 shows the total number of surveys which are returned and the response rate for each facility. The average participation is 57%. Note that several operators at facility A have filled in multiple surveys regarding different product groups, since they are multi-skilled. On the other hand, the total number of surveys does not necessarily mean that each activity included in the survey has the same number of process time estimations, which is caused by missing values.

Table 23: Number of survey respondents per product group per facility

Facility	Product group			Participants	Response rate
	Safety	On/Off	Control		
A	8	5	5	8	67%
B	7	1	2	10	48%
C	3	4	1	8	62%
Total	**18**	**10**	**8**	**26**	**57%**

Table 23 shows that most surveys are filled in regarding the product group safety valves. Since surveys are developed iteratively due to new insights about the processes involved in the maintenance process, sufficient data is only available regarding the product group safety valves to determine the processing times. Therefore, it is decided to analyze only the surveys with respect to this product group. Table 24 visualizes the total responses conducted for each activity per facility and per surveyed product.

Table 24: Number of surveys conducted per activity regarding the product group safety valves

Task No.	Activity	Facilities												Total responses			
		A				B				C							
		S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
1	Completeness check	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	Pretest	2	2	2	2	6	6	6	6	2	2	2	2	10	10	10	10
4	Dismantle	8	7	5	7	6	6	6	6	2	2	2	2	16	15	13	15
5a	Cleaning and/or brushing at workbench	8	7	5	7	0	0	0	0	2	2	2	2	10	9	7	9
5b	Cleaning in cleaning machine	0	0	0	0	6	6	6	6	2	2	2	2	2	2	2	2
5c	Cleaning in cabine	8	7	6	7					2	2	2	2	10	9	8	9
6	Inspection	8	7	6	7	6	6	6	6	2	2	2	2	16	15	14	15
6c	Inspection with photo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20g	Priming	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	2
8a	Mechaninal machining seat and cover	2	1	0	1	1	1	1	1	2	2	2	2	5	4	3	4
8b	Mechaninal machining flanges	1	0	0	0	0	0	0	0	1	1	1	1	2	1	1	1
9a	Mannual patching	8	7	5	6	6	6	6	6	2	2	2	2	10	9	7	8
9b	Mechanical patching	8	7	6	7					2	2	2	2	10	9	8	9
10	Polishing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	Recovering screw thread	8	7	6	7	5	5	4	4	2	2	2	2	15	14	12	13
14	Installing seals and gaskets	7	6	5	6	5	5	5	5	2	2	2	2	14	13	12	13
15	Reassembling	8	7	6	7	6	6	6	6	2	2	2	2	16	15	14	15
16	Producing identiy plate	8	8	8	8	6	6	6	6	2	2	2	2	16	16	16	16
17	First test	3	2	2	2	5	5	5	5	2	2	2	2	7	7	7	7
18	Test Report	7	6	6	6												
17b	Second test	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	Acceptance test with client or Inspection services	0	0	0	0	5	5	5	5	2	2	2	2	7	7	7	7
20	Conserving	6	5	4	5	3	3	2	1	2	2	2	2	11	10	8	8
20a	Conserving with spray can	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20b	Conserving with specialized equipment	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	Preparing transportation	6	5	4	5	4	4	4	4	2	2	2	2	12	11	10	11

A.2 Valve Tracking Procedure

The valves tracking procedure is designed for various purposes. First, data obtained from this procedure can be used to determine the current service level performance during a non-TAR demand period. Second, the data can be used to determine the input parameters regarding order-sizes, lead times, interarrival times and the probabilities a particular process is executed. Last, data from this procedure can be used to assess valves' routings.

The incoming valve tracking procedure starts from the moment a valve arrives at the facility. Then, a form (Figure 20) is added to the valve before any overhaul activity is executed. Furthermore, the arrival date and time of the valve are noted. Once the valve is released for the overhaul process (i.e. an operator starts with the first overhaul activity), the starting date and time are reported on the form. Subsequently, the operator mentions all activities in sequence of execution, which he has performed in order to successfully overhaul the particular valve. Once the operator(s) finishes the overhaul, operator's last step is to denote the finish date and- time on the form. Next, the researcher checks all collected forms for their correctness first (i.e. in case standard activities such as dismantling or reassembling are missing, they are added to the routing path according to the flow charts) before they are digitalized. Finally, additional data columns obtained from SAP are added to each tracked valve.

The Incoming valves are tracked during a three week period at facility B. Facilities A and C have tried to start the data gathering process, but because of the high workload it is decided to stop the data recording. Table 25 shows the total number of tracked valves at each facility per product group. Based on the returned forms, it is decided to analyze only the safety valves at Facility B during this stage of the master thesis project. The overall response rate regarding the collected forms at facility B during the three week period is equal to 79% (121 out of 153), which is based on the registered incoming valves that are manually recorded at the registration area (i.e. logistic center).

Table 25: Number of tracked valves returned per facility per product group

Facility	Product group [valves]		
	Safety	On/Off	Control
A	0	0	0
B	103	9	9
C	3	0	0
Total	**106**	**9**	**9**

ID 64 JK

VEILIGHEDEN

Logistiek Centrum (formulier bij spoelformulier)

- **Ontvangst Logistiek centrum:** Datum: 3-2-17 Tijd: 15u
- **TAG-nummer:** 9.1155 9-11951

Uitvoerder (formulier bij SO)

- **Start werkzaamheden:** Datum: 2-3 Tijd: 15.30
- **Eind werkzaamheden (vóór IVG):** Datum: 3-3 Tijd: ~~[illegible]~~ 8^{15}
- **Eind werkzaamheden (ná IVG):** Datum: .... Tijd: ....

Monteur (Routing) (letter kan meerdere keren worden genoteerd)

Revisie soort:
- ☐ In-shop
- ☐ In-shop & On-site

- **A.** Check Volledigheid
- **B.** Inspectie met foto
- **C.** Pretest (opdracht klant)
- **D.** Testen balg / nozzle (bijv. tegendruk)
- **E.** Demonteren (evt. opmeten)
- **F.** Stralen (straalcabine)
- **G.** Stralen (grote machine)
- **H.** Reinigen (werkbank)
- **I.** Inspecteren (gedemonteerde staat)
- **J.** Wachten (goedkeuring klant of wvb)
- **K.** Mechanisch opzuiveren klep & zitting
- **L.** Mechanisch opzuiveren flenzen
- **M.** Läppen (handmatig)
- **N.** Läppen (machinaal)
- **O.** Polijsten
- **P.** Schroefdraad gangbaar maken (niet mechanisch)
- **Q.** Nieuwe dichtingen en pakkingen aanbrengen
- **R.** Aanmaken en monteren identiteitsplaatje
- **S.** Montage (evt. opmeten)
- **T.** Afstellen, Testen
- **U.** Final test 2e testmonteur
- **V.** Testrapport
- **W.** Afnametest met IVG
- **X.** Conserveren (spuitinstallatie)
- **Y.** Conserveren (handmatig)
- **Z.** Transport gereed maken (verzendbon, pallet, beschermend materiaal)
- **AA.** ....

Taak Nummer	Taak Letter	Taak Nummer	Taak Letter
1	A	21	
2	C	22	
3	E	23	
4	F	24	
5	H	25	
6	I	26	
7	K	27	
8	H	Tijmen 28	
9	P	H 29	
10	Q	30	
11	S	31	
12	T	32	
13	U	33	
14	V	34	
15	W	35	
16	Y	36	
17	Z	37	
18		38	
19		39	
20		40	

Overige info (invullen door Tijmen)

1. **Gepland retour klant:** Datum: .... Tijd: ....
2. **Balg:** Ja / Nee
3. **Nozzle:** Ja / Nee
4. **DN-maat:** 25 Millimeter / Inch
5. **PN-klasse:** 64
6. **Fabricaat:** B+R
7. **SO-nummer:** 200341760

Figure 20: Example of a collected form from the valve tracking procedure

Appendix B - Data Analysis: input parameters for the simulation model

B.1 Job Type Distribution

The distribution to determine the job type d_j for a particular job j is determined from data about the safety valves overhauled between January 2014 till August 2016. In total, the sample size n equaled 10641. This data was grouped together to the job types (job' DN-sizes) PLVS recognizes such that an empirical distribution is fitted on this data. These groups are shown in Table 4. However, the empirical distribution is not useful for the simulation model, since the simulation model distinguishes only three different job types (DN-25, DN-50 and DN-80). As such, the DN-sizes are grouped together and normalized to derive an empirical distribution.

First, all n observations were grouped regarding their DN-size into $k = 4$ adjacent intervals of the form $< a_0, a_1]$, $< a_1, a_2], \dots, < a_{k-1}, a_k]$. Suppose each interval is denoted by i, where $i = \{1,2, \dots, \tilde{\imath}\}$. Then $i = 1$ represents the jobs belonging to job type DN-25, $i = 2$ the job types DN-50, $i = 3$ the job types DN-80 and, lastly, $i = 4$ consists of jobs with job types bigger than DN-80. Furthermore, let's denote n_i as the number of observations in interval i. The values for the n_i's are used to specify an empirical distribution for d_j, which is formulated below:

$$d_j(u) = \begin{cases} 1, & if \quad 0 < u \leq \dfrac{n_1}{n_1 + n_2 + n_3} \\ 2, & if \quad \dfrac{n_1}{n_1 + n_2 + n_3} < u \leq \dfrac{n_2}{n_1 + n_2 + n_3} \\ 3, & if \quad \dfrac{n_2}{n_1 + n_2 + n_3} < u \leq 1 \\ 0, & Otherwise \end{cases}$$

Where $u \sim U(0,1)$ is a random number.

Table 26: Normalized probabilities to determine the job type d_j j for all jobs j in the simulation model.

DN size	i	n_i	$\dfrac{n_i}{n_1 + n_2 + n_3}$	CDF
DN-25	1	6100	0.681	0.681
DN-50	2	1825	0.204	0.884
DN-80	3	1035	0.116	1
> DN-80	4	1681		

B.2 Processing Time Distribution

There are several methods available in literature to determine the process times for an activity. One of the most suitable methods consists of a time-motion study. During a time motion study, data about process times is collected using a stop watch and recording the start and end time of a certain task (Sammet & Hassler, 1951). The gathered data is analyzed to determine the required statistics. Since this data collection method is very time consuming (Sammet & Hassler, 1951), it is decided to use a different appropriate technique which relate to the beta-PERT distribution. In here, the best-case, most likely, and the worst-case process times are estimated for each task individually, denoted by the variables a, m, and b respectively. Based on these input parameters the statistics such as the average process time can be approximated.

In this study, the input parameters $a_{d,pr}$, $m_{d,pr}$, $b_{d,pr}$ for job type $d \in D$ at process $pr \in PR$ are estimated from the data gathered by the surveys (Appendix A.1). This is done according to the following procedure. Let's denote VOI as the variable of interest such that $VOI = \{a, m, b\}$. Furthermore, let $VOI_{d,pr,x}$ be the returned value for input parameter $VOI_{d,pr}$ with $x = \{0,1,2,\dots,n\}$ where n equals the maximum returned values for the input parameter of interest. Then, all $VOI_{d,pr}$ are determined by subtracting the minimum and maximum value observed and dividing by $n-2$. This procedure is often used for low sample sizes. Note that when 1 or 2 observations were obtained, the $VOI_{d,pr}$ were determined without subtracting the minimum and maximum values. Furthermore, for those processes without having any observation (i.e. process 1 and process 13), processing times are determined in cooperation with PLVS' employees. This results in deterministic times for process 1 and the input parameters for process 13 equals the input parameters for process 12.

Using these input parameters, the processing times $t_{j,d,pr}$ for job j of job type $d \in D$ at process $pr \in PR$ in the simulation model are sampled from a BetaPERT distribution, such that $t_{j,d,pr} \sim BetaPERT(a_{d,pr}, m_{d,pr}, b_{d,pr})$. Using this distribution, the mean $\mu_{d,pr}$ and standard deviation $\sigma_{d,pr}$ are determined according to the equations below (source http://www.statisticshowto.com/pert-distribution/):

$$\mu_{d,pr} = \frac{a_{d,pr} + 4m_{d,pr} * b_{d,pr}}{6}$$

$$\sigma_{d,pr} = \frac{b_{d,pr} - a_{d,pr}}{6}$$

Table 27 shows the input values, mean and standard deviation for each process and process type individually.

Table 27: Input values, mean and standard deviation regarding the three job types used in the simulation model.

	DN-25					DN-50					DN-80				
pr	$a_{1,pr}$	$m_{1,pr}$	$b_{1,pr}$	$\mu_{1,pr}$	$\sigma_{1,pr}$	$a_{2,pr}$	$m_{2,pr}$	$b_{2,pr}$	$\mu_{2,pr}$	$\sigma_{2,pr}$	$a_{3,pr}$	$m_{3,pr}$	$b_{3,pr}$	$\mu_{3,pr}$	$\sigma_{3,pr}$
1	3,0	3,0	3,0	3,0	0,00	3,0	3,0	3,0	3,0	0,00	3,0	3,0	3,0	3,0	0,00
2	6,6	9,6	17,2	10,3	1,77	7,5	11,8	20,3	12,5	2,13	9,4	14,0	21,9	14,5	2,08
3	9,6	15,7	22,5	15,8	2,14	12,7	19,1	27,3	19,4	2,42	15,0	21,9	30,8	22,2	2,63
4	8,1	13,1	21,9	13,8	2,29	11,7	18,3	30,0	19,2	3,06	17,1	20,7	30,0	21,7	2,14
5	5,0	10,0	10,0	9,2	0,83	5,0	10,0	10,0	9,2	0,83	5,0	10,0	10,0	9,2	0,83
6	8,4	13,8	19,4	13,8	1,83	11,0	18,0	23,0	17,7	2,00	11,4	17,1	22,1	17,0	1,79
7	5,5	9,9	16,1	10,2	1,76	6,9	11,3	18,1	11,7	1,86	7,2	11,8	17,5	12,0	1,72
8	8,3	13,3	16,7	13,1	1,39	10,0	15,0	15,0	14,2	0,83	12,5	15,0	20,0	15,4	1,25
9	6,9	12,5	21,3	13,0	2,40	7,5	13,3	21,7	13,8	2,36	9,3	15,0	23,6	15,5	2,38

10	12,5	18,4	26,3	18,7	2,29	14,0	18,4	24,0	18,6	1,67	13,3	17,5	23,3	17,8	1,67
11	12,5	18,4	26,3	18,7	2,29	14,0	18,4	24,0	18,6	1,67	13,3	17,5	23,3	17,8	1,67
12	6,8	11,0	19,2	11,7	2,08	9,3	14,8	25,0	15,6	2,62	8,3	13,4	21,8	13,9	2,26
13	5,5	8,3	13,3	8,7	1,31	5,5	7,9	12,5	8,3	1,17	6,2	8,7	13,2	9,0	1,17
14	10,1	15,0	22,9	15,5	2,12	14,2	19,0	25,8	19,3	1,94	17,3	23,8	31,5	24,0	2,37
15	5,1	8,0	12,1	8,2	1,17	5,1	8,0	12,1	8,2	1,17	5,1	8,0	12,1	8,2	1,17
16	11,0	18,4	25,0	18,3	2,33	14,0	21,4	28,0	21,3	2,33	16,0	22,0	30,0	22,3	2,33
17	6,3	10,3	16,7	10,7	1,72	7,0	10,8	19,0	11,5	2,00	8,4	13,4	20,0	13,7	1,93
18	10,8	15,0	21,3	15,3	1,75	12,5	17,5	22,5	17,5	1,67	11,7	15,7	21,7	16,0	1,67
19	10,0	15,0	15,0	14,2	0,83	10,0	15,0	15,0	14,2	0,83	15,0	20,0	20,0	19,2	0,83
20	6,1	9,3	14,4	9,6	1,38	7,4	10,4	15,0	10,6	1,27	8,3	11,4	17,2	11,9	1,48

B.3 Routings

Another input parameter to the simulation model relates to the routings how valves move through the overhaul process. These routings can be determined using various techniques. In this study, we have proposed to determine the routings using process mining and linear regression. Finally, based on interviews with operators an algorithm is developed which uses the probabilities that a particular activity is executed.

Process mining is the activity to determine the different types of paths (i.e. routes) and the probabilities that a certain path occurs (Dumas, La Rosa, Mendling, & Reijers, 2013). The data from the valve tracking procedure at facility B regarding the product group safety valves are used to assess which routes exist in the valve overhaul process.

First, the 103 collected forms are analyzed at an aggregate level, which results affect the sample size to determine the existing paths. Table 28 shows that 16 (±16%) valves are not overhauled according to the overhaul procedure as visualized in the flow charts. 14 Of these valves were brand-new and PLVS was contracted to execute an inspection (at PLVS this is called ‘ingangskeuring’), which means that at least step 5 till 14c are never executed. The two other valve overhauls were disrupted during the overhaul process. One reason relates to the delivery of a wrong valve, and the other valve was assessed being amortized after the inspection step. As a result, the sample size to determine the type of paths is decreased from 103 to 87.

Table 28: Aggregate results of the process mining study for the safety valves

Aggregate Results Process Mining				
Description	**Count**	**p**	**Can be normally approached?**	**95%CI on p**
New valve inspection procedure	14	14%	Yes	6,6%
Valves with disrupted overhaul process	2	2%	No	N.A.
Valves succesfully overhauled	87	84%	Yes	7,0%
Totals	**103**	**100%**	No	N.A.

The sample size is even further reduced to 65 due to an updated form which is used after the first 22 valves were tracked. As already mentioned in previous section about the results of the flow charts, the flow charts have changed iteratively which is a result of new insights obtained from collected data. In line with the adjusted flow charts, the incoming valve tracking forms are changed accordingly.

Table 29: Results of the process mining study for the safety valves

Results Process Mining	
Valves succesfully overhauled	**87**
Total valves tracked with first form	22 -
Total valves tracked used for detailed process mining analysis	**65**
Unique routes	55
Routes observed multiple times	4
Number of routes with rework	2
Average number of tasks per overhaul	15,9

Table 29 depicts the results of the process mining analysis. The table shows that only four routes are observed multiple times. Two of these routes are detected four times, and the other routes are recorded both three times. Since the number of unique routes are relatively high and the fact that we expect that not all routes are already established, it is decided to develop an algorithm which determines the sequence in which jobs flow through the system.

Algorithm

An algorithm is used to determine the sequence in which jobs move through the simulation model. This algorithm is invoked whenever a process is finished. The algorithm is based on the probabilities that a process is executed and on the interdependencies of processes. How these probabilities and interdependencies are determined is explained next.

Data from the valve tracking procedure is used to determine the probabilities that a certain process is executed.

Appendix C - Data Analysis: input parameters regular demand case

In this Section we explain how the input probability distribution functions are determined regarding the interarrival-time, lead time and order size for the regular demand case. According to Law and Kelton (2015), three approaches exist to specify a distribution based on collected data about the variable of interest, which are:

1. The collected data values can be used directly in the simulation. This approach is recommended to validate the model;
2. Based on the collected data, an empirical distribution function can be defined. One can sample from this distribution whenever an input value is needed;
3. Last, a theoretical distribution can be fitted on the data from which one can sample if an input value is needed. Theoretical distribution functions are preferred over empirical distributions, since it 'smooths out' the data such that it may provide information about the overall underlying distribution. Furthermore, values outside the range of the collected data can be generated as well. Another characteristic of interest to argue for theoretical distributions relates to the easiness of change. For example, if one wants to perform a sensitivity analysis, he/she can easily change the input parameters of interest to assess how the system behave under different circumstances (Law & Kelton, 2015).

In the next sections, the theoretical distributions regarding the interarrival-times, lead times and order size are explained in succession.

C.1 Interarrival-Times Distribution

The distribution to determine the interarrival-times between successive customer order arrivals is estimated based on data collected from the valve tracking procedure. Table 30 and Table 31 show the data points and the descriptive statistics for the interarrival-time data, respectively.

Table 30: $N = 39$ interarrival-times (minutes) sorted in increasing order

Interarrival-time data			
0	45	116	218
1	45	120	270
5	60	120	270
15	67	135	300
15	72	150	300
20	78	165	350
23	93	165	405
30	100	172	550
40	101	180	600
45	110	205	

Table 31: Descriptive statistics for the interarrival-time data

Descriptive statistic	Value
Sample Size	39
Minimum	0
Maximum	600
Mean	147.59
Median	110
Std. Deviation	143.687
Skewness	1.570
Kurtosis	2.464

The software @Risk is used to hypothesize appropriate distributions with their estimated parameters for the interarrival-time data. Table 32 shows the MLEs of the real input parameters and the results of the Kolmogorov-Smirnov (K-S) test statistic.

Table 32: Distribution estimation for the interarrival-times

Parameter	$\hat{\boldsymbol{f}}(\boldsymbol{x}) \sim \boldsymbol{Exp}(\hat{\boldsymbol{\beta}})$	$\hat{\boldsymbol{f}}(\boldsymbol{x}) \sim \boldsymbol{\Gamma}(\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}})$
Parameter 1	$\hat{\beta} = 147.59$	$\hat{\alpha} = 1.0377$
Parameter 2		$\hat{\beta} = 145.96$
K-S test statistic $\boldsymbol{D_n}$	0.04489	0.0588*

The density-histogram plot shows how the probability density functions for both distributions fit on the empirical probability density function (Figure 21). Since the distributions are similar to the empirical probability density function, it seems reasonable to conclude that these distributions represent the input distributions. Next, a goodness-of-fit test is executed to assess whether or not we should reject the null hypothesis. Since the lowest K-S test statistic relates to the exponential distribution, we have hypothesized this distribution on its goodness-of-fit. When substituting $D_n = 0.04489$, we conclude that we are not allowed to reject the null hypothesis ($0.262 < 1.308 = c_{1-\alpha}$, at the $\alpha = 0.01$ level). Therefore, the arrival times X_i are sampled from the theoretical distribution $X_i \sim \mathrm{expo}(147.59)$ during the simulation study.

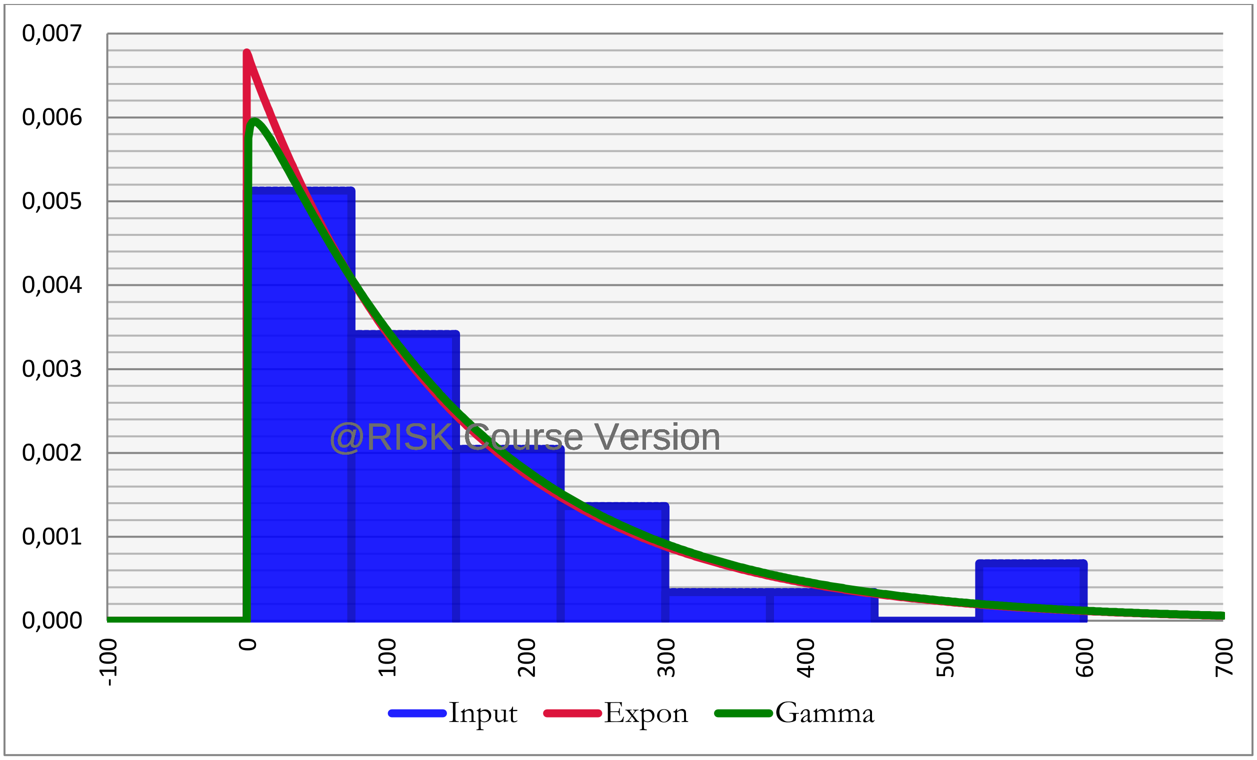

Figure 21: Density-histogram plot for the fitted exponential distribution (Red), gamma distribution(Green) and the interarrival-time data (blue).

C.2 Lead Time Distribution

The distribution to determine the lead times LT_{co} for each customer order co is derived from the data collected from the valve tracking procedure. Table 33 and Table 34 show the data points and the descriptive statistics for the lead time data, respectively.

Table 33: Descriptive statistics

Descriptive statistic	Value
Sample Size	36
Minimum	150
Maximum	4440
Mean	1106.14
Median	603.50
Std. Deviation	999.60
Skewness	1.422
Kurtosis	5.097

Table 34 N=36 lead times (minutes) sorted in increasing order

Lead time data			
150	360	1020	2150
300	360	1050	2190

300	367	1155	2430
305	375	1200	2456
315	390	1530	3150
330	390	1669	4440
330	400	1830	
330	570	1860	
345	637	1965	
350	845	1977	

The software @Risk is used to hypothesize appropriate distributions with their estimated parameters for the lead time data. Table 35 shows the MLEs of the real input parameters and the results of the Kolmogorov-Smirnov (K-S) test statistic for the log-logistic, Pearson type V and the lognormal distributions, respectively.

Table 35: Distribution estamitations regatrding the lead time for regular demand data

Parameter	$\hat{\boldsymbol{f}}_{\mathbf{1}}(\boldsymbol{x}) \sim \boldsymbol{LL}(\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}) + \hat{\boldsymbol{\gamma}}$	$\hat{\boldsymbol{f}}(\boldsymbol{x}) \sim \boldsymbol{PT5}(\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}) + \hat{\boldsymbol{\gamma}}$	$\hat{\boldsymbol{f}}(\boldsymbol{x}) \sim \boldsymbol{LN}(\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\sigma}}^{\mathbf{2}}) + \hat{\boldsymbol{\gamma}}$
Parameter 1	$\hat{\alpha} = 1.3833$	$\hat{\alpha} = 1.4332$	$\hat{\mu} = 1061.3$
Parameter 2	$\hat{\beta} = 531.3656$	$\hat{\beta} = 675.2731$	$\hat{\sigma} = 1659.6$
Parameter 2	$\hat{\gamma} = 140.3986$	$\hat{\gamma} = 40.9265$	$\hat{\gamma} = 117.1660$
K-S test statistic $\boldsymbol{D}_{\boldsymbol{n=36}}$	0.2015	0.2033	0.2088
Adjusted K-S test statistic $\boldsymbol{D}_{\boldsymbol{n=36}}^{\boldsymbol{Adjusted}}$	$\sqrt{n} * D_n = 1.2089$	N.A.	N.A.

The density-histogram plot shows how the probability density functions for the three distributions fit on the empirical probability density function (Figure 22). Although the graphs look similar to the input data, the D_n's result in undesired high values. Since the adjusted K-S test statistic is higher than the critical value $c_{n,1-\alpha}$ ($D_{36}^{Adjusted} = 1.2089 > 0.854 = c_{20,0.99}$, at the $\alpha = 0.01$ level), we have to reject the null hypothesis.

Rejecting the null hypothesis means that it is not recommended from a statistical point of view to use the log-logistic distribution as a theoretical distribution to sample from whenever a lead time variable is required.

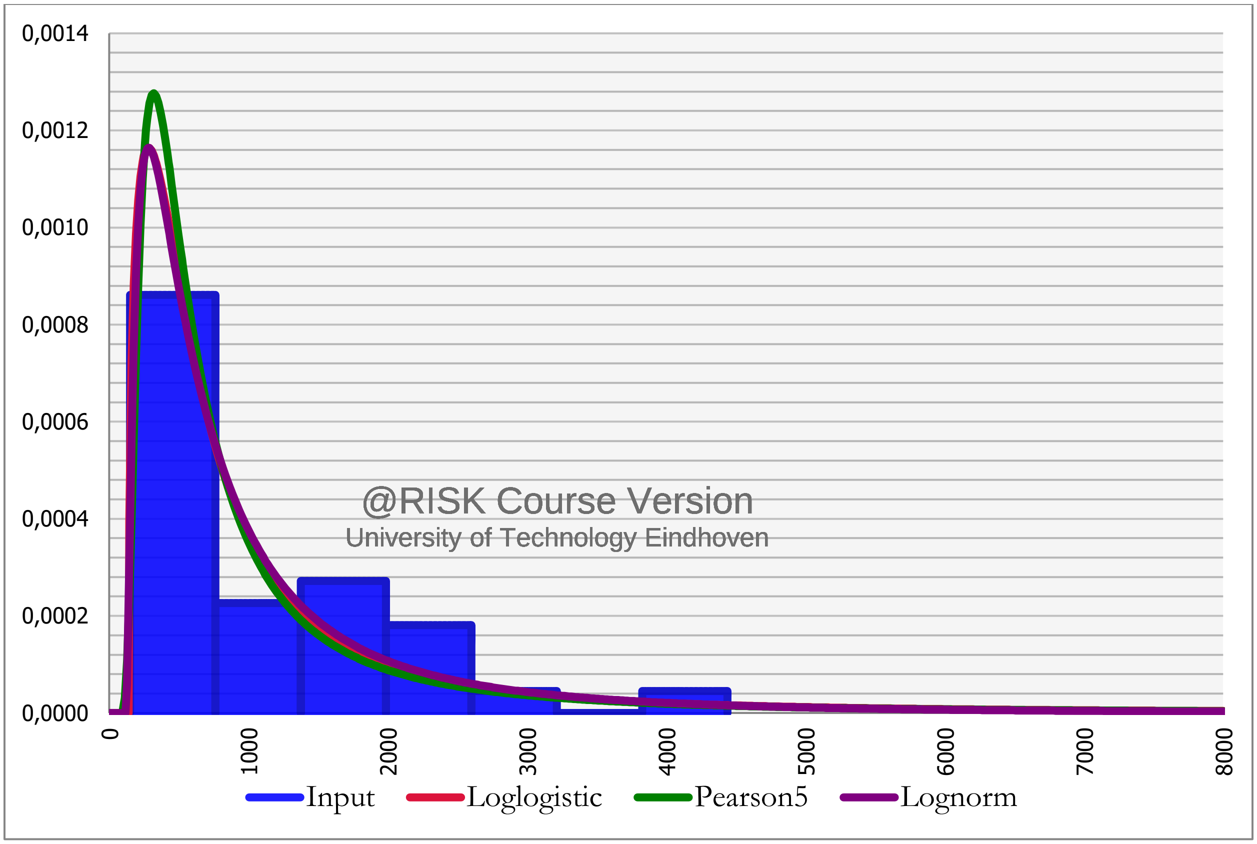

Figure 22:Density-histogram plot regarding the lead time for a regular demand period

C.3 Order Size Distribution

The distribution to determine the order size Q_{co} for each customer order co is derived from the data collected from the valve tracking procedure. In contrast to the previous two variables of interest, the distributions examined in this section are only discrete distributions since customer orders consist of only real positive numbers.

Table 36 and Table 37 show the data points and the descriptive statistics for the order size data, respectively.

Table 36: Descriptive statistics

Descriptive statistic	Value
Sample Size	41
Minimum	1
Maximum	15
Mean	2.171
Median	1
Std. Deviation	2.635
Skewness	3.441
Kurtosis	17.082

Table 37: N=41 order size per customer order sorted in increasing order

Order Size data				
1	1	1	2	15
1	1	1	2	
1	1	1	3	
1	1	1	3	
1	1	1	4	
1	1	1	4	
1	1	1	4	
1	1	1	6	
1	1	2	6	
1	1	2	8	

The software @Risk is used to hypothesize appropriate discrete distributions with their estimated parameters for the order size data. Table 38 shows the MLEs of the real input parameters and the results of the Chi-Square (χ^2) test statistic. Note that the negative binominal distribution is similar to the geometric distribution if $\hat{s} = \mathbf{1}$.

Table 38: Distribution estimation based on @Risk software

Parameter	$\hat{\boldsymbol{f}}(\boldsymbol{x}) \sim \boldsymbol{negbin}(\hat{\boldsymbol{s}}, \hat{\boldsymbol{p}}) + \hat{\boldsymbol{\gamma}}$	$\hat{\boldsymbol{f}}(\boldsymbol{x}) \sim \boldsymbol{geom}(\hat{\boldsymbol{p}}) + \hat{\boldsymbol{\gamma}}$
Parameter 1	$\hat{s} = 1$	$\hat{p} = 0.46067$
Parameter 2	$\hat{p} = 0.46067$	$\hat{\gamma} = -1$
Parameter 3	$\hat{\gamma} = -1$	
$\boldsymbol{\chi^2}$	8.8713	8.8713

The frequency comparison graph (Figure 23) shows how the probability density functions for both distributions fit on the empirical probability density function. Although the empirical distribution have relatively many more orders with order size equal to 1, the pattern of the theoretical distribution is similar to the empirical distribution. Next, a goodness-of-fit test is executed to assess whether or not we should reject the null hypothesis. Since we examine a discrete distribution, we cannot use the K-S statistic but we will use the χ^2 test statistic. We conclude that we are not allowed to reject the null hypothesis ($\chi^2 = 8.8713 < 22.2 = \chi^2_{40,0.99}$). As such, the order sizes Q_{co} are sampled from the theoretical distribution $Q_{co} \sim \text{negbin}(1,0.46067)$ during the simulation study.

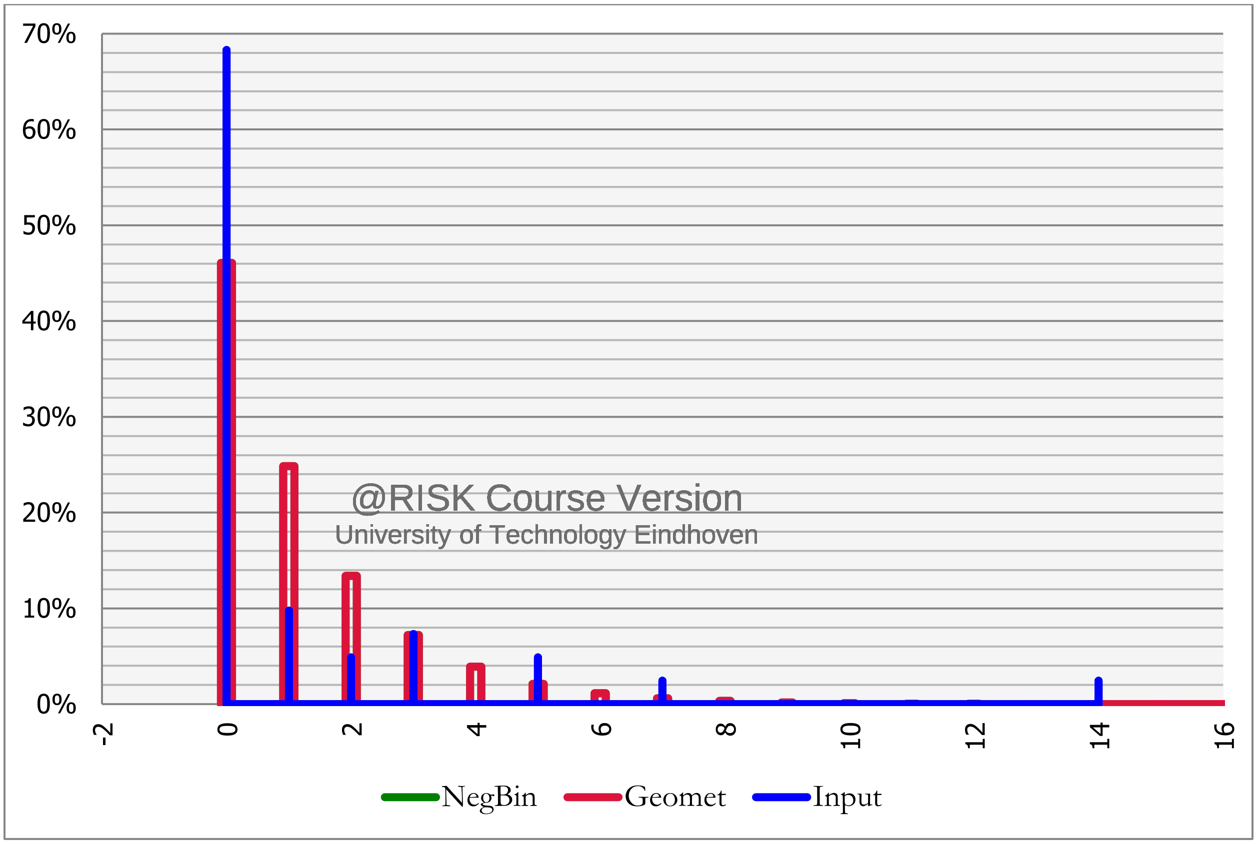

Figure 23: Frequency comparison graph regarding the order sizes

Appendix D - Data Analysis: input parameters TAR demand case

In this Section we explain how the input probability distribution functions are determined regarding the interarrival-time, lead time and order size for the TAR demand case. These distributions are determined according to the same procedure used to determine the input distribution functions for the regular demand case. In the next sections, the theoretical distributions regarding the interarrival-times, lead times and order size are explained in succession.

D.1 Interarrival-Times Distribution

The distribution to determine the interarrival-times between successive customer order arrivals is estimated based on the TAR data.

The software @Risk is used to hypothesize appropriate distributions with their estimated parameters for the interarrival-time data. Figure 24shows the MLEs of the real input parameters and the results of the Kolmogorov-Smirnov (K-S) test statistic.

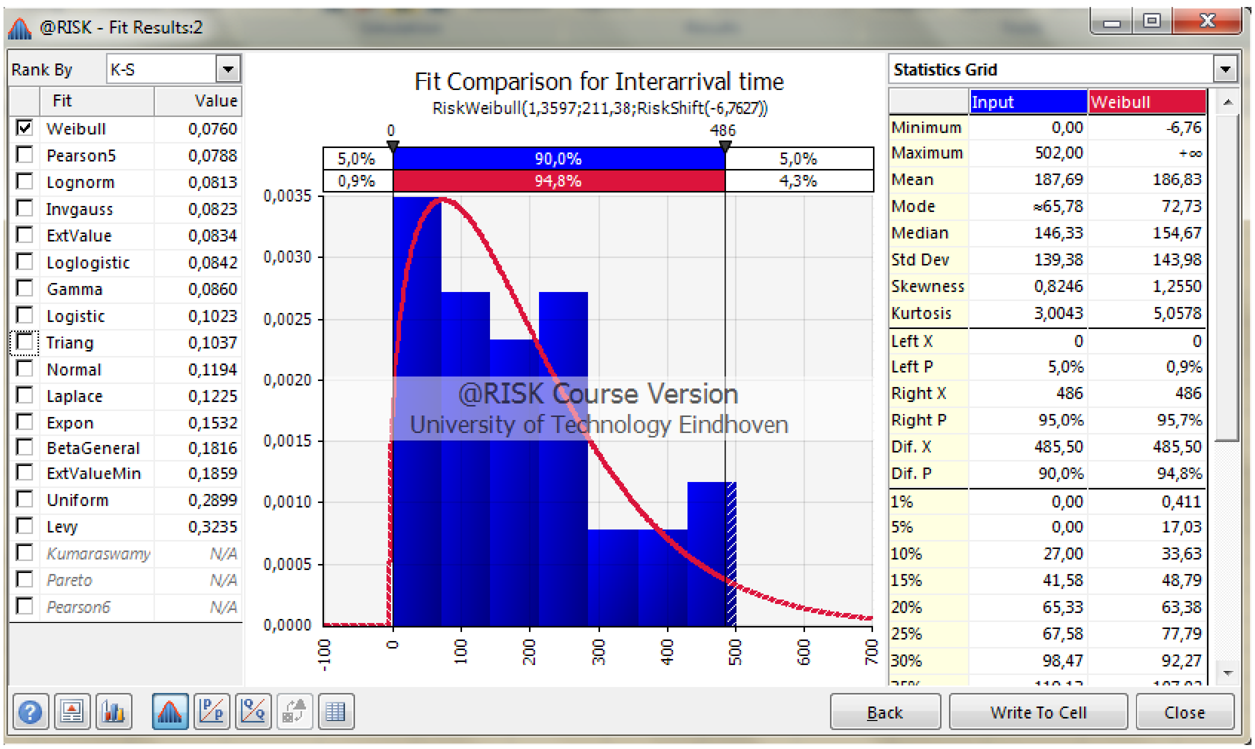

Figure 24: Histogram of the estimated distribution for the interarrival-times regarding the TAR demand data

D.2 Lead Time Distribution

The distribution to determine the lead times LT_{co} for each customer order co is derived from the TAR data. **Error! Reference source not found.** and **Error! Reference source not found.** show the data points and the descriptive statistics for the lead time data, respectively.

The density-histogram plot shows how the probability density functions for the three distributions fit on the empirical probability density function (Figure 25). This plot shows that the best fitted theoretical distribution does not fit well with the empirical distribution. Moreover, the adjusted K-S test statistic is higher than the critical value $c_{n,1-\alpha}$ ($D_{36}^{Adjusted} = 1.2089 > 0.854 = c_{20,0.99}$, at the $\alpha = 0.01$ level). As such, we have to reject the null hypothesis. Rejecting the null hypothesis means that it is not recommended from a statistical point of view to use the log-logistic distribution as a theoretical distribution to sample from whenever a lead time variable is required.

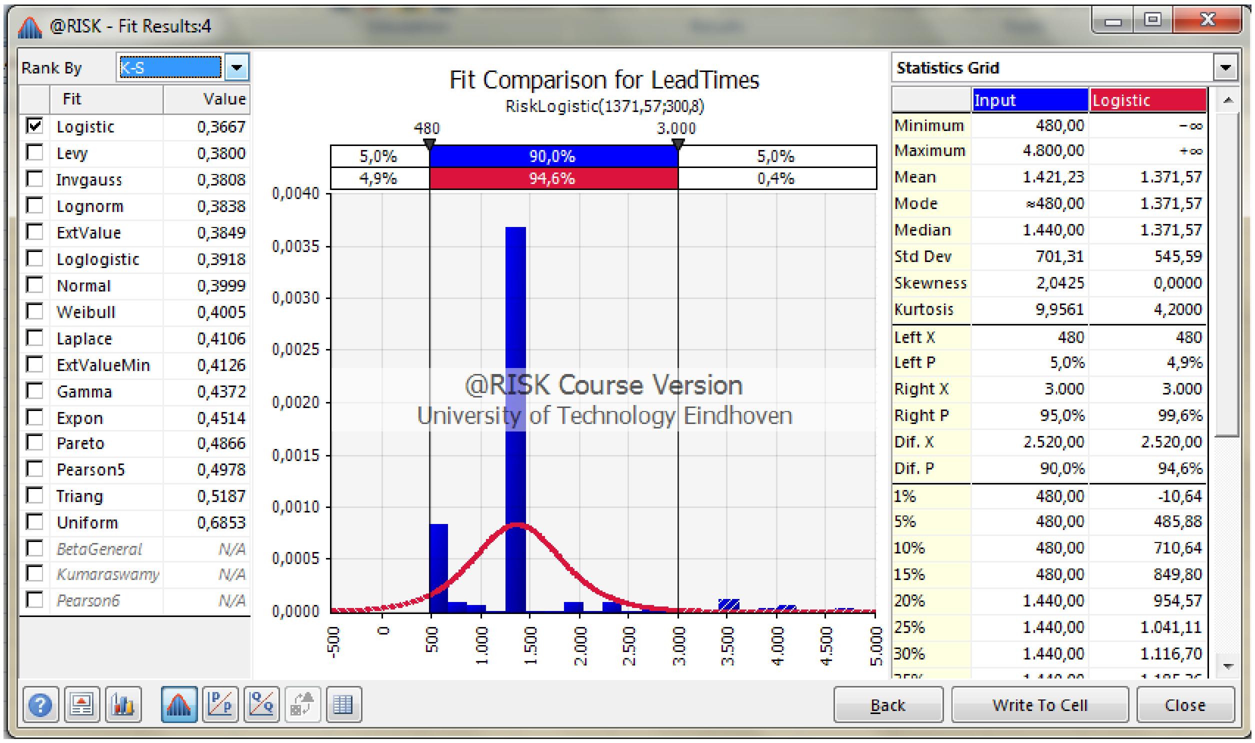

Figure 25: Density-histogram plot for the lead times regarding the TAR demand data

Since the theoretical distribution does not fit appropriately based on both the density-histogram plot and the K-S test statistic, the empirical data is used to specify an empirical distribution Table 39.

Table 39: Empirical cumulative distribution function of the lead times regarding the TAR demand data

Lead times [minutes]	CDF
480	15.1%
600	16.2%
720	17.9%
960	19.0%
1440	91.1%
1920	92.2%
2040	92.7%
2400	94.4%
2760	95.0%
3000	95.5%
3600	97.8%
3960	98.3%
4200	99.4%
4800	100.0%

D.3 Order Size Distribution

The distribution to determine the order size Q_{co} for each customer order co is derived from the TAR data. In contrast to the previous two variables of interest, the distributions examined in this section are only discrete distributions since customer orders consist of only real positive numbers.

The software @Risk is used to hypothesize appropriate discrete distributions with their estimated parameters for the order size data. Table 40 shows the MLEs of the real input parameters and the results of the Chi-Square (χ^2) test statistic. Note that the negative binominal distribution is similar to the geometric distribution if $\hat{s} = 1$.

Table 40: Distribution estimation regarding the order size distribution

Parameter	$\hat{\boldsymbol{f}}(\boldsymbol{x}) \sim \boldsymbol{negbin}(\hat{\boldsymbol{s}}, \hat{\boldsymbol{p}}) + \hat{\boldsymbol{\gamma}}$	$\hat{\boldsymbol{f}}(\boldsymbol{x}) \sim \boldsymbol{geom}(\hat{\boldsymbol{p}}) + \hat{\boldsymbol{\gamma}}$
Parameter 1	$\hat{s} = 1$	$\hat{p} = 0.46067$
Parameter 2	$\hat{p} = 0.46067$	$\hat{\gamma} = -1$
Parameter 3	$\hat{\gamma} = -1$	
$\boldsymbol{\chi^2}$	8.8713	8.8713

The frequency comparison graph (Figure 26) shows how the probability density functions for the geometric distribution fit on the empirical probability density function. Although differences are observed, both functions show a decreasing pattern except for one outlier in the tail of the empirical distribution. Next, a goodness-of-fit test is executed to assess whether or not we should reject the null hypothesis. Since we examine a discrete distribution, we cannot use the K-S statistic but we will use the χ^2 test statistic. We conclude that we are not allowed to reject the null hypothesis ($\chi^2 = 8.8713 < 22.2 = \chi^2_{40,0.99}$). As such, the order sizes Q_{co} are sampled from the theoretical distribution $Q_{co} \sim \mathrm{negbin}(1{,}0.46067)$ during the simulation study.

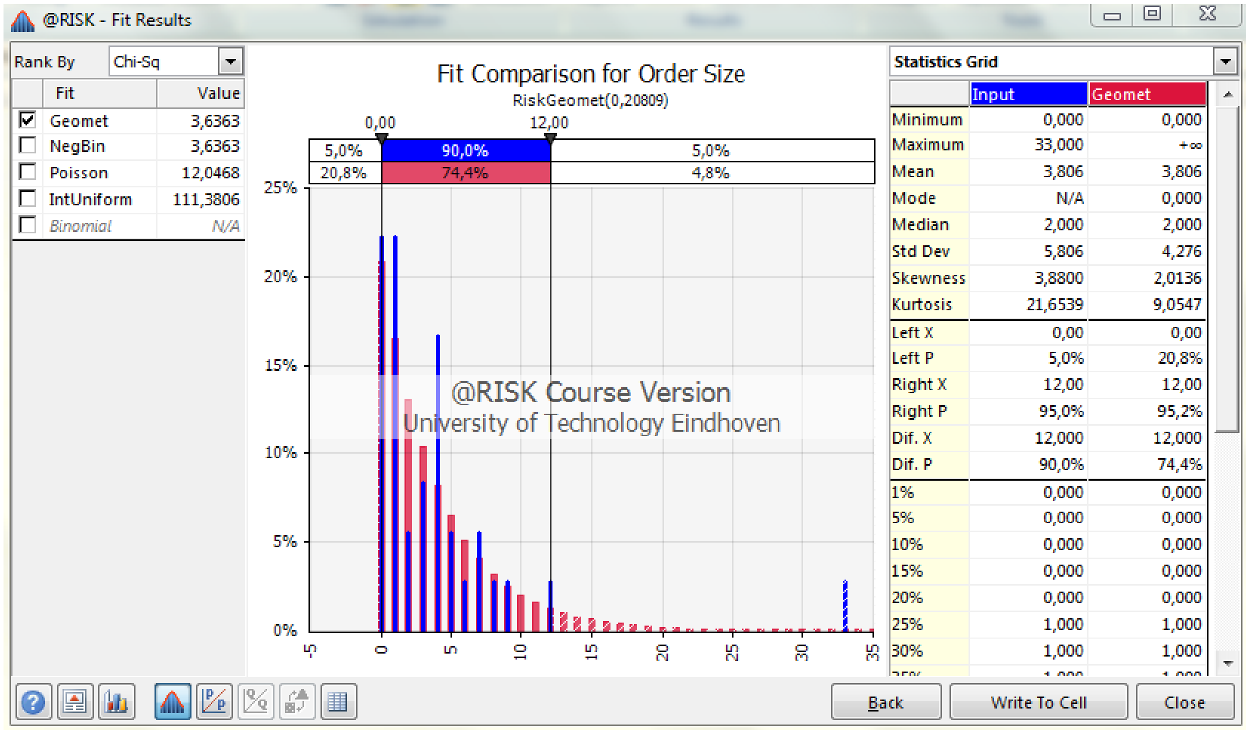

Figure 26: Frequency probability plot of the order size regarding a TAR demand Period

Appendix E - Results Simulation Experiments

E.1 Variable Explanation

Table 41: List of variables used in the simulation model

Formulations and Comments *Fixed input variables for each model*	Units
$pr \in PR, \quad for\ PR = \{1,2,\dots,20\}$ Set of indices regarding the number of processes. The total number of processes $\tilde{j}$ equals 20.	Dimensionless
$sk \in SK, \quad for\ SK = \{A,B,C,D\}$ Set of indices representing the operator skill classes.	Dimensionless
$pr \in PR_A, \quad for\ PR_A = \{\dots\dots\dots\}$ Subset of processes which can be executed by operators with skill class A.	Dimensionless
$pr \in PR_B, \quad for\ PR_B = \{\dots\dots\dots\}$ Subset of processes which can be executed by operators with skill class B.	Dimensionless
$pr \in PR_C, \quad for\ PR_C = \{\dots\dots\dots\}$ Subset of processes which can be executed by operators with skill class C.	Dimensionless
$pr \in PR_D, \quad for\ PR_D = \{\dots\dots\dots\}$ Subset of processes which can be executed by operators with skill class D.	Dimensionless
Notice that $PR = PR_A \cup PR_B \cup PR_C \cup PR_D \cup 8$	
$k \in K, \quad for\ k = \{1,2,3,4,5,6\}$ Set of indices which describe a machine of type k. $k = \{1,2,3,4,5,6\}$ are related to workbenches, test machines, cleaning cabins, cleaning machines, lapping machines and conserving equipment, respectively.	Dimensionless
$pr \in PR_1, \quad for\ PR_1 = \{\}$ Subset of processes which makes use of machine $ma \in MA_1$	Dimensionless
$pr \in PR_2, \quad for\ PR_2 = \{\}$ Subset of processes which makes use of machine $ma \in MA_2$	Dimensionless
$pr \in PR_3, \quad for\ PR_3 = \{\}$ Subset of processes which makes use of machine $ma \in MA_3$	Dimensionless
$pr \in PR_4, \quad for\ PR_4 = \{\}$ Subset of processes which makes use of machine $ma \in MA_4$	Dimensionless
$pr \in PR_5, \quad for\ PR_5 = \{\}$ Subset of processes which makes use of machine $ma \in MA_5$	Dimensionless

$pr \in PR_6, \quad for\ PR_6 = \{\}$ Subset of processes which makes use of machine $ma \in MA_6$	Dimensionless
  Notice that $PR = PR_1 \cup PR_2 \cup PR_3 \cup PR_4 \cup PR_5 \cup PR_6$	
$pr \in PR_{Rew}, \quad for\ PR_{Rew} = \{3,7,10,13,14,16\}$ Subset of processes which have to be executed again and in sequence if a job requires rework.	Dimensionless
$a_{d,pr}, \quad \forall\ d \in D\ \ \forall\ pr \in PR$ Minimum processing times for job type d at process pr.	minutes
$b_{d,pr}, \quad \forall\ d \in D\ \ \forall\ pr \in PR$ Maximum processing times for job type d at process pr.	minutes
$ml_{d,pr}, \quad \forall\ d \in D\ \ \forall\ pr \in PR$ Most-likely processing times for job type d at process pr.	minutes
$r_{pr}, \quad \forall\ \ pr \in PR$ Rate at which jobs arrive at process pr.	Dimensionless
$r_{OH} = 0.05$ Rate at which jobs are put on hold after inspection (process $pr = 7$)	Dimensionless
$r_{Rew} = \dfrac{2}{87}$ Rate at which jobs are faced with rework activities	Dimensionless
$pt_{pr}^{MM} = 480$ The total time a job spent at the mechanical machining department in case a job requires mechanical machining activities (process $pr = 8$).	minutes
$pt_{pr}^{OH} = 480$ The total time a job is put on hold in case the required spare parts are out of stock.	minutes
$d \in D, \quad for\ D = \{1,2,3\}$ The index d represents the job type. $d = \{1,2,3\}$ represent the job types DN25, DN50 and DN80, respectively. The total number of job types is denoted as $\tilde{d} = 3$.	
$c_{sk} = \{30,40,45,60\}, \quad \forall sk \in SK$ Costs per operator from skill class sk.	Euros/hour
$n \in N, \quad for\ N = \{1,2, \dots, \tilde{n}\}$	Dimensionless

Set of indices used for replications with $\tilde{n}$ representing the maximum number of replications.

E.2 Welch's Approach: warm-up period

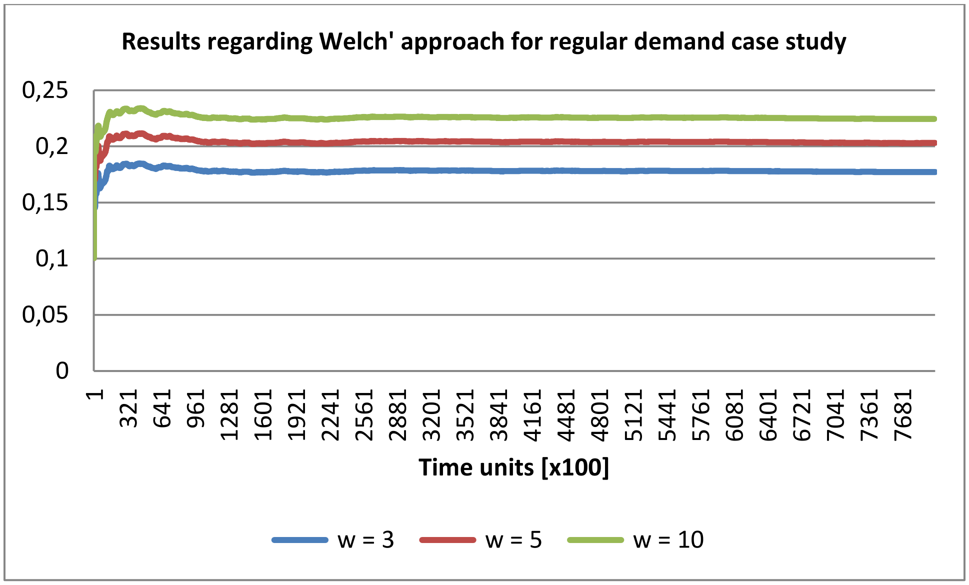

Figure 27: Results of Welch's approach for the regular demand data

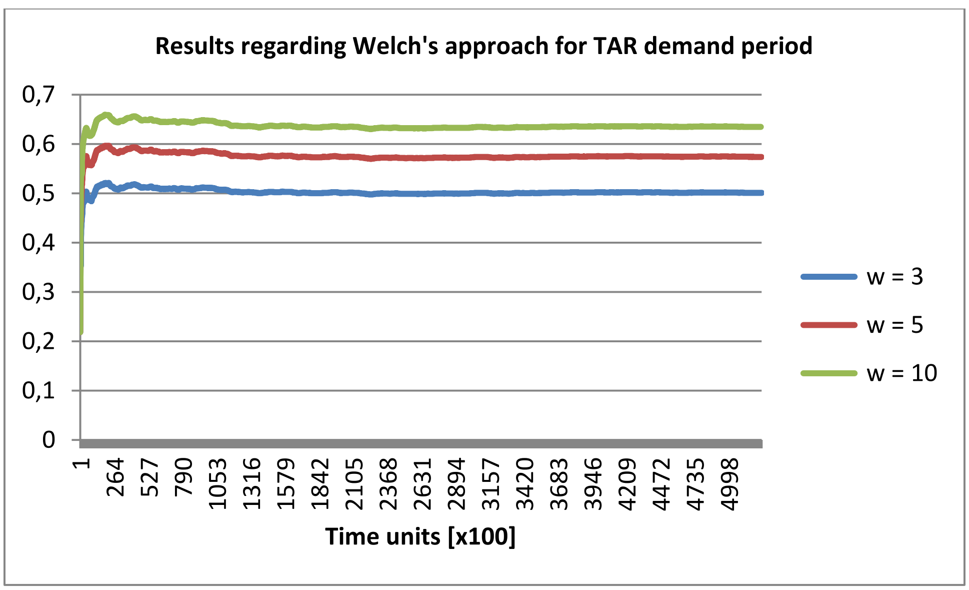

Figure 28: Results of Welch's approach for the TAR demand data

E.3 Common Random Numbers

The common random number generator from Kelton and Law (2015) is applied in this study.

E.4 Simulation

All simulation models are programmed in Visiual Basic for Applications (VBA). Since the code is extremely large, the code is removed from the thesis. One who is interested in the code, can send an e-mail to the researcher.

E.5 Results simulation Experiments

Due to confidential reasons, the results are removed from the appendix.