Master Thesis **Guusje Scheijen**

Quantifying the required resources for a central sterile supply department using a decomposition method

Leids Universitair Medisch Centrum

TU Delft

QUANTIFYING THE REQUIRED RESOURCES FOR A CENTRAL STERILE SUPPLY DEPARTMENT USING A DECOMPOSITION METHOD

by

Guusje Scheijen

in partial fulfillment of the requirements for the degree of

Master of Science
in Applied Mathematics

at the Delft University of Technology,
to be defended publicly on Friday December 18, 2020 at 14:00.

Thesis committee:	Prof. dr. D.C. Gijswijt,	TU Delft
	Dr. ir. J.T. van Essen,	TU Delft
	Dr. ir. M. Keijzer,	TU Delft
	Dr. ir. A.J. Schneider,	LUMC

Preface

This thesis presents the work performed during my graduation project for the master Applied Mathematics, with a specialization in optimization, at Delft University of Technology. This final report also represents the closure of a seven-year phase, that has lead me from the freshmen courses of the bachelor degree of Civil Engineering, up to the completion of my master degree in Applied Mathematics. The journey has been full of challenges, opportunities and great experiences. In this preface, I would like to thank several people that helped me during my graduation project.

First and foremost, I would like to thank my supervisor Theresia for her availability and guidance during these past months. Your commitment really made a difference and motivated me to perform at my best. Thank you for the endless proofreading and for running my models on the cluster, which was somewhat of a bumpy journey. Furthermore, I would like to thank Thomas for introducing me to healthcare logistics and provide the possibility to work at the LUMC capacity center. Likewise, thank you, Anne, Judith, Nanette and the rest of the staff at the CSSD, for making me feel welcome and offer plenty of opportunities to discuss and answer all my questions. Finally, I want to thank Marleen Keijzer and Dion Gijswijt for taking the time to be part of my graduation committee.

Next, I would like to thank my friends and family. My roommates for offering some much appreciated distractions during this period. My study friends met during my master, thanks for helping me to get started on the theoretical mathematics, the fun times during long study nights, and for always being in for dinner parties. Due to COVID-19, this thesis is written mostly from home, so I would like to thank everyone who offered me a work space during these times for a change of scenery. For people I forgot to mention, thank you for being part of this journey. Last, I want to express my gratitude to my family for their support and advice. A special thanks to Nelleke, for providing a working space and some much needed advice to finish this thesis. Finally, I want to thank Aubin for helping me where needed and for simply being there.

For now, I hope to see everyone soon!

Guusje Scheijen
Delft, December 2020

Abstract

Optimizing supply chain management in hospitals can lead to a significant reduction in costs. One of the supply chain processes that can be optimized is the sterilization of reusable instruments used during surgical procedures. This process takes place at the Central Sterile Supply Department (CSSD) and consists of two main steps, 'washing and disinfection' and 'sterilization'. These steps are executed by batch processing machines, with a setup time prior to each step. The setup at each stage is executed manually. The machines of a CSSD are renewed every 10 years, which provides a opportunity to assess all capacity planning decisions. In this thesis, the aim is to determine the required resources of the CSSD, while minimizing the total costs and guarantying the availability of instruments for scheduled surgeries. Costs include: acquiring machines, machine batch costs, machine maintenance costs, and staff costs depending on the number of opening hours. This thesis contributes to current research by proposing a framework for the capacity planning decisions at a CSSD, by extending existing models by taking specific characteristics of the CSSD into account, and considering a new objective function, namely minimizing the total costs.

Capacity planning decisions are considered on three hierarchical levels. First, the strategic level involves long-term decisions, where the number and type of required machines have to be determined. Second, on a tactical level, the amount of opening time has to be determined. Third, on an operational level, the instrument sets have to be scheduled within batches and machines. The sterilization process is formulated as a mixed integer linear problem (MILP). The problem is described as a multi-stage hybrid flow shop with additional constraints to represent the specific characteristics of the CSSD. This model takes into account capacity planning decisions on all three levels. The MILP formulation is proven to be NP-hard. The demand for sterilized instruments is determined from historical data from the Leiden University Medical Center. To evaluate the model, three instances with a timespan of a week are created.

Preliminary results showed that the multi-stage flow shop is difficult to solve for real-life instances. Hence, a decomposition, based on the three hierarchical levels, is proposed. The decomposition leads to three levels of optimization models. The strategic model takes into account the scheduling of instruments per day, while the tactical model schedules per day parts, and the operational models determine a specific point in time.

The proposed models are individually tested on their performance. The results from the strategic model are used as input for the tactical model. Results show that the strategic model underestimated the required amount of opening time, as it does not take into account the spread of release times. Furthermore, the computational results show that the tactical and operational models are difficult to solve for real-life instances. Hence, a heuristic approach is proposed by forming a chain of the models. The best results were obtained by setting a minimum amount of opening time for the strategic model and using the resulting machines as input for the tactical model. The results show that the instrument sets are equally spread over the week.

To conclude, the results of this thesis contribute to quantifying the required resources for a sterilization process within a hospital. However, to obtain more practical results, future research is required. Suggestions for future research include: taking uncertainties within the process into account, the application of metaheuristics, and the required number of employees.

GLOSSARY

BPMN	Business Process Model and Notation
CSSD	Central Sterile Supply Department
ENT	Ear-Nose-Throat
FS	Flow shop
FSS	Flexible/Hybrid flow shop
ILP	Integer linear program
LUMC	Leiden University Medical Center
MILP	Mixed integer linear program
MIP	Mixed integer program
OR	Operation room
UMC	University Medical Center
FIFO	First In First Out
FFP	First Fit Procedure

Nomenclature

Here, all notation used in the mathematical programming formulations is gathered. For each hierarchical level, a list of all sets, parameters, and variables is presented.

Strategic model

Sets

D	Set of days
H^j	Set of machines at stage $j \in J$
I	Set of jobs
J	Set of stages

Parameters

c^j_{1h}	Purchase cost of machine $h \in H^j$ at stage $j \in J$
c^j_{2h}	Batch cost of machine $h \in H^j$ at stage $j \in J$
c_3	Cost for an employee during normal hours
l_i	Lead time in days of job $i \in I$
e^j	Maximum duration in days before or at stage $j \in J$
γ	Fraction of time in which machines can be used each day
M	Large number
p^j_h	Processing time at machine $h \in H^j$ at stage $j \in J$
r_i	Release day of job $i \in I$
s^j_i	Processing time of job $i \in I$ at stage $j \in J$
u^j_h	Machine capacity of machine $h \in H^j$ at stage $j \in J$
v^j_d	Number of operators at stage $j \in J$ on day $d \in D$
z^j_i	Size of job $i \in I$ at stage $j \in J$

Variables

P^j_h	Binary variable which is one when machine $h \in H^j$ at stage $j \in J$ is purchased, and zero otherwise
K^j_{hd}	Integer variable to linearize ceiling $\left\lceil \frac{\sum_{i \in I} S^j_{ih} Y^j_{id} z^j_i}{u^j_h} \right\rceil$
L^j_{hd}	Integer variable to linearize floor $\left\lfloor \frac{\gamma O_d}{p^j_h} \right\rfloor$
O_d	Amount of opening time on day $d \in D$
Q_d	Amount of irregular opening time on day $d \in D$
S^j_{ih}	Binary variable which is one when job $i \in I$ is assigned to machine $h \in H^j$ at stage $j \in J$, and zero otherwise
X^j_{ihd}	Binary variable to linearize the term $S^j_{ih} Y^j_{id}$
Y^j_{id}	Binary variable which is one when job $i \in I$ at stage $j \in J$ is processed on day $d \in D$, and zero otherwise

TACTICAL MODEL

Sets

G	Set of day parts
H^j	Set of machines at stage $j \in J$
I	Set of jobs
J	Set of stages

Parameters

c^j_{1h}	Purchase cost of machine $h \in H^j$ at stage $j \in J$
c^j_{2h}	Batch cost of machine $h \in H^j$ at stage $j \in J$
c_3	Cost for an employee during normal hours
l_i	Lead time in day parts of job $i \in I$
e^j	Maximum duration in day parts before or at stage $j \in J$
γ	Fraction of time in which machines can be used each day
M	Large number
p^j_h	Processing time at machine $h \in H^j$ at stage $j \in J$
r_i	Release day part of job $i \in I$
s^j_i	Processing time of job $i \in I$ at stage $j \in J$
u^j_h	Machine capacity of machine $h \in H^j$ at stage $j \in J$
v^j_g	Number of operators at stage $j \in J$ during day part $g \in G$
z^j_i	Size of job $i \in I$ at stage $j \in J$

Variables

P^j_h	Binary variable which is one when machine $h \in H^j$ at stage $j \in J$ is purchased, and zero otherwise
K^j_{hg}	Integer variable to linearize ceiling $\left\lceil \frac{\sum_{i \in I} S^j_{ih} Y^j_{ig} z^j_i}{u^j_h} \right\rceil$
L^j_{hg}	Integer variable to linearize floor $\left\lfloor \frac{\gamma O_g}{p^j_h} \right\rfloor$
O_g	Amount of opening time during day part $g \in G$
Q_g	Amount of irregular opening time during day part $g \in G$
S^j_{ih}	Binary variable which is one when job $i \in I$ is assigned to machine $h \in H^j$ at stage $j \in J$, and zero otherwise
X^j_{ihg}	Binary variable to linearize the term $S^j_{ih} Y^j_{ig}$
Y^j_{ig}	Binary variable which is one when job $i \in I$ at stage $j \in J$ is processed during day part $g \in G$, and zero otherwise

Operational models

As the notation of the operational models changes between Chapter 4 and Chapter 5, a specific notation for each chapter is added. The third and/or fourth column indicate for which elements of the set mentioned in the second column, a set, parameter, or variable is introduced. Additionally, for the third and fourth column, an 'x' indicates that the notation is used as already stated in the second column, and an '-' indicates that the symbol is not used in the corresponding chapter.

Sets

		Chapter 4	Chapter 5
B^j	Set of batches at stage $j \in J$	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
D	Set of days	x	x
F^j	Set of job families at stage $j \in J$	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
H^j	Set of machines at stage $j \in J$	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
I	Set of jobs	x	x
J	Set of stages	x	x
O_d^j	Set of operators at stage $j \in J$ on day $d \in D$	$\forall j \in \{1,3\} \subset J$	-
R	Set of payment rates	x	x

Parameters

		Chapter 4	Chapter 5
c_{1h}^j	Purchase cost of machine $h \in H^j$ at stage $j \in J$	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
c_{2h}^j	Batch cost of machine $h \in H^j$ at stage $j \in J$	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
c_{3r}	Cost for an employee during opening hours at rate $r \in R$	x	x
c_4	Additional costs for an employee in overtime	x	x
l_i	Lead time of job $i \in I$	x	x
e^j	Maximum duration before or at stage $j \in J$	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
f_{ik}^j	Binary parameter equal to one if job $i \in I$ and $k \in I$ are part of the same job family $f \in F^j$ at stage $j \in J$, and zero otherwise.	x	-
M	Large number	x	x
p_h^j	Processing time at machine $h \in H^j$ at stage $j \in J$	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
p_1, p_2, p_3, p_4	Tipping point of different payment rates, 07:00, 08:00, 12:00, and 20:00, respectively	x	x
r_i	Release date of job $i \in I$	x	x
s_i^j	Processing time of job $i \in I$ at stage $j \in J$	$\forall j \in J$	$\forall j \in \{1,3\} \subset J$
u_h^j	Machine capacity of machine $h \in H^j$ at stage $j \in J$	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
v_d^j	Number of operators at stage $j \in J$ on day $d \in D$	$\forall j \in J$	$\forall j \in \{1,3\} \subset J$
z_i^j	Size of job $i \in I$ at stage $j \in J$	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$

Variables

		Chapter 4	Chapter 5
A^j_{id}	Binary variable which is one when $Y^j_{id} = 1$ and the setup process of job $i \in I$ at stage $j \in J$ is executed the day before, and zero otherwise	x	-
A^j_{ik}	Binary variable which is one when job $k \in I$ is processed after job $i \in I$ at stage $j \in J$, and zero otherwise	-	$\forall j \in \{1,3\} \subset J$
P^j_h	Binary variable which is one when machine $h \in H^j$ at stage $j \in J$ is purchased, and zero otherwise	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
G_{dp_1}	Variable to linearize terms $N_{dp_1}(n_d + q_d)$	x	x
G_{dp_2}	Variable to linearize terms $N_{dp_2}(n_d + q_d)$	x	x
G_{dp_3}	Variable to linearize terms $M_{dp_3} m_d$	x	x
G_{dp_4}	Variable to linearize terms $M_{dp_4} m_d$	x	x
m_d	Opening time on day $d \in D$	x	x
M_{dp_4}	Binary variable which is one when the opening time on day $d \in D$ is after p_4= 20:00 , and zero otherwise	x	x
M_{dp_3}	Binary variable which is one when the opening time on day $d \in D$ is after p_3= 12:00 , and zero otherwise	x	x
n_d	Closing time on day $d \in D$	x	x
N_{dp_1}	Binary variable which is one when the closing plus overtime on day $d \in D$ is before p_1= 07:00 , and zero otherwise	x	x
N_{dp_2}	Binary variable which is one when the closing plus overtime on day $d \in D$ is before p_1= 08:00 , and zero otherwise	x	x
q_d	Overtime on day $d \in D$	x	x
S^j_{ibh}	Binary variable which is one when job $i \in I$ is assigned to batch $b \in B^j$ at machine $h \in H^j$ at stage $j \in J$, and zero otherwise	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
S^j_{iod}	Binary variable which is one when job $i \in I$ is assigned to operator $o \in O$ at stage $j \in J$ on day $d \in D$, and zero otherwise	-	$\forall j \in \{1,3\} \subset J$
t^j_i	Completion time of job $i \in I$ at stage $j \in J$	x	x
t^j_{bh}	Completion time batch $b \in B^j$ at stage $j \in J$	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$
V_{dr}	Amount of opening time for which rate $r \in R$ applies on day $d \in D$	x	x
W_{dp_1}	Amount of opening time before p_1 = 07:00 on day $d \in D$	x	x
W_{dp_2}	Amount of opening time before p_2 = 08:00 on day $d \in D$	x	x
W_{dp_3}	Amount of opening time after p_3 = 12:00 on day $d \in D$	x	x
W_{dp_4}	Amount of opening time after p_4 = 20:00 on day $d \in D$	x	x
X^j_{id}	Difference between batch setup time on day $d \in D$ and the process time of job $i \in I$ at stage $j \in J$	x	-
Y^j_{id}	Binary variable which is one when job $i \in I$ at stage $j \in J$ is processed on day $d \in D$, and zero otherwise	x	x
Z^j_{bh}	Binary variable which is one when batch $b \in B^j$ is assigned to machine $h \in H^j$ at stage $j \in J$, and zero otherwise	$\forall j \in J$	$\forall j \in \{2,4\} \subset J$

Contents

1

Introduction

In the upcoming years, the operating room (OR) center at Leiden University Medical Center (LUMC) will be renewed. The aim is to finish in 2024. This project offers opportunities to optimize the processes around the OR from a strategical point of view. One important secondary process is the sterilization of the reusable instruments used during a surgery. At LUMC, the instruments are sterilized by the Central Sterile Supply Department (CSSD), which is part of the OR center. The CSSD will also be renewed. Currently, it is not clear how many resources are required to sterilize all instruments and which characteristics influence the required number of resources. As the entire department will be renewed, it is important to determine the required resources in the future situation.

More generally, during the last decade an increasing amount of research concerning the CSSD has been conducted, as it shows promising opportunities to reduce costs within healthcare. Based on a site visit to the CSSD of the University Medical Center Utrecht (UMC Utrecht), expert judgement and a literature review, it can be concluded that the sterilization process of reusable instruments consists of similar steps within other organizations in the Netherlands. Although this research had been conducted at the LUMC, the process regarding the sterilization consists of similar steps within other healthcare facilities or dedicated sterilization companies. Hence, this research is not only useful regarding decision making within the LUMC, but also for other organizations where the process of sterilization of instruments occurs.

In this chapter, the sterilization process is concisely described and a problem description is presented. Next, the problem description is translated to a research goal and corresponding research questions. Again, a distinction has been made between the specific goal for the LUMC, and the general contribution of this thesis. Finally, a preliminary scope is discussed and a thesis outline is given.

1.1. Process description

In Figure 1.1, a simplified overview of the main process at the CSSD is shown using a Business Process Model and Notation (BPMN) model. This notation will be further explained in Section 2.3. At the LUMC, besides instruments from the OR, the CSSD also sterilizes instruments from the outpatient clinics. At the CSSD, the instruments are manually cleaned and organized in different trays by the staff, after which the trays are put in the washing disinfection (WD) machines. After the instruments are washed and disinfected by the WD machines, they are checked and assembled as individual item or set. After wrapping the individual item or set, the instruments are sterilized in autoclaves. Finally, the sterilized instruments are transported to the OR storage and outpatient clinics. To conclude and define terms, there are four main steps within the process:

- Clean: Removal of visible and invisible dirt from the instruments. This is partly done manually in the cleaning room and partly by the WD machines.
- Disinfect: Kill micro organisms, to an acceptable level, from the instruments. This is done within the WD machines.
- Check and assemble: Check all instruments and assemble and wrap them in sets or individual items.
- Sterilize: Removing micro organisms from the instruments until the chance that such organisms are still found alive is less than one in a million. This is done by the autoclaves.

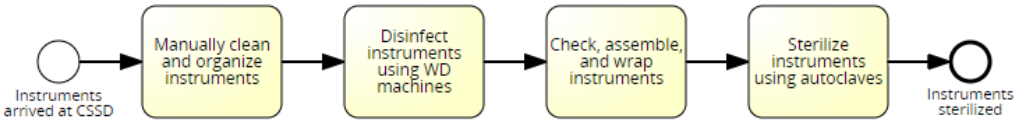


Figure 1.1: Simplified business process diagram.

1.2. PROBLEM DESCRIPTION

Currently, there are no guidelines regarding the number of resources which are required to sterilize all instruments. These resources include: WD machines, autoclaves, cleaning stations and staff hours. First of all, the resources are dependent on the incoming flow of instruments from the OR and the outpatient clinics. Secondly, different working methods can have impact on the number of resources required. Different machine sizes could also influence the costs of sterilization. For example, smaller autoclaves could provide extra flexibility in case of an emergency or a small demand. However, multiple smaller autoclaves could also mean higher investments costs and additional space requirements. Furthermore, the number of staff and the amount of opening time of the CSSD influence the required machine capacity. If the opening time is increased, less machines and working stations are required. However, it is both more expensive and not desired to let staff work through the night. Finally, the urgency in which instrument sets have to be sterilized has an influence on the required capacity. If instrument sets have to be returned urgently, the resources are impacted by peak and low demand. The purchase of additional instrument sets could solve the urgent requests, although it also leads to additional costs. As the process occurs in the hospital, a high service level is required. A tardy job means that a surgery is rescheduled or cancelled, which could have a significant impact on the patient's well being.

Related to determining the required resources, is the scheduling of different process steps. According to the multi-year plan for the CSSD at the LUMC, written by Adank [1], the number of machines could be limited by adjusting the daily schedule. The process should always satisfy the demand as there could be severe consequences if a surgery has to be rescheduled or cancelled. Hence, to determine the number of machines that are needed, an operational job scheduling problem has to be solved.

Currently, the CSSD at the LUMC works with a push approach. The instruments are replenished to the storage at the OR and outpatient clinics as soon as possible, even though instruments might not be required the next day. As earlier research suggests, a pull approach could reduce costs and unnecessary sterilization of instruments (van de Klundert *et al.* [2]). In that case, the instruments are only sterilized and brought to the storage when they are required for a surgery, appointment or emergency storage. This working method will be explained in more detail in Chapter 2.

1.3. RESEARCH GOALS

The goal of this research is to analyze the required resources to sterilize a certain number of arriving instrument sets. The aim is to minimize the costs of handling the sterilization of all reusable instruments. Potential costs include: acquiring machines, machine batch costs, maintenance costs and staff costs. The CSSD at the LUMC was used as a case study for this thesis. As mentioned before, to determine the required resources, a scheduling problem has to be solved. All jobs, the instruments, should be assigned to a batch and a machine in each step of the sterilization process. Implicitly, it can be said that the aim is to minimize the makespan to process all instruments. However, the main objective is to minimize costs, which may not coincide with minimizing the makespan. The right number of resources can only be determined if the makespan for that number of resources and jobs is known.

1.3.1. RESEARCH QUESTION

The goal of this research can be captured in the next question:

"How can the number of required resources for a sterilization process within a hospital be quantified?"

In order to structure the research and answer the main question, several sub questions are formulated. The first three questions concern the general problem description, followed by questions that are more specific to the input data obtained from the LUMC.

1. How can the sterilization process be described and what is the position of the CSSD within a hospital?
First, the process introduced in Section 1.1 has to be explained in more detail. Furthermore, the position of this process within a hospital is further explained.

2. Which techniques are used in literature to solve such an optimization problem?
The last decade, an increasing amount of research has been conducted concerning the CSD (Saif and Elhedhli [3]). In Rossi *et al.* [4], a sterilization plant is scheduled as a two stage hybrid flow shop problem with parallel batching. Parallel batching, in this context, means that jobs in a batch are processed simultaneously. The two stages represent the WD machines and the autoclaves, respectively. Furthermore, for other departments with a similar process structure, a hybrid flow shop problem has been applied as well. In Leeftink *et al.* [5], a histopathology laboratory is described as a three-stage flow shop problem.

3. Which techniques can be applied to the optimization problem at the CSSD?
This type of optimization problem could have been studied before. However, the model has to have distinctive features dictated by the characteristics of the sterilization process.

4. What is the demand for the sterile instruments within the LUMC?
Earlier research already shows the number of arriving sets at the CSSD at the LUMC (Adank [1]). However, this report only takes into account the number of products scanned and not their size. This could differ from a single individual instrument to a larger surgery net. In addition, the schedule of the OR and outpatients clinics has to be taken into account. Currently, a list is being developed at the LUMC which indicates all sets and individual items required during an appointment or surgery. Hence, it will be possible to schedule the sterilization of instrument sets over a timespan of a week. In that way, there is a clear overview in case there are infeasibilities within the schedule. Historical data will be used to determine the demand of the OR and the outpatient clinics.

5. What are the due dates for the different instrument sets?
Currently, the staff manually looks through the instruments that have arrived to determine which should be processed first. By assigning due dates to the arriving instruments, the schedule can be optimized with the due dates as constraints. These due dates depend on the available number of sets of a specific type, the OR and outpatients clinic schedule, the current number of sets within storage and requests from the OR. The assignment of due dates and priorities has already been done by Rossi *et al.* [4]. However, this is done empirically.

6. What are the solutions from the optimization problem for different parameter settings?
There are various parameters within the models proposed in this thesis, for which the aim is to determine the influence on the solution. A distinction can be made between the actual solutions and the possibility to solve the model for large instances.

7. Which conclusions and recommendations can be drawn from this research?
Conclusions based on the results of the optimization problem are stated. From the results, recommendations can be given for the LUMC and future research.

1.3.2. SCOPE
In Hulshof *et al.* [6], a framework is presented to subdivide capacity planning decisions within the health care delivery process. The hierarchical levels are divided in strategic, tactical and operational planning. Strategic planning involves long-term decisions such as: machine capacity, location and process design. Tactical and operational planning involves more short-term decisions. The tactical level sets a blueprint in which the operational decisions can be made. The operational level is subdivided in offline and online planning. Offline planning schedules the jobs based on the given capacity and due dates in advance. Online planning also takes into account emergency requests which cannot be scheduled in advance (Keseler [7]). Although Hulshof *et al.* [6] only focuses on primary processes, which does not include instrument sterilization, the same hierarchical decomposition can be used for the CSSD.

As already mentioned, in order to answer the research question, decisions regarding all hierarchical levels have to be taken into account. The research goal is to achieve a strategic and tactical planning. First, on a strategic level, the capacity of the resources required to sterilize all instruments are determined. Second, the amount of opening time of the CSSD and the number of employees each day are determined as a blueprint for the operational planning. To accomplish this goal, the operational schedule has to be taken into account to determine a makespan given a certain number of resources and jobs. Based on expert judgement, it is decided that first the amount of opening time is taken into account as a tactical decision. The number of employees will be an input parameter. A more elaborate overview of the hierarchical decomposition of the decision is presented in Section 2.7.

1.4. THESIS OUTLINE

This thesis is structured around the sub questions. First, in Chapter 2, the process to sterilize instrument sets is further explained. It also includes a more in depth overview of all logistic proceedings around the CSSD at the LUMC, and finally, introduces a view on the future situation at the CSSD on which the rest of this thesis is based. This chapter answers question 1. Next, Chapter 3 answers question 2 and partly question 3 by presenting a small literature review. Within Chapter 4 and 5, question 3 is further answered by introducing the optimization model and formulation, and subsequent solution approaches to solve this model. Then, Chapter 6 is a data analysis of the data gained from the CSSD to answer question 4. In addition, a method to answer question 5 is proposed. After the models are presented and the input data is described, the results of various computational experiments are presented in Chapter 7. This chapter answers question 6. Finally, Chapter 8 describes the conclusions of this research, the recommendations to the CSSD at the LUMC, and the recommendations for future research. This chapter answers question 7.

2

Situational analysis

This chapter gives a concise overview of the flow of reusable instruments within the LUMC and the position of the CSSD within this process. Additionally, a detailed description of the processes that occur at the CSSD is given. First, in Section 2.1, as an introduction, the term reusable instruments is further defined. In Section 2.2, an overview is given of the flow of reusable instruments and the position of the CSSD. This includes an overview of the scheduling at the OR and the outpatient clinics, as they are the main customers of the CSSD. Hereafter, the processes at the CSSD are described in more detail. The processes are described using a Business Process Model and Notation (BPMN) model. In Section 2.3, a concise description of BPMN is given. In Section 2.4, a BPMN model of the CSSD is developed to illustrate the processes at the CSSD. This section is divided into four subsections for each of the four subprocesses. Moreover, the different areas where the process takes place are described. In Section 2.5, the aspired future situation is described, on which the models presented in this thesis are based. Finally, in Section 2.7, the scope of this thesis is further defined. Although this chapter is mainly based on the processes and working methods at the LUMC, the description of the future situation gives a more general overview of a CSSD within a hospital.

2.1. Reusable instruments

Within the LUMC, there is a wide range of instruments available. According to van Blijswijk [8], the estimated number of available instruments equals roughly 40,000. These instruments are available as an individual item or as part of a set. Individual instruments are individually wrapped and often used in addition to a set. Sets consist of two or more instruments and are used for a specific surgery or requested by a specific surgeon. A set can be used for several surgeries and multiple sets can be required for a surgery. Depending on the size, a set is packed in double laminate or a basket which is packed in two layers of polypropylene, a combination of paper and plastic. Sets of reusable instruments are mentioned under multiple names in literature, including, basket, tray and net. Within this thesis a general term, ‘instrument set’, is used for both individual items as well as for sets. If there is the need for a distinction between different types, the terms ‘individual item’ and ‘tray’ are used.

In Figure 2.1, three examples are presented that show the range of possible instruments. Figure 2.1a shows a Metzenbaum scissors individually packed in double laminate. Figure 2.1b shows an acute surgery basket consisting of 90 instruments according to van Blijswijk [8]. As the name suggests, this set is used for emergency surgeries. However, it is also often used as an additional set for other surgeries. Figure 2.1c shows an universal basic surgery set composed of 12 basic instruments according to van Blijswijk [8]. Each instrument set has a specific cleaning instruction. There are specialized cleaning stations and different autoclave and washing machines programs. These programs have a different washing duration, capacity and handling costs. As a result, not all instrument sets can be batched together.

Note, the CSSD at the LUMC also handles the disinfection of scopes. This process is outside of the scope of this thesis.

2.2. Flow of reusable instruments

The flow of reusable instruments in a hospital can be described as a cycle. As mentioned before, the main users of reusable instrument sets are the OR and the outpatient clinics. Hence, these are the main customers

(a) Metzenbaum scissors (b) Acute surgery basket [8] (c) Universal basic surgery set [8]

Figure 2.1: Range of instruments

of the CSSD. The demand of the OR and the outpatient clinics is directly related to the number of resources that are needed at the CSSD. The scheduling of the OR and the outpatient clinics are described in Subsection 2.2.1 and 2.2.2, respectively. From the OR and the outpatient clinics, a logistic team delivers the instrument sets to the OR. After each surgery at the OR, the instrument sets are collected an transported to the CSSD. At the outpatient clinics, the instrument sets used for a treatment are stored in mobile carts after use. These carts are brought to the CSSD once a day and are to be returned as soon as all instruments are sterilized. As visualized in Figure 2.2, after usage at the OR, the instruments go back to the CSSD to be sterilized, after which they are transported to the storage until a next usage at the OR. Currently, the CSSD works with a push approach. The instruments are replenished to the storage at the OR and outpatient clinics as soon as possible.

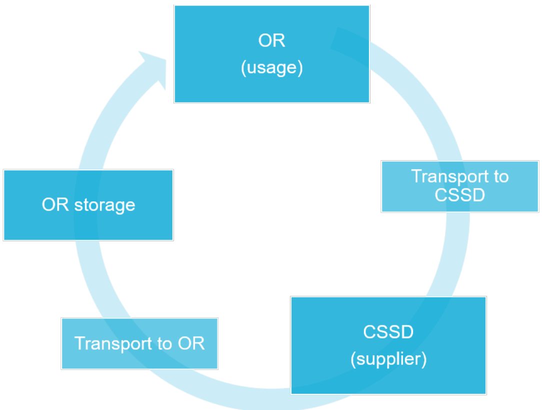


Figure 2.2: Reusable instrument flow

2.2.1. OR SCHEDULING

Each quarter of a year, the available capacity at the OR is determined based on staff hours. This available OR capacity consists of the number of OR sessions, with each OR session represented as a time slot between 08:00-16:00. Based on historical data, waiting lists and preferred surgery types, these slots are distributed over the specialties at the hospital. For certain specialties, it is not possible to finish a surgery within one OR time slot. Hence, each day, there are extended hours possible within the schedule. Depending on the week, at most two or three OR sessions can finish at 18:00 the latest and one OR at 21:00 the latest. Note that several weeks a year (e.g. Christmas or summer), only half of the OR schedule is executed. These weeks are determined before the start of the year and taken into account in the OR scheduling.

Considering the distribution of time slots and the extended hours over the specialties, a blueprint OR schedule is created. Within the OR schedule, one OR session per day is scheduled for urgent surgeries. The planning within an OR session is up to the speciality. It could be filled with one long surgery or multiple short ones. Hence, the planning is decentralized, which makes it difficult to plan the required resources, such as instrument sets. All surgeries in a week have to be scheduled on Wednesday a week in advance. On Thursday morning, the OR schedule is reviewed on feasibility, order, staff availability, and resource availability. At the end of Thursday, the whole schedule is known for the next week. However, there are still tens of OR schedule changes each week. For example, in 2018 there were up to 400 changes each month. During the day, a management team is in charge of the OR schedule. Deployment of the OR session scheduled for urgent surgeries is decided by this management team.

Consequently, the schedule of sterilizing instrument sets can be based on the OR schedule, taking into account the scheduled surgeries as due date. In addition, there has to be a basic safety stock available at the OR for urgent surgeries. Urgent surgeries are categorized in:

- S1, now
- S2, within 8 hours
- S3, within 24 hours

As a sterilization cycle takes 5-6 hours, the instrument sets required for surgeries of type S3 can be sterilized after deciding the surgery has to take place. Although this also holds for surgeries of type S2, it could induce overtime and emergency jobs in the CSSD. Hence, for surgeries of type S2 and S3, a basic safety stock at the OR has to be used.

The OR schedule can be taken into account on two different levels:

- Tactical: each speciality has its own specific instrument sets. Using the blue print of the OR schedule, it can be determined how fast the instrument sets of a specific specialty has to be sterilized. This is mainly interesting for smaller specialties which do not have OR slots on every day. Note, this blueprint changes every quarter.
- Operational: the planned surgeries are known one week in advance, hence, the required instrument sets can be determined. A schedule for processing these instrument sets can be made based on these specific surgeries, the required basic safety stock and the current stock level at the OR.

In this thesis, a method considering the executed surgeries during a year is proposed. This method is described in Chapter 6.

2.2.2. Outpatient scheduling

After each appointment at an outpatient clinic, used instrument sets are collected into bins in mobile carts. At fixed times, the logistic team swaps these carts for empty ones. The filled carts are transported to the CSSD, at which instrument sets from the outpatient clinic arrive between 17:00 and 18:00. The CSSD has arrangements with each department about the time frame in which the instrument sets of the collected carts have to be returned. The general agreement is that instrument sets are returned to the outpatient clinics within 24 hours. There two exceptions to this rule, namely for the 'Ear-Nose-Throat (ENT)' and 'Mouth care' outpatient clinics the instruments have to be returned before 13:00 the next day. The scheduling of the outpatient clinics is decentralized and there is not much information available about the used instruments. In this thesis, the total number of instrument sets originating from the outpatient clinics is estimated from expert judgement. These numbers can be found in Chapter 6.

2.3. BPMN 2.0

As the CSSD processes are described using a BPMN model, a concise summary of the notation is given. Nowadays, BPMN is one of the most used languages to model business processes [9]. As said in [10], BPMN models describe the execution ordering of activities, and the human, physical and informational resources involved in the process. The model consists of different blocks and lines which have different meanings. Below, a list of the used elements:

- **Activities:** These are the main blocks of the model and represent units of work. The blocks are represented as rectangles with rounded edges. In addition, a little square with a '+' can be added when the block contains a subprocess. By making different hierarchical levels, a model is more readable and understandable.
- **Gateways:** These blocks control the divergence and convergence of the process flow. The blocks are represented as diamonds with an 'x', '+' or an 'o'. The 'x' represents an exclusive gateway, a decision point in the process where a certain stated condition is evaluated. Hence, only one of the given branches is executed. The '+' represents a parallel gateway where work is done parallel and both

branches are executed. The 'o' represents an inclusive gateway, also a decision point in the process, where multiple branches can be executed.

- **Events:** These blocks represent an event which is not a work unit. The two main events are start and end event. Events are represented as circles with a normal line for a start event and a bold line for an end event. Additionally, in the model, catching error and message events are used. The error events are used to indicate that a check is not passed and the process is quit for that instrument set. An example is the pressure test for scopes. The message events indicate an information message from the database, for example the type of washing program that is required for a specific net.
- **Continuous line:** These lines indicate the order in which the activities are performed.
- **Dashed line and database:** A dashed line represents communication between the two blocks. In this case, it represents data that is stored or retrieved in the database T-DOC. A database is presented by a cylinder and a name.

For this model, BPMN 2.0 in Signavio Process Manager [11] is used. The model has two different hierarchical levels, the main process, and for each step in the main process, a more detailed sub process.

2.4. CSSD PROCESSES

The main process consists of four subprocesses: 'Manually clean instrument set', 'Disinfect instrument set using WD machines', 'Check and assemble instrument set' and 'Sterilize instrument set using autoclaves'. This main process is shown in Figure 2.3. Each subprocess will be further explained in a subsection. The corresponding and more elaborate BPMN models can be found in Appendix A.

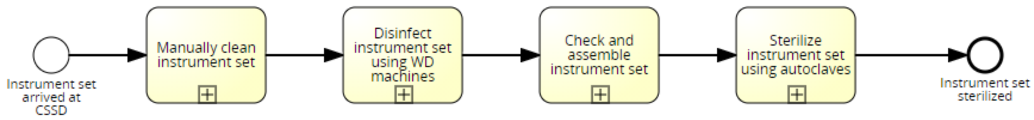


Figure 2.3: Core processes CSSD

The CSSD is divided into two main areas, a decontamination zone and an assembly zone. Additionally, there are some grey areas, including the transporting area and the offices of the staff. All instruments arrive in the decontamination zone, where they are manually cleaned. Instruments that have to be manually disinfected will also be disinfected here. The manually cleaned instruments go into the WD machines to be cleaned and disinfected. The washing machines are used as a gateway from the contaminated room to the clean room. Hence, if the wash program is done, the instruments arrive in the clean room. The instruments that are disinfected manually are transported through a serving hatch to the clean room. In the clean room, the instruments are checked, assembled, and packed as individual items or into trays. After this, they go into the autoclaves to be sterilized. These autoclaves are also used as a gateway from the clean room to a sterile area.

The CSSD can be characterized by highly specialized manual labor and two stages of batching machines. Each instrument set has specific cleaning and assembly instructions, and there is a wide variety of instrument sets. Employees require specific knowledge and have to work accurately as careless handling can lead to severe complications for patients. Figure 2.4 gives an impression of the processes at the CSSD.

2.4.1. MANUALLY CLEAN

The instruments arrive from two different sources: the OR and the outpatient clinics. The logistic employees of the OR bring the used instruments within an open cart to the cleaning room after each surgery. Generally, the first surgeries start at 08:00, so the first sets of that day arrive around 12:00. Beforehand, the instrument sets used during the night arrive at 07:00. The used instruments from the outpatient clinic arrive at the end of the day between 17:00 and 18:00. They are stored in closed carts, which are switched for empty carts when they are picked up. The instrument sets are scanned as soon as they arrive in the decontamination zone.

(a) Manually clean instrument set (b) Disinfect instrument set using WD machines (c) Check and assemble instrument set (d) Sterilize instrument set using autoclaves

Figure 2.4: CSSD processes

Upon arrival of instrument sets at the CSSD, the CSSD employees look into the different carts to see which instrument sets have the highest priority. This priority can be based on: requests from the OR, the number of sets of a specific instrument set and the number of sets of a specific instrument set already at the CSSD. The first step is manually cleaning the instruments at a washing station. The employee scans the instrument set to see the information, guidelines and possible remarks on cleaning the specific set. After being washed, the instruments are laid open in multiple baskets to ensure they are cleaned properly in the washing machines. These extra baskets are called DIN baskets and have four main sizes, 1, 1/2 and 1/4 DIN. Additionally, the instruments are sorted for different washing programs. Hence, an instrument set can be divided over multiple washing machines according to the different washing programs. After manually cleaning, an ultrasonic machine is used to remove caked contamination. The guideline is to include this step for each instrument set with exceptions for sensitive sets such as instrument sets from the ‘eye’ outpatient clinic.

2.4.2. DISINFECT USING WD MACHINES

After the cleaning step, the DIN trays are put on a cart. Each cart corresponds to a batch in the WD machines. When there is no rush, the cart will be filled, after which it is ready to be disinfected. The first step is a prerinse process. As soon as a cart is put in front of a washing machine, the corresponding washing program is automatically selected based on the cart type. For the majority of the instruments, the disinfecting step is performed by the washing machines. There are different programs for different types of materials: enzymatic, alkaline and a washing program specific for eye instruments and implants. A few instruments have to be disinfected manually, for example cables and filters. These are handed through a serving hatch to the clean room. As a result, not all instruments from a set are in the same washing machine. After the different disinfect wash programs, an employee checks the batch and machine and releases the instruments for the next step.

2.4.3. CHECK AND ASSEMBLE

When the instruments are disinfected, several manual steps have to be taken depending on the type of instrument. This includes: oiling instruments, blow through lumen and putting instruments in a drying cabinet. After these steps, the instruments are divided over multiple working stations. The aim is to collect the instrument sets for each working station from the different disinfecting processes. At a working station, the employee scans the instrument set to see all the specific information. All individual instruments are checked and assembled. At the same time, the completeness of an instrument set is checked. If the instrument set is complete and checked, it has to be wrapped. This packaging ensures that instruments remain sterile after the process. As mentioned before, there are two main types; individual items and trays. Individual items are wrapped in laminate. Trays are wrapped in a double layer of polypropylene, a combination of paper and plastic. After wrapping, a bar code is printed and the step is indicated as finished in the database.

2.4.4. STERILIZE INSTRUMENT SET USING AUTOCLAVES

After the assembling step, the wrapped instrument sets are put on a cart. Again, each cart corresponds to a batch in the autoclaves. There are two different autoclaves, a heat autoclave and a plasma autoclave. The heat autoclave has two different programs, 123 degrees Celsius and 141 degrees Celsius. According to the instrument sets on a cart, the autoclave program is selected. In addition, a flash autoclave can be used in case there is an urgent request. After sterilization, an employee checks the batch and machine and releases the instruments for transport to the OR or the outpatient clinics.

2.5. FUTURE SITUATION

Together with the renewal of the CSSD and OR, the aim is to change the working methods from a push to a pull approach. As this thesis is used to support decisions concerning the new situation, the preferred future process is described in this section. This situation sketch is based on a site visit to the University Medical Center (UMC) Utrecht, the new system of Boikon B.V. Medische Automatisering - Boikon B.V. [12], and expert judgement. As there is less information about the decentralized planning of the outpatient clinics and the required instrument sets, this pull approach method is mainly focused on the demand from the OR. In the future situation, the agreements of the outpatient clinics can be reviewed to ensure that instrument sets arrive more evenly over the day. Currently, all instrument sets from the outpatient clinics arrive between 17:00 and 18:00. However, these changes are not taken into account in this thesis.

For each type of surgery at the OR, there is a list of the required instrument sets. Hence, it is known which instrument sets are required for each planned surgery. As the planned surgeries are reviewed a week in advance, a weekly schedule for the CSSD can be made. Within this schedule, it is known when a set has to be returned to the OR for a surgery. For emergency surgeries, there has to be a predetermined safety stock level present at the OR storage. This safety stock level is determined in consultation with operating assistants and surgeons. The safety stock level is based on the frequency of usage of an instrument set during emergency surgeries and the number of available sets. The weekly schedule of the CSSD can be adjusted if there is a change within the OR schedule and the required instruments sets, or if there is an emergency surgery and the safety stock level has to be replenished. With this system, employees of the CSSD have a better overview of which instruments sets have to sterilized that day and which can be stored to be sterilized later. In this way, there is no peak in workload when instrument sets from the surgeries and the outpatient clinics arrive at the end of the afternoon. Even though the arrival of instrument sets is not evenly distributed over the days, the work for the employees at the CSSD can be evenly distributed over the week by having the additional information. In addition, there should be less urgent requests from the OR. Both the OR and the CSSD know better which instrument sets should be in storage and which are being processed for planned surgeries. As a result, the workload is less for the CSSD employees and the department can work with a more evenly distributed capacity. Thus, reducing the required peak capacity.

On an operational level, instrument sets are processed based on their due date and their priority. The due date is based on a planned surgery. The priority is based on the required safety stock level, the current stock level at the OR, and the scheduled surgeries. Based on the method used in the UMC Utrecht, 6 priority classifications are indicated as follows:

- 1: Tardily
- 2: Scheduled today
- 3: Scheduled tomorrow
- 4: Low stock level
- 5: No stock
- 6: No priority which requires the instrument set.

In reality, there will always be urgent requests, hence a 'priority 1' has to be included. Priorities 2 and 3 are in place to know which sets have to be sterilized for upcoming planned surgeries. Lastly, priority 4 indicates that the safety stock level of an instrument set is beneath the specified level. Note, this is only for instrument sets which are used for emergency surgeries. For instruments that are not used for emergency surgeries, there is no stock required. At the CSSD, the instrument sets are sterilized in order of these priorities. First, the instrument sets which are already late, then the sets which are due for surgeries the same day. Lastly, sets which have no priority are sterilized as soon as all other jobs are completed. Note that these priorities change for each instrument set as soon as new surgeries are scheduled or as there are emergency surgeries etc.

For employees of the CSSD, the primary processes are manually clean and organize instruments sets within the decontamination zone and assemble and check instruments sets within the assembly zone. Currently, employees spend time on secondary processes such as: loading instrument sets on carts, loading WD machines or autoclaves and assigning instrument sets to working stations. As employee hours are very costly, a future situation in which these processes are automated is desired. In this way, employees can focus only on the primary processes.

2.6. HIERARCHICAL DECOMPOSITION

As already introduced in Subsection 1.3.2, in Hulshof *et al.* [6], planning and control decisions are divided into four hierarchical levels and four managerial areas. The four hierarchical levels are strategic, tactical, and operational, which can be divided in an offline and online operational planning. The four managerial areas are medical planning, financial planning, materials planning, and resource capacity planning. The planning decisions which are considered in this thesis are part of the resource capacity management. As stated by Hulshof *et al.* [6], this managerial area addresses the dimensioning, planning, scheduling, monitoring, and control of renewable resources. In the paper of Hulshof *et al.* [6], only primary processes are taken into account. Hence, instrument sterilization, a supporting activity, is not considered. In this section, the decomposition of the planning decisions regarding the CSSD are described.

In Figure 2.5, this decomposition is graphically illustrated. As described by Schneider [13], capacity planning decisions have to be integrated 'top-down' and 'bottom-up'. 'Top-down' integration translates strategy into operations and 'bottom-up' provides feedback to improve decision making on a higher level. The aim of this thesis is to determine the acquisition of machines, the determination of the amount of opening time and the scheduling of instrument sets. Employee numbers and assignment to working stations are used as input parameters. Note, as the instrument sets are purchased by the OR specialties and the CSSD is supportive to the OR, decisions regarding the number of items of each instrument set and the tray composition are not taken into account. However, the capacity planning decisions of the CSSD have to take these restrictions into account, which can be described as external alignment.

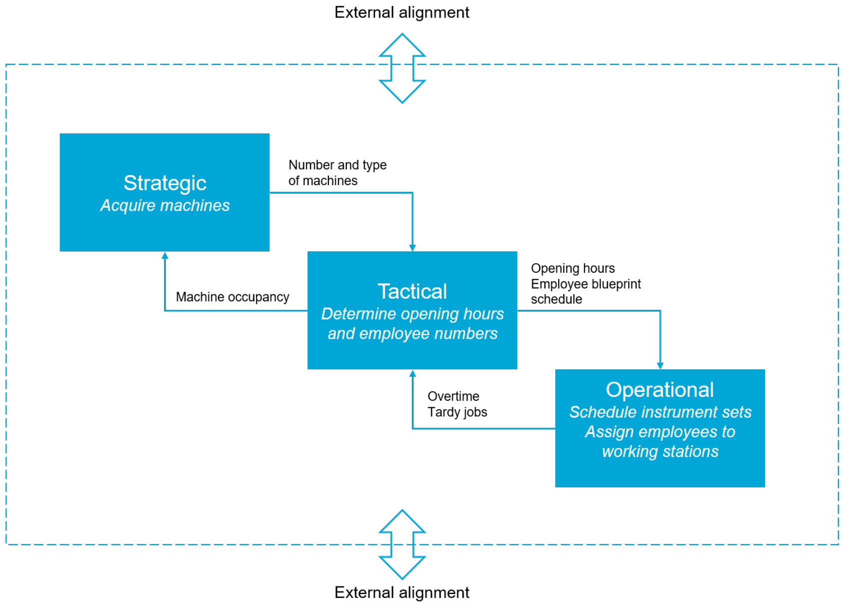


Figure 2.5: Framework planning decisions CSSD, based on Figure 2.1 of Schneider [13].

External alignments which have to be taken into account include:

- The number of instrument sets of each type. The scheduled surgeries and the stock level at the OR indicate the time at which an instrument set has to be returned to the OR storage. When there are not enough items of a specific instrument set, it can lead to regular urgent requests from the OR. This can lead to a required peak capacity to handle these urgent requests.
- The scheduling of the OR, the arrival time and due date of instrument sets is directly dependent on the scheduling of surgeries. In case additional extended hours are scheduled, more instrument sets arrive late at the CSSD. In addition, the scheduling of the CSSD is dependent on the blueprint of the OR.
- The scheduling and agreements with the outpatient clinics, including when the instrument sets are collected from the outpatient clinics and when they have to be returned to the outpatient clinics.
- The usage of disposable instruments. According to Adank [1], the number of processed instrument sets

has decreased since 2009. This could be due to an increasing usage of disposables instead of reusable instrument sets.

On a strategic level, the number and type of WD machines and autoclaves have to be determined. This decision has a planning horizon of 10 years and is part of the dimensioning of the process. These numbers are input for the tactical capacity decisions. At this level, the number of employees and the amount of opening time is determined. The amount of hours has to be determined for weekdays and weekend days, and for weeks with a half OR schedule. A blueprint of the required staff hours on each day and for each step within the process can be determined. This blueprint serves as input for the operational level. On an operational level, employees are assigned to the working stations and instrument sets are assigned to a machine and a batch. At the online level, employee changes and changes in the OR schedule are taken into account to adjust the schedule.

2.7. SCOPE

In this section, the scope of this thesis is further defined. Given the large number of decisions which have to be taken into account, the number of employees is used as an input parameter. As described in Section 2.6, the number of employees and the amount of opening time are capacity planning decisions on a tactical level. Based on expert judgement, it has been chosen to explore the required amount of opening time and use the number of employees as parameter setting. In future research, the required number of employees can be explored with the opening time as input, or even both as variables.

As the OR schedule is known a week in advance, the considered planning horizon is one week. Even though the OR blueprint is a bi-weekly schedule, after studying these blueprints from the past year, there are no significant changes between the two weeks. Considering all jobs arriving during a week, the aim is to sterilize all sets before Monday morning or earlier according to their due dates.

The process at the CSSD is defined as a linear process consisting of the four main steps. Exceptions, such as instruments which have to be disinfected manually, are not taken into account. There are no rejected machine batches, so no returning instrument sets. For the manually cleaning and the assemble step, for each instrument set a standard time is used. This time has to be an average based on the measurements at the CSSD. The process time of an autoclave depends on the outside pressure condition, which changes based on the weather. In this thesis, a fixed process time is assumed.

There are no strict rules concerning the amount of time between steps within the CSSD. However, within guidelines [14], it is noted that the time between disinfection and packaging should be minimized to prevent sedimentation of airborne particles. In practise, it is preferable to wash the instruments as soon as possible after arriving at the CSSD. In this way, the filth is not yet caked to the instruments and can be removed easily. Based on these remarks and expert judgement, it is assumed that the maximum time until disinfection is 24 hours, and the maximum time between disinfection and sterilization is 48 hours.

3

Background

This chapter presents a concise literature study and background information about the CPLEX solver. With this chapter, the research questions: 'Which techniques are used in literature to solve such an optimization problem?' and 'Which techniques can be applied to the optimization problem at the CSSD?' are answered.

3.1. Literature review

The last decade an increased amount of research about the CSSD has been conducted. Previously, the focus was on optimizing the OR, as this is a primary process within healthcare. The CSSD has a supportive role to the OR and outpatient clinics, and is involved in the logistics of reusable instruments. However, as indicated in van de Klundert *et al.* [2], optimizing the logistics of goods and pharmaceuticals can lead to significant reduction in costs. The financial savings can be used to improve primary processes.

In Subsection 3.1.1, an overview of previous work that was conducted on healthcare, more specifically, the CSSD, is given. The scheduling problem, as described in Chapter 1, can be described as a multi-stage Hybrid Flow Shop. Hence, in Subsection 3.1.2, an overview of recent research on Hybrid Flow Shops is given. Processes in healthcare face specific challenges regarding high service levels and no margin for errors or tardy jobs. Additionally, the processes have a non-deterministic nature. There are last minute changes and urgent requests, since not everything can be planned in advance. A model should have distinctive features that are matched to healthcare processes. As one of the main challenges of processes within healthcare is the non-deterministic behaviour, Subsection 3.1.3 discusses solution approaches that take these uncertainties into account. Finally, in Subsection 3.1.4, a concise summary of the findings and the contribution of this thesis to research is given.

3.1.1. Literature applied on the CSSD

Previous work regarding the CSSD varies in subject. There are literature reviews (Moons *et al.* [15], Ahmadi *et al.* [16]), research on the optimization of surgical trays (Dollevoet *et al.* [17]), process evaluation (Huynh *et al.* [18]), van Blijswijk [8]), Brooks *et al.* [19], Al Hasan *et al.* [20]), resource pooling (Saif and Elhedhli [3]), design decisions (Keseler [7]) and machine scheduling (Ozturk [21], Rossi *et al.* [4], Rossi *et al.* [22], Di Mascolo and Gouin [23]). The wide range of subjects enables the development of a broader view on the processes at the CSSD and place the case study at the LUMC in perspective. First, relevant findings from the literature studies and the process evaluations are stated. These findings include methods which can be used to solve the the optimization problem as stated in Chapter 1. Second, the research on machine scheduling is discussed These findings can be applied to the problem on an operational level.

Moons *et al.* [15] presents existing literature on the performance of the internal hospital supply chain in the OR environment. It emphasizes the importance of logistics-related activities to make sure the right supplies are delivered in the right condition to the right patients at the right time. The costs of logistic processes has increased and the supply chain has to be integrated with the patient care system to guarantee high quality patient care. In Ahmadi *et al.* [16], the main focus is on inventory management as well. This review paper is divided into two parts: papers that propose optimization methods and papers that contain practitioners reports. They concluded that, for practical use, stochastic models have to be developed that take into account a service level. However, they also noticed that availability of data plays a key role in the development of analytical methods.

In van Blijswijk [8], a demand driven supply method in combination with Unique Device Identification (UDI) is proposed for the CSSD at LUMC. Van Blijswijk concludes that the production of the CSSD is not based on a planning. The main focus is to sterilize all arrived instruments as soon as possible. This is in line with the observations used to set up the research question of this thesis. The conclusion is supported by data regarding the distribution of the storage time of an instrument set and the demand from the OR. There is a significant variation in storage time, since a small part of the instrument sets uses most of the storage time. In addition, the volatility for each instrument set is calculated, based on usage of an instrument set in a year and the OR planning. A low volatility indicates that an instrument set is used frequently and the demand is predictable, a high volatility indicates an instrument set is used irregular and the demand is unpredictable. These numbers are calculated using a Fuzzy Logic Controller. Furthermore, Van Blijswijk studied the number of urgent surgeries and planning mutations at the OR. In 2014, on an average day, 10.9% of the surgeries are urgent, however, 80% is processed as planned. These numbers further strengthen the statement that a pull approach can be beneficial even though changes in the schedule were made.

In Keseler [7], all strategic and operational design decisions to construct a CSSD are enumerated. On a strategic level these include: location within the hospital, the required capacity, the lay out, and environmental requirements. For this thesis, the required capacity is of most interest. The capacity is divided into capacity of the department itself and storage at the CSSD. Regarding the capacity of the department, it is stated that the capacity of the machines is of great importance as this is the rigid capacity which influences the operational performance. Although there are many manual processes at a CSSD, it is more likely that problems that occur there can be addressed on the operational level later on. For machine capacity, a degree of flexibility has to be incorporated in order to handle demand uncertainty. On an operational level, the design decisions include: service definition, technology, and human resources. The service definition also covers the lead time of instrument sets. It is argued that this can be described as both an operational and a strategic design decision as the lead time is a prerequisite to determine the design of the CSSD. The strategic and operational decisions are highly correlated, which causes the requirement of specific process knowledge.

Finally, Brooks *et al.* [19] indicate the importance of a good communication between the OR and the CSSD. Huynh *et al.* [18] presents a method in which the CSSD and the OR communicate each time a possible instrument shortage could occur. In case of a shortage, changes regarding the surgery schedule or desired instruments for a surgery can be made.

In Rossi *et al.* [4], a sterilization plant is represented as a two stage Hybrid Flow Shop with parallel batching. The two stages represent the washing machines and the autoclaves. Pre-cleaning, checking and assembling are included as setup times for those machines. Minimizing the number of tardy jobs and the makespan are considered as performance indicators. To solve this problem, two heuristic approaches are proposed which make use of fragmenting batches. In other words, closing batches early instead of waiting until they are completely filled. The heuristic approaches are tested on a selected peak day. In addition, several scenarios are tested with a varying number of resources. In Rossi *et al.* [22], the mathematical model is extended to an S-stage Flow Shop problem. Job priority is dynamically determined by a critical ratio between the available time to due date and the remaining process time. An heuristic is proposed in which batches are closed after a certain time window, similar to the batch fragmentation. They suggest that decreasing machine capacity, while increasing the number of machines, could be a good recommendation. Future research recommendations are to use metaheuristics and optimizing batch sizing and machine resources. Later, in Lanzetta *et al.* [24], the model is further developed by taking into account uncertainty within manual process times.

In Ozturk [21], a scheduling strategy is proposed for the disinfecting step, often indicated as bottleneck at the CSSD. It is a multi-criteria scheduling problem in which the makespan and the flow time, i.e., sum of processing times, are minimized. A lower bound is given by solving a special case allowing job splitting, (Ozturk *et al.* [25]). In addition, in Ozturk *et al.* [26], the scheduling problem is solved with a semi-online heuristic based on a 'First Fit Procedure' (FFP), where partial information is available about the job type and arrival time.

In Di Mascolo and Gouin [23], a generic discrete event simulation is used to improve the processes of the CSSD. The model can be used to acquire knowledge about the process behaviour, compare different CSSD departments and working methods. For batch creation, different rules such as 'First In First Out' (FIFO) and FFP are used. The number and capacity of washing machines, autoclaves, and working stations are used as input data. The model is made with ARENA, a simulation software.

Leeftink *et al.* [5] represent a histopathology laboratory as a three phase hybrid flow shop with parallel batching machines in one stage. The goal is to reduce the physical workload in between the phases. In other words, minimize the intermediate storage room. A new 2-phased decomposition approach is developed to solve this problem. First, a daily cyclic batching schedule is created while minimizing the batch completion intervals per batch type. Second, jobs are scheduled within these batches, to minimize the tardiness of the jobs.

To conclude, the discussed studies form a good basis to formulate a mathematical model and an initial solution direction. The research indicates that quantitative studies at a CSSD can be beneficial and the hierarchical level of capacity planning decisions has to be taken into account. Furthermore, the relation to the OR is of great importance.

3.1.2. HYBRID FLOW SHOP

The process at the CSSD can be described as a multi-stage Hybrid/Flexible Flow Shop (FFS) with parallel batching. In previous research, the terms hybrid and flexible are used alternately. More specifically, the process can be described as a two-stage FFS with parallel batching and setup times. In addition, the process can also be modelled as a four-stage FFS in case the setup processes are modelled as a stage. As described in González-Neira *et al.* [27], a standard flow shop (FS) problem consists of m machines in series. There are n jobs that have to be processed on each machine. The jobs have to processed in sequence, starting on the first machine, then on the second machine, and so on. A FFS problem is a combination of two fundamental scheduling problems, FS scheduling and parallel machines scheduling problems. At least one stage has multiple parallel machines and a job has to be processed at one of the machines at each stage. In Figure 3.1, a diagram of a FFS problem is presented. A generalization of the FFS is an environment where machines can process multiple jobs simultaneously, which is called parallel batching. This is the case in the problem regarding the CSSD.

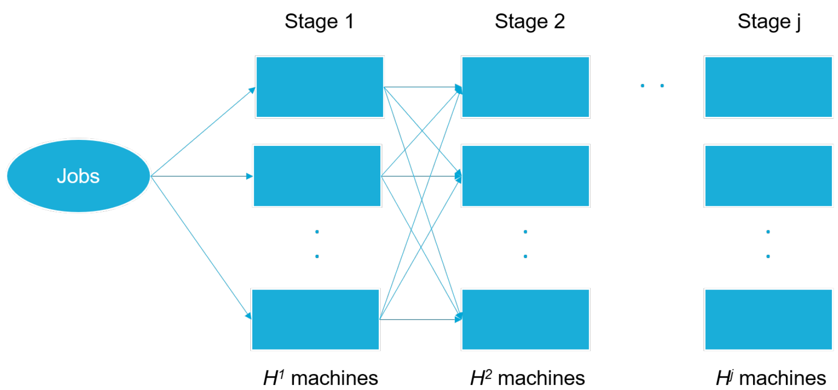


Figure 3.1: Hybrid Flow Shop environment based on Morais *et al.* [28].

In previous research, FFS problems are extensively studied. Three recent literature reviews are given by González-Neira *et al.* [27], Lee and Loong [29] and Morais *et al.* [28]. However, less research is available on environments including parallel batching. Within the literature studies, FFS with parallel batching is mentioned, however, the focus is on the classical FFS. Hence, a set of recent literature published in 2018, 2019 and 2020 is presented, covering FFS with parallel batching. Each research covers additional environment characteristics, namely, the process can have incompatible job families (Li and Dai [30]), unequal job release dates (Abedi *et al.* [31], Tan *et al.* [32]), maintenance activities (Lu *et al.* [33]), limited waiting time (Li and Dai [30], Wang *et al.* [34]), non-identical machines (Liu *et al.* [35]), or take into account non-deterministic behaviour. In Shahidi-Zadeh *et al.* [36], a process with one stage of parallel batching machines is optimized using a bi-objective mathematical model. The aim is to minimize the makespan, and determine the optimal set of machines to acquire. The paper presents a multi-objective mixed integer non-linear programming model. This model takes into account capacity constraints, due dates, release dates, and different processing times per machine. Combined, these papers represent all relevant characteristics of the process described in

Chapter 2. Hence, the formulation as stated in Chapter 4 can be build up from the formulations as presented in the stated research.

In Lee and Loong [29], a comprehensive review on FFS problems is given. In addition, González-Neira *et al.* [27] focuse on FFS problems under uncertainties, and Morais *et al.* [28] focuse on FFS problems with multi-criteria objective functions. In these papers, three different machine environments are considered, namely, 'identical parallel machines', 'uniform parallel machines', and 'unrelated parallel machines'. 'Identical parallel machines' indicates that the process time of a job is not dependent on the specific machine on which it is processed. This machine environment is most studied in literature. According to Lee and Loong [29], 78% of the studied literature is associated with this type of machine environment. 'Uniform parallel machines' indicates that the job process time depends on a general job process time and a machine speed. 8% of the literature studies this type of machine environment. Finally, 'unrelated parallel machines' indicates different machine efficiencies, which is the case in the scheduling problem related to the CSSD. There are low and high end machines from different manufactures available for purchase. 14% of the literature analyzed contributes to this type of machines

The reviews also classify the problems encountered in literature based on additional job constraints. In Lee and Loong [29], additional buffer and setup sequence constraints are mentioned. In this thesis, unlimited buffer capacity is assumed in terms of space. However, there are constraints regarding the maximum duration before and in between stages. For the setup sequence constraints, there is a division between sequence independent and sequence dependent setup times for machines. For sequence dependent setup times, the job variety and the sequence determines the setup time of a machine. On the other hand, with sequence independent setup times, the setup time is not affected by the order in which jobs are processed. For the problem regarding the CSSD, sequence independent setup times are applicable, which is less complex than sequence dependent setup times. In Morais *et al.* [28], a table of all the additional constraints is presented. Relevant additional constraints regarding the CSSD problem are: different release dates, different due dates, maintenance, uncertain due dates, and setup times.

Besides classifying problems based on constraints and machine environment, different objective functions are considered. In Lee and Loong [29], previous literature is divided into three categories, time-related objectives, job-related objectives and multi-objectives, which are studied in 67%, 14% and 19% of the cases, respectively. The most used objective function is the makespan, however, in recent years, objectives functions have shifted towards tardiness minimization. The costs are only taken into account in multi-objectives. In fact, in González-Neira *et al.* [27], only 2% of previous literature focuse on minimizing the costs of the resources.

Looking at the solution methods, Lee and Loong [29] states that heuristics are most used, before metaheuristics and hybrid methods. For literature which takes into account uncertainties, more than half of the papers use metaheuristics, among which 42% used a genetic algorithm. The use of genetic algorithms is also endorsed by Morais *et al.* [28] for multi-objective studies. All three literature reviews recommend to look into the use of hybrid algorithms, which are studied by an increasing number of studies. As stated in Lee and Loong [29], 'hybrid approaches can be defined as the combination of two or more approaches'. As every approach has its benefits and disadvantages, it can be useful to combine approaches in order to enhance the performance.

To summarize, there is many previous research studying FFS problems, however, each study has specific additional constraints based on the practical situation it is applied on. In comparison to the studies that have been conducted specifically on the CSSD, multiple additional constraints and other objective functions, such as the acquiring costs of machines, are considered. The recommended solution approaches are hybrid algorithms and metaheuristics.

3.1.3. UNCERTAINTY MEASURES

Processes within hospitals are affected by uncertainties, which for the CSSD include: emergency surgeries or surgeries which require additional instrument sets, the failure of machines, and the uncertain time requirements of the manual setup processes. As stated in Hall [37], the greater the variability in a system, the greater the capacity required to meet a given service standard on availability or timely access to the service. This section suggests several methods to include these uncertainties in an optimization model.

In González-Neira *et al.* [27], a review of FS and FFS problems under uncertainty is given. FFS under uncertainty is studied less in comparison to the deterministic variant. However, the last four years of the literature study (2001-2016), there has been an increase in papers published on this subject. There are many approaches available to take uncertainty into account, including: sensitivity analysis, fuzzy logic, robust optimization, and stochastic programming. Sensitivity analysis focuses on the model results and the extent in which they are influenced by changing the input parameters. However, this method is not often used for scheduling problems due to their complexity. Fuzzy logic can be used if the value of parameters are not certain and can be described better in natural language, such as: Quite true, more or less true, and almost true (Tamir *et al.* [38]). For example, in Sadati *et al.* [39], fuzzy parameters are use in a bi-objective model representing parallel batching machines. The objective function minimizes makespan and maximum tardiness simultaneously. The paper states that uncertainty is inherent in scheduling environments and that data quality and quantity can be questionable. Hence, fuzzy processing times, fuzzy ready times and fuzzy due dates are considered. To solve this model, two metaheuristics are proposed. Robust optimization is a risk averse method which ensures that the solution of any possible scenario, is close to the optimal solution of the model. Finally, stochastic programming takes into account the known probability distribution of a variable. In correspondence with the strategic, tactical and operational level, the problem can be described as a two-stage stochastic process. Capacity planning decisions should be based on the information available at that point in time, so before the realization of the second stage uncertain parameters. In other words, the number of machines has to be determined, before the exact demand of instrument sets is known. At the first stage, the objective function consists of a deterministic part considering the purchase of machines and the expectation of the uncertain parameters (Shapiro *et al.* [40]).

To summarize, there are several methods to take into account uncertainties. Two-stage stochastic programming appears the most promising as it consider the capacity planning decisions on different hierarchical levels. The addition of uncertainties adds to the computational complexity of a model. Hence, before uncertainties can be taken into account, the model performance of the deterministic variant has to be evaluated. Furthermore, properties that influence the model complexity should be known. Given that a model considering the specific characteristics of the CSSD is not found in literature, combined with findings of Subsection 3.1.2, in this thesis, the focus is on exploring the model properties and the decisions on the different hierarchical levels. Future research is required to explore the possibilities to incorporate uncertainty measures.

3.1.4. CONCLUSION

In this section, literature covering varying subjects regarding the CSSD is discussed. It can be concluded that the logistic flow of reusable instruments within a hospital is an upcoming and promising research field with the aim to reduce costs and improve efficiency. Furthermore, the importance of the alignment with the demand of the OR is emphasized. This thesis contributes to research with the following aspects:

- A framework is proposed to indicate the capacity planning decisions on a strategic, tactical and operational level for a CSSD. This includes a selection from the capacity planning decisions as stated by Keseler [7], with the addition of a tactical hierarchical level.
- A new objective function is taken into account; the costs related to sterilization. Multiple articles state that significant cost reductions are possible, however, most scheduling problems minimize makespan or the number of tardy jobs. By minimizing the costs, the makespan will implicitly be minimized as well. However, this also depends on the acquired machines. Instead of minimizing the makespan given a set of resource constraints, the resource constraints are yet to determined.
- An extension of the model as proposed by Rossi *et al.* [4]. The formulation is linearized and extended to a time horizon of a week, taking into account daily opening hours and the purchase of different machine types.

3.2. CPLEX SOLVER

As the problems in this thesis are solved using the commercial CPLEX solver, this section shortly describes its algorithm. In addition, it is noted which parameters can be adjusted to improve the performance to solve a Mixed Integer Problem (MIP). CPLEX solves a MIP using a dynamic search algorithm. This algorithm is based on a Branch-and-Cut algorithm and includes the following basic steps:

- **Preproccessing:** The aim of this step is to reduce the size of the problem and improve the formulation. A tighter formulation is obtained by improving bounds and probing. Probing is defined as fixing a binary variable to zero or one and check the logical implications.

- **Branch and cut:** An algorithm which finds feasible solutions and valid lower bounds by solving a series of relaxed subproblems. These subproblems form a tree where each subproblem is a node. The root of this tree is the relaxation of the preproccesed MIP. If this solution has one or more fractional variables, CPLEX branches on a fractional variable and creates two new subproblems with additional cuts to avoid the fractional value. The result of subproblems can be integer solutions, infeasibilities or again a fractional solution. The branch is pruned or the subproblem is again branched on a fractional variable. Within this each step of this process, a node has to be selected, where after a variable to branch on has to be selected.

- **Heuristics:** CPLEX automatically invokes heuristics in the branch-and-cut algorithm if it appears to be beneficial. These heuristics are used to quickly find integer solutions at fractional nodes, to improve the current integer solution at a node or provide a better lower bound.

To obtain better solutions, after initial experiments, the node logs of CPLEX are studied. Table 3.1 shows a small example of the main part of the node log. The first four columns show the current node number, the number of nodes left, the objective function value of the current node, and the number of integer-infeasible variables. Next, the column 'Best Integer' presents the best found integer solution and the column 'Cuts/Best Node' shows the best found upper bound in case of a maximization, and lower bound in case of minimization. If the word 'Cuts' appears, it indicates that various cuts were generated. The last column presents the relative gap between the best integer and best node. The column 'ItCnt' records the cumulative iteration count.

	Node	Nodes Left	Objective	IInf	Best Integer	Cuts/Best Node	ItCnt	Gap
*	0+	0			0.0000	3261.8212	8	—
*	0+	0			3148.000	3261.8212	8	3.62%
	0	0	3254.5370	7	3148.0000	Cuts: 5	14	3.38%
	0	0	3246.0185	7	3148.0000	Cuts: 3	24	3.11%
*	0+	0			3158.0000	3246.0185	24	2.79%
	0	0	3245.3465	9	3158.0000	Cuts: 5	27	2.77%
	0	0	3243.4477	9	3158.0000	Cuts: 5	32	2.71%
	0	0	3242.9809	10	3158.0000	Covers: 3	36	2.69%
	0	0	3242.8397	11	3158.0000	Covers: 1	37	2.69%
	0	0	3242.7428	11	3158.0000	Cuts: 3	39	2.68%
	0	2	3242.7428	11	3158.0000	3242.7428	39	2.68%
	10	11	3199.1875	2	3158.0000	3215.1261	73	1.81%
*	20+	11			3168.00000	3215.1261	89	1.49%
	20	13	3179.0028	5	3168.0000	3215.1261	89	1.49%
	30	15	3179.9091	3	3168.0000	3197.5227	113	0.93%
*	39	3	integral	0	3186.0000	3197.3990	126	0.36%
	40	3	3193.7500	1	3186.0000	3197.3990	128	0.36%

Table 3.1: Example CPLEX node log (IBM [41])

The information from the node logs can be used to get a better understanding of the difficulty to solve an instance and adjust parameters to improve the performance of the optimizer (IBM [41]). In this thesis, the following parameter settings are used:

- **Variable selection strategy:** After a node is selected for branching, this parameter sets a rule to determine the variable which is chosen for branching.
  - Pseudo reduced costs, a computational less expensive strategy that is based on pseudo-shadow prices.
  - Strong branching, a strategy that first partially solves a number of subproblems, after which it selects the most promising branch.

- **Probing:** This parameter sets the amount of probing before branching. Probing can dramatically increase the performance, however can be computational expensive. In this thesis the parameter is set to 'Very aggresive probing level'.

- **Emphasis switch:** The default setting aims to balance the trade-off between finding good feasible solutions and a lower bound to prove optimality. However, this emphasis can be switched to focus on finding more feasible solutions or moving the lower bound and prove optimality. In this thesis the emphasis is set to 'Optimality', which causes the solver to put less effort into finding feasible solution.
- **Turning off heuristic for node 0:** To decrease the computation time spent on the calculation of node 0, the heuristic can be turned off for the root node.
- **Aggresive cut generation:** During the optimization, CPLEX generates cuts to restrict the solution space. Several parameters can be used to decide how often these cuts are generated. In this thesis, the parameters for cut types 'Cover', 'Clique', 'Disjunctive', 'Locally Valid Implied Bound', and 'Lift and Project' are set to a 'very aggresively'.

4

Problem description

In this chapter, the problem statement is formally introduced. The problem can be described as a two stage hybrid flow shop with parallel batching and setup time at each stage. Stage one is the disinfection step, executed by the WD machines, and stage two is the sterilization, executed by the autoclaves. The steps 'manually clean' and 'check and assemble' are setup processes before disinfection and sterilization, respectively. In Section 4.1, the constraints and objective function is proposed, and in Section 4.2, the problem characteristics are stated.

4.1. Problem formulation

This section will formally introduce the optimization problem regarding the CSSD. Hereafter, this problem is called 'CSSD Planning Problem'. In Subsection 4.1.1, the constraints of the CSSD Planning Problem are described, and in Subsection 4.1.2, the objective function is defined. All relevant sets, variables, and parameters are introduced in the text and listed in the front matter of this thesis. The model is written based on the situation analysis in Chapter 2, more specifically, the future situation as described in Section 2.5.

4.1.1. Constraints

While sterilizing all instrument sets, there are multiple constraints that have to be taken into account. For readability, this subsection is divided into multiple subsubsections based on the type of constraints.

Batch and machine assignment

Formally, there is a set I of instrument sets, also called jobs, which have to be sterilized by a two-stage flow shop. These stages are denoted by set J, and each stage consists of a set of parallel batching machines H^j by which a set of batches B^j has to be processed. Each job has to be processed in one batch and at one machine at each stage. Binary decision variables Z^j_{bh} and S^j_{ibh} are introduced to indicate in which batch and at which machine a job is processed. Z^j_{bh} is equal to one if batch $b \in B^j$ is processed at machine $h \in H^j$ at stage $j \in J$, and zero otherwise. S^j_{ibh} is equal to one if job $i \in I$ is processed in batch $b \in B^j$ at machine $h \in H^j$ at stage $j \in J$, and zero otherwise. Constraints (4.1) ensure that each job is assigned to one batch and one machine at each stage.

$$\sum_{b \in B^j} \sum_{h \in H^j} S^j_{ibh} = 1 \quad \forall i \in I, \quad \forall j \in J \tag{4.1}$$

Beforehand, it is not known how many batches are needed. Hence, the initial set B^j consist of a predetermined number, which is higher than the required number of batches. If a batch is used, it should be assigned to a machine. Constraints (4.2) guarantee that each batch is assigned to at most one machine at each stage. Constraints (4.3) and (4.4) ensure that if a batch is assigned to a machine, at least one job is assigned to the batch. Reversely, if a batch is not assigned to a machine, no jobs are assigned to the batch.

$$\sum_{h \in H^j} Z^j_{bh} \leq 1 \quad \forall b \in B^j, \quad \forall j \in J \tag{4.2}$$

$$\sum_{i \in I} S^j_{ibh} \geq Z^j_{bh} \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in J \tag{4.3}$$

$$\sum_{i \in I} S^j_{ibh} \leq M Z^j_{bh} \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in J \tag{4.4}$$

Similar to the number of batches, the number of machines that are required is not known in advance. In addition, the set of machines consists of machines with different processing times, p^j_h, and capacities, u^j_h. These different machine types are represented in sufficiently large numbers in the set H^j. Binary decision variables P^j_h are introduced to indicate if machine $h \in H^j$ at stage $j \in J$ is purchased. Formally, P^j_h is equal to one if machine $h \in H^j$ is purchased at stage $j \in J$, and zero otherwise. The costs to purchase machine $h \in H^j$ at stage $j \in J$ is given by c^j_{1h}. Constraints (4.5) ensure that if a batch is processed at a machine $h \in H^j$ at stage $j \in J$, this machine is purchased.

$$\sum_{b \in B^j} Z^j_{bh} \leq M P^j_h \quad \forall h \in H^j, \quad \forall j \in J \tag{4.5}$$

In addition, there is a set F^j of job families at each stage $j \in J$. These job families correspond to the different programs of the WD machines and autoclaves. Each job $i \in I$ is part of one of these job families. Jobs can only be processed in the same batch if they are from the same job family $f \in F^j$. Binary parameters f^j_{ik} are introduced for each job pair $i \in I$ and $k \in I$ to indicate if they are from the same job family and can be processed together. Parameter f^j_{ik} is equal to one if job $i \in I$ and $k \in I$ are part of the same job family $f \in F^j$ at stage $j \in J$, and zero otherwise. Constraints (4.6) ensure that jobs can only be processed in the same batch if they are from the same job family. These constraints are added for completeness only, since due to the complexity of the mathematical program, job families are not taken into account in this thesis. Furthermore, most instrument sets are processed on one particular program on both stages.

$$\sum_{h \in H^j} \left(S^j_{ibh} + S^j_{kbh} \right) \leq 1 + f^j_{ik} \quad \forall (i < k) \in I, \quad \forall b \in B^j, \quad \forall j \in J \tag{4.6}$$

MACHINE CAPACITY

Instrument sets are packed differently at each stage $j \in J$. Hence, the job size z^j_i of job $i \in I$ differs for each stage $j \in J$. Constraints (4.7) ensure that the sum of the job sizes of each batch does not exceed the capacity of the assigned machine at the corresponding stage.

$$\sum_{i \in I} z^j_i S^j_{ibh} \leq u^j_h \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in J \tag{4.7}$$

Note that Constraints (4.4) and (4.7) can be merged as shown in Constraints (4.8).

$$\sum_{i \in I} z^j_i S^j_{ibh} \leq u^j_h Z^j_{bh} \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in J \tag{4.8}$$

RELEASE TIME AND LEAD TIME

The planning time horizon of the CSSD Planning Problem is a week. Jobs can be processed at any day and the timescale is in minutes. Considering all jobs arriving during a week, the aim is to sterilize all sets before Monday morning. Hence, at Monday morning there are no jobs left at the CSSD and a new cycle starts.

Before each stage $j \in J$, a setup process of duration s^j_i for job $i \in I$ has to be executed. Several variables are used to indicate when the setup process and job are scheduled. First, integer decision variables t^j_i are used to indicate the completion time of a job $i \in I$ at stage $j \in J$. Constraints (4.9) ensure that a job $i \in I$ cannot be processed before its release time r_i. The order in which the jobs are handled is partly determined by the due date. The due date is a strict deadline, based on the OR schedule, urgent requests, a predefined basic stock level in case of an emergency, and agreements with the OR. Constraints (4.10) ensure that a job is finished at stage two before the due date. The due date is defined as release time r_i plus lead time l_i. The lead time is determined for each type of instrument set, using the method described in Chapter 6. Note that the 2 within Constraints (4.10) indicates the stage and not the square of t_i.

$$t_i^1 \geq r_i + s_i^1 + \sum_{h \in H^1} \sum_{b \in B^1} p_h^1 S_{ibh}^1 \quad \forall i \in I \tag{4.9}$$

$$t_i^2 \leq r_i + l_i \quad \forall i \in I \tag{4.10}$$

In addition, assumptions are made on the maximum amount of time an instrument set is kept before or in between stages. Before the disinfect step, the maximum duration is 24 hours, and between disinfection and sterilization the maximum duration is 48 hours. The maximum duration before a stage $j \in J$ is denoted by e^j. Constraints (4.11) and (4.12) ensure that the maximum time between the release time and the start of stage one is e^1, and the maximum duration between completion times of the stages one and two is e^2 minutes for each job $i \in I$.

$$t_i^1 - \sum_{h \in H^1} \sum_{b \in B^1} p_h^1 S_{ibh}^1 - r_i \leq e^1 \quad \forall i \in I \tag{4.11}$$

$$t_i^2 - \sum_{h \in H^2} \sum_{b \in B^2} p_h^2 S_{ibh}^2 - t_i^1 \leq e^2 \quad \forall i \in I \tag{4.12}$$

As jobs are processed in batches, decision variables t_{bh}^j are used to indicate the completion time of batch $b \in B^j$ at machine $h \in H^j$ at stage $j \in J$. Constraints (4.13) and (4.14) are used to define the batch completion time t_{bh}^j of batch $b \in B^j$ at machine $h \in H^j$ at stage $j \in J$. A machine can only process one batch at a time. Constraints (4.15) ensure that a batch cannot be scheduled earlier than the completion time of the previous batch at the same machine.

$$t_{bh}^j \geq t_i^j - M\left(1 - S_{ibh}^j\right) \quad \forall i \in I, \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in J \tag{4.13}$$

$$t_i^j \geq t_{bh}^j - M\left(1 - S_{ibh}^j\right) \quad \forall i \in I, \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in J \tag{4.14}$$

$$t_{bh}^j + M\left(1 - Z_{bh}^j\right) \geq t_{b'h}^j - M\left(1 - Z_{b'h}^j\right) + p_h^j \quad \forall b, b' < b \in B^j, \quad \forall h \in H^j, \quad \forall j \in J \tag{4.15}$$

As the CSSD Planning Problem is a flow shop, the jobs have to be processed at the stages in sequential order. Additionally, a setup process has to be finished before each stage. Constraints (4.16) assure that for each job, the previous stage and the preceding set-up process have to be finished before a new stage can start. Note that since there is no transportation time in between stages, a job can be scheduled at a next stage at the same time as the previous stage has ended. Furthermore, it is assumed that there is unlimited storage between stages.

$$t_i^j \geq t_i^{j-1} + s_i^j + \sum_{h \in H^j} \sum_{b \in B^j} p_h^j S_{ibh}^j \quad \forall i \in I, \quad \forall j \in J \tag{4.16}$$

OPENING TIME

The set of days on which a job can be processed is given by set D. To keep track of the day at which a job is processed, binary decision variables Y_{id}^j are introduced. Y_{id}^j is equal to one if job $i \in I$ at stage $j \in J$ is processed on day $d \in D$, and zero otherwise. In Figure 4.1, the timescale is graphically displayed. The scale starts at $t = 0$ and finishes at $t = 10080$, the end of day 7. For each day $d \in D$, decision variables m_d represent the opening times and decision variables n_d represent the closing times of the CSSD. A job can only be processed during opening hours. The days in the model are denoted as the interval between the opening time of a day and the opening time of the next day. The days are shown in the colored blocks beneath the timeline. Note that as the closing time can be after 00:00, the actual end of the time horizon has to be larger than $t = 10080$.

Constraints (4.17) and (4.18) assign a value to Y_{id}^j given the completion time of a job at a certain stage. Constraints (4.19) ensure that a job is scheduled on exactly one day.

$$t_i^j + M\left(1 - Y_{id}^j\right) \geq m_d \quad \forall i \in I, \quad \forall j \in J, \quad \forall d \in D \tag{4.17}$$

$$t_i^j - M\left(1 - Y_{id}^j\right) \leq m_{d+1} \quad \forall i \in I, \quad \forall j \in J, \quad \forall d \in D \tag{4.18}$$

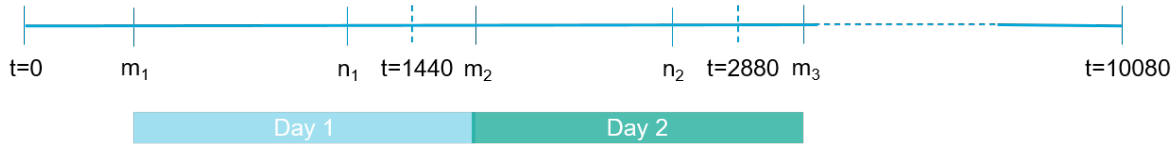


Figure 4.1: Timescale used in the formulation.

$$\sum_{d\in D} Y_{id}^{j} = 1 \quad \forall i \in I, \quad \forall j \in J \tag{4.19}$$

The CSSD operates with fixed opening hours during week and weekend days. Constraints (4.20) and (4.21) ensure that each weekday has the same opening and closing times, given that each day has 1440 minutes. Constraints (4.22) and (4.23) ensure that the opening and closing times each weekend day are equal as well.

$$m_d = m_{d-1} + 1440 \quad \forall d \in \{2,3,4,5\} \subset D \tag{4.20}$$

$$n_d = n_{d-1} + 1440 \quad \forall d \in \{2,3,4,5\} \subset D \tag{4.21}$$

$$m_7 = m_6 + 1440 \tag{4.22}$$

$$n_7 = n_6 + 1440 \tag{4.23}$$

Setup process

The setup process of a job can be executed the same day or the day before the job is processed at the successive stage. As it is not allowed to have the WD machines and autoclaves still running after employees leave, each day there is time left after the start of the last batch. During this time, the setup processes of the jobs scheduled for the next day can already be executed in order to save time the next morning. Binary decision variables A_{id}^{j} are introduced, for which A_{id}^{j} is equal to one if job $i \in I$ is processed on day $d \in D$ and the setup process is executed the day before, and zero otherwise. Constraints (4.24), (4.25), (4.26) and (4.27) assign a value to A_{id}^{j}. Constraints (4.24) ensure that the setup process of job $i \in I$ can only be executed on day $d-1 \in D$ when the job is scheduled on day $d \in D$. Constraints (4.25) set the variable A_{id}^{j} to zero on day 1 as there is no previous day on which a setup process can be executed. Constraints (4.26) ensure that if the two stages are scheduled on the same day, the setup for stage 2 cannot be executed the day before. Constraints (4.27) ensure that the setup process before stage one can only be executed on day $d \in D$ if the release time of job $i \in I$ is before the closing time on that day.

$$A_{id}^{j} \leq Y_{id}^{j} \quad \forall i \in I, \quad \forall j \in J, \quad \forall d \in D \tag{4.24}$$

$$A_{i1}^{j} = 0 \quad \forall i \in I, \quad \forall j \in J, \quad \forall d \in D \tag{4.25}$$

$$A_{id}^{2} \leq 2 - Y_{id}^{1} - Y_{id}^{2} \quad \forall i \in I, \quad \forall d \in D \tag{4.26}$$

$$r_i - M\left(1 - A_{id}^{1}\right) \leq n_{d-1} - s_i^{1} \quad \forall i \in I, \quad \forall \in D \tag{4.27}$$

Batch setup time

Besides the individual setup time for each job, also the total setup time for a batch at the second and successive stage has to be taken into account. The batch setup time depends on the number of employees, the operators, that are working on a day. The number of operators at stage $j \in J$ on day $d \in D$ is denoted by v_d^{j}. Then, the batch setup time is defined by

$$\frac{\sum_{i\in I}\sum_{h\in H^j} s_i^{j} S_{ibh}^{j}}{v_d^{j}} \quad \forall b \in B^j, \quad \forall j \in J, \quad \forall d \in D. \tag{4.28}$$

Constraints (4.29) assure that for each job the previous stage and the preceding setup process for the corresponding batch have to be finished. While calculating the batch setup time, only the setup processes of jobs not yet executed the day before are taken into account. This is done by using the term $(1 - A^j_{kd})$. The big-M term are added to ensure the relation between t^j_i and t^{j-1}_i only has to be satisfied if the jobs are processed on the day by the same machine. Note that Constraints (4.29) overestimate the setup duration of a batch. According to the model, the batch setup process starts when all jobs are completed at the previous stage. However, in reality, as soon as the first job is completed at the previous stage, the setup process of this job can be executed. Consequently, the setup process for the corresponding batch partly starts earlier than the completion time of the last job. Note that Constraints (4.29) have a quadratic term.

$$t^j_i \geq t^{j-1}_i + \frac{\sum_{k\in I}\sum_{h\in H^j} s^j_k S^j_{kbh}\left(1 - A^j_{kd}\right)}{v^j_d} + \sum_{h\in H^j}\sum_{b\in B^j} p^j_h S^j_{ibh} - M\left(1 - \sum_{h\in H^j} S^j_{ibh}\right) - M\left(1 - Y^j_{id}\right) \quad \forall i \in I, \quad \forall b \in B^j, \quad \forall j \in J, \quad \forall d \in D \tag{4.29}$$

Similar to the constraints for the setup time in between stages, there are two constraints to ensure a job or setup process cannot start before the opening time. Constraints (4.30) ensure a job cannot be processed before the opening time, taking into account the individual setup process time. Constraints (4.31) ensure a job cannot be processed before the opening time, taking into account the batch setup process time. Note that Constraints (4.31) have a quadratic term.

$$t^j_i - \sum_{h\in H^j}\sum_{b\in B^j} p^j_h S^j_{ibh} - s^j_i\left(1 - A^j_{id}\right) + M\left(1 - Y^j_{id}\right) \geq m_d \quad \forall i \in I, \quad \forall j \in J, \quad \forall d \in D \tag{4.30}$$

$$t^j_i - \sum_{h\in H^j}\sum_{b\in B^j} p^j_h S^j_{ibh} - \frac{\sum_{k\in I}\sum_{h\in H^j} s^j_k S^j_{kbh}\left(1 - A^j_{kd}\right)}{v^j_d} + M\left(1 - Y^j_{id}\right) + M\left(1 - \sum_{h\in H^j} S^j_{ibh}\right) \geq m_d \quad \forall i \in I, \quad \forall b \in B^j, \quad \forall j \in J, \quad \forall d \in D \tag{4.31}$$

In addition to Constraints (4.9) which ensure a job cannot be processed before the release time, Constraints (4.32) take into account the batch setup process time after the release time.

$$t^1_i \geq r_i + \sum_{h\in H^1}\sum_{b\in B^1} p^1_h S^1_{ibh} + \frac{\sum_{k\in I}\sum_{h\in H^1} s^1_k S^1_{kbh}\left(1 - A^1_{kd}\right)}{v^1_d} - M\left(1 - Y^1_{id}\right) - M\left(1 - \sum_{h\in H^1} S^1_{ibh}\right) \quad \forall i \in I, \quad \forall b \in B^1, \quad \forall d \in D \tag{4.32}$$

OVERTIME

If there are urgent requests, employees can work in overtime. To keep track of the amount of overtime, a day runs from the opening time, until the opening time of the next day. The amount of overtime is denoted by nonnegative decision variables q_d for each day $d \in D$. The amount of overtime is dependent on the latest completion time of a job on that day and the setup processes that are executed after the process of the last jobs is started. Nonnegative decision variables X^j_{id} are introduced to keep track of the amount of overtime if the time setup process exceeds the process time of the last batch. These variables are introduced for each $i \in I$, $j \in J$, and $d \in D$, as its value depends on which machine and stage a job is processed, and the overtime has to be determined for each day. In that case the completion of the setup is normative and executed in overtime. Constraints (4.33) assign a value to X^j_{id}. Note that Constraints (4.33) have a quadratic term.

$$X^j_{id} \geq \frac{\sum_{k\in I}\sum_{h\in H^j} s^j_k A^j_{k(d+1)}}{v^j_d} - \sum_{h\in H^j}\sum_{b\in B^j} p^j_h S^j_{ibh} - M\left(1 - Y^j_{id}\right) \quad \forall i \in I, \quad \forall j \in J, \quad \forall d \in D \tag{4.33}$$

Constraints (4.34) and (4.35) determine the overtime each day at each stage. The overtime depends on the completion time of the last batch, the closing time and the difference between the process time of the last batch and the duration of the setup processes executed for the next day. There are two cases, the job completion time, t^j_i, is normative, or the executed setup processes are normative. In the first case, the process time of any job $i \in I$ is longer than the time required for the execution of the setup processes, in that case, X^j_{id} is zero. In the second case, the execution of the setup processes takes longer than the processing time of any job $i \in I$ at stage $j \in J$, X^j_{id} is bigger than zero and denotes the difference between the processing time and the execution of setup processes that day. Constraints (4.35) ensure that a setup process for the second stage cannot be executed before all jobs at the first stage are finished. This formulation is an overestimation as the setup can only start after the last batches at both stages have started. In reality, it could be that the second stage actually starts earlier.

$$q_d \geq t^1_i + X^1_{id} - n_d - M\left(1 - Y^1_{id}\right) \quad \forall i \in I, \quad \forall d \in D \tag{4.34}$$

$$q_d \geq t^j_i + X^2_{id} - n_d - M\left(1 - Y^2_{id}\right) \quad \forall i \in , \quad \forall j \in J, \quad \forall d \in D \tag{4.35}$$

SURCHARGES

In addition to standard employee costs, there are surcharges for working irregular hours. According to the collective labor agreement (LOAZ [42]) for university medical centers, the following surcharges apply for the CSSD of LUMC:

- 47% for hours on weekdays between 00:00 and 07:00, and after 20:00, as well as for hours on Saturday between 00:00 and 08:00 and after 12:00
- 72% for hours on Sundays or holidays.

Outside opening hours, there is a on-call service. In case an instrument set has to be sterilized urgently, employees have to go to the CSSD to handle the request. Employees get a on-call service compensation of 6% of the salary during weekdays and 12% of the salary on weekend days. If an employee actually has to work during on-call time, the compensation consists of leave equal to the number of hours worked or a salary based on the number of hours worked.

For this model, for simplification purposes, only the salary and surcharges during opening hours and overtime are taken into account. There will always be on-call services, however, these hours cannot be reduced by a more efficient schedule or other resources. In addition, for overtime it is assumed that this can only take place directly after opening hours. On an operational level, taking into account the assumption that opening hours have to be equal during weekdays, this ensures that the opening hours are not based on one peak day. For example, if each day the closing time is 18:00, when on Tuesday there are more arriving instrument sets, the work has to be continued until 19:00. Without overtime the closing time would be 19:00 for each weekday, but now the closing time can still be 18:00 and on Tuesday there is 1 hour overtime. In the model, the number of employees stays constant during overtime.

The set R is introduced to indicate the three different payment rates, 1.0, 1.42, and 1.72, respectively. Parameters p_1, p_2, p_3, and p_4 are used to indicate the tipping points between the different rates. In this case, these are defined as: p_1 = 07:00, p_2 = 08:00, p_3 = 12:00, and p_4 = 20:00. Continuous decision variables V_{dr} are introduced to indicate the total opening time on day $d \in D$ at which the rate $r \in R$ is applicable. Trivially, the equation $V_{d1} + V_{d2} + V_{d3} = n_d - m_d$, for each day $d \in D$, holds. Figure 4.2 illustrates the time spans with the corresponding rates for a weekday, Saturday and Sunday.

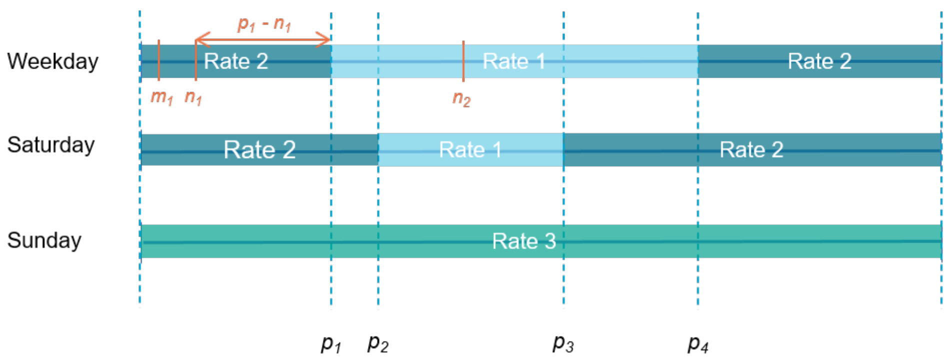


Figure 4.2: Time spans with the corresponding rate for a weekday, Saturday and Sunday.

For weekdays, the binary decision variables M_{dp_4} and N_{dp_1} are introduced. M_{dp_4} is equal to one if the opening time m_d, on day $d \in \{1,2,3,4,5\} \subset D$, is after $p_4 = 20:00$, and zero otherwise. N_{dp_1} is equal to one if the closing time n_d plus overtime q_d, on day $d \in \{1,2,3,4,5\} \subset D$, is before $p_1 = 07:00$ and zero otherwise. In the same sense, the binary decision variables M_{dp_3} and N_{dp_2} are introduced for Saturday ($d = 6$). Constraints (4.36), (4.37), (4.38), and (4.39) set the value M_{dp_4}, N_{dp_1}, M_{dp_3}, and N_{dp_2} to zero in case the opening or closing time is not before or after the considered point in time.

$$m_d + M\left(1 - M_{dp_4}\right) \geq p_4 \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{4.36}$$

$$\left(n_d + q_d\right) - M\left(1 - N_{dp_1}\right) \leq p_1 \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{4.37}$$

$$m_6 + M\left(1 - M_{6p_3}\right) \geq p_3 \tag{4.38}$$

$$\left(n_6 + q_6\right) + M\left(1 - N_{6p_2}\right) \leq p_2 \tag{4.39}$$

Nonnegative decision variables W_{dp_1}, W_{dp_2}, W_{dp_3}, and W_{dp_4} are introduced to keep track of the used time span within in each interval. For weekdays, W_{dp_1} represents the used time span before p_1 = 07:00, and W_{dp4} represents the used time span after p_4 = 20:00, both at rate 2. Constraints (4.40) and (4.41) assign values to W_{dp_1} and W_{dp_4}. Note, both constraints contain a quadratic term, $N_{dp_1}(n_d + q_d)$ and $M_{dp_4} m_d$, respectively.

$$W_{dp_1} \geq p_1 - m_d - N_{dp_1}\left(p_1 - \left(n_d + q_d\right)\right) \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{4.40}$$

$$W_{dp_4} \geq \left(n_d + q_d\right) - p_4 - M_{dp_4}\left(m_d - p_4\right) \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{4.41}$$

Constraints (4.42) define the total time span at rate 2 for all weekdays. Using the assumption that every weekday has the same opening times, it is sufficient to define the time span for one day only.

$$V_{d2} = W_{dp_1} + W_{dp_4} \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{4.42}$$

Constraints (4.43) and (4.44) assign values to W_{dp_2} and W_{dp_3}. W_{3d} represents the used time span before $p_2 = 08:00$ and W_{4d} represents the time after $p_3 = 12:00$ on Saturday. Note, again, both constraints contain a quadratic term, $N_{dp_2}(n_d + q_d)$ and $M_{dp_3} m_d$, respectively.

$$W_{6p_2} \geq p_2 - m_6 - N_{6p_2}\left(p_2 - \left(n_6 + q_6\right)\right) \tag{4.43}$$

$$W_{6p_3} \geq \left(n_6 + q_6\right) - p_3 - M_{6p_3}\left(m_6 - p_3\right) \tag{4.44}$$

Constraint (4.45) define the total time span at rate 2 for Saturday.

$$V_{6,2} = W_{6p_2} + W_{6p_3} \tag{4.45}$$

Constraints (4.46) define the time span at rate 3 on Sunday.

$$V_{7,3} = \left(n_7 + q_7\right) - m_7 \subset D \tag{4.46}$$

Finally, Constraints (4.47) and (4.48) complete the definition of D_{dr} on day $d \in D$ and rate $r \in R$. Constraints (4.47) ensure that V_{dr} cannot become a negative value. Constraints (4.48) define the time span at rate 1 based on the total opening time and the time span in rate 2 for both weekdays as well as Saturday.

$$V_{dr} \geq 0 \quad \forall d \in D, \quad \forall r \in R \tag{4.47}$$

$$V_{d1} = m_d - \left(n_d + q_d\right) - V_{d2} \quad \forall d \in \{1,2,3,4,5,6\} \in D \tag{4.48}$$

To clarify the used formulation, two examples which are indicated in orange in Figure 4.2, are explained. First, given opening time m_1, closing time n_2 and no overtime q_d, Constraints (4.36) and (4.37) set decision variables N_{dp_1} and M_{dp_4} to zero. Next, Constraints (4.40) and (4.41) become $W_{dp_1} \geq p_1 - m_1$ and $W_{dp_4} \geq n_2 - p_4$, in combination with Constraints (4.47), $W_{dp_4} \geq 0$ as $n_2 - p_4$ is smaller than zero. Second, given opening time m_1, closing time n_1 and no overtime q_d, Constraints (4.36) and (4.37) set decision variables N_{dp_1} to one and M_{dp_4} to zero. Next, Constraints (4.40) and (4.41) become $W_{dp_1} \geq n_1 - M_1$ and $W_{dp_4} \geq n_2 - p_4$, in combination with Constraints (4.47), $W_{dp_4} \geq 0$ as $n_2 - p_4$ is smaller than zero.

4.1.2. OBJECTIVE FUNCTION

The aim, as indicated by the research question, is to determine the number of resources required to sterilize all instrument sets. While satisfying all constraints, the objective of the CSSD Planning Problem is to minimize the total costs to obtain the required resources. The total costs is the sum of the machine purchase costs, machine batch costs and employee costs. Parameters c^j_{1h} and c^j_{2h} indicate the purchase price and the batch price of machine $h \in h$ at stage $j \in J$, respectively. Parameter c_{3r} indicates the cost of an operator during regular opening hours at rate $r \in R$, and an additional cost can be added for hours in overtime, denoted by c_4. Hence, the first term, $P^j_h c^j_{1h}$, denotes the machine purchase costs. The second term, $Z^j_{bh} c^j_{2h}$, denotes the machine batch costs. The third term, $V_{dr} v^j_d c_{3r}$, denotes the employee costs during regular opening hours. The last term, $q_d c_4$, denotes the employee costs related to overtime. The costs c_4 indicate an additional cost to ensure that overtime is more expensive than normal hours as these are less desirable.

$$\min \sum_{b\in B^j} \sum_{h\in H^j} \sum_{j\in J} P^j_h c^j_{1h} + \sum_{b\in B^j} \sum_{h\in H^j} \sum_{j\in J} Z^j_{bh} c^j_{2h} + \sum_{j\in J} \sum_{d\in D} \sum_{r\in R} V_{dr} v^j_d c_{3r} + \sum_{d\in D} q_d c_4 \tag{4.49}$$

4.2. PROBLEM CHARACTERISTICS

In this section, the problem characteristics are discussed. First, in Subsection 4.2.1, the problem is classified using the classification of scheduling problems introduced by Graham *et al.* [43]. Second, in Subsection 4.2.2, a concise summary about complexity theory is given, and a proof that the CSSD Planning Problem is NP-hard, is formulated.

4.2.1. TRIPLET NOTATION

According to Graham *et al.* [43], scheduling problems can be described by a triplet $\alpha|\beta|\gamma$. Field α denotes the system layout and production flow type, field β defines the job characteristics and field γ denotes the performance indices. In other words, field α represents the machine environment, field β defines the scheduling constraints and field γ denotes the objective function. The problem described in this thesis can be formulated as:

$$FQ(m_1, m_2) \left| p - batch, r_j, w^i_j, d_j, B, ST_{si,b}, m_d, n_d \right| \sum C \tag{4.50}$$

The notation is chosen similar as, in several other papers regarding flow shop problems (Ozturk *et al.* [26], Rossi *et al.* [4], Leeftink *et al.* [5]), and thus different from the notation in the remainder of this thesis. Here, within field α, F indicates a two stage flow shop, with m_1 and m_2 resources at the first stage and second stage, respectively. Q indicates that the machines are not identical and have different processing times. In field β, $p - batch$ indicates parallel batching at each stage. Each job j has a release time r_j, a due date d_j and a size w^i_j, which is different for each stage i. B stands for the machine capacity and $ST_{si,b}$ stands for setup time, which is sequence-independent (si), for each batch b. m_d and n_d indicate opening and closing times, which also form scheduling constraints. There is no previous literature that takes into account these parameters, hence the notation from this thesis is used. Field γ indicates that the objective is to minimize the sum of all costs. There is no commonly used notation to specify this objective as this is not often the chosen objective in scheduling literature. Using the same notation as in this thesis, the triplet becomes:

$$FQ\left(H^1, H^2\right) \left| p - batch, r_i, z^j_i, r_i + l_i, u^j_h, s^j_i, ST_{si,b}, m_d, n_d \right| \sum C \tag{4.51}$$

Here, within field α, $FQ(H^1, H^2)$ indicates a two stage flow shop with not identical resources H^1 and H^2 at the first and second stage, respectively. In, field β, again, $p - batch$ indicates parallel batching at each stage $j \in J$. Each job $i \in I$ has a release time, r_i, and a due date, $r_i + l_i$. s^j_i indicates the setup time, and z^j_i indicates the size of job $i \in I$ at stage $j \in J$. Again the setup time is sequence independent (si). Furthermore, u^j_h indicates the capacity of machine $h \in H^j$ at stage $j \in J$. Field γ indicates that the objective is to minimize the sum of all costs C.

4.2.2. COMPLEXITY

In this section, the complexity of the CSSD Planning Problem is discussed. First, a concise introduction on complexity theory is given, including a structure to proof NP-hardness. Second, it is proven that the CSSD Planning Problem is NP-hard. Theory and definitions are based on Papadimitriou and Steiglitz [44] and van Iersel [45].

According to Papadimitriou and Steiglitz [44], given an optimization problem, a closely related 'recognition' problem can be formulated. As the bin packing problem is used in the proof, this problem is used to illustrate the optimization and recognition representations. As in Korte and Vygen [46], the bin packing problem can be described as follows: '*Suppose we have n objects, each of a given size, and some bins of equal capacity. We want to assign the objects to the bins, using as few bins as possible. Of course the total size of the objects assigned to one bin should not exceed its capacity*'. Without loss of generality, the capacity of a bin is 1.

First, there is the 'optimization version', given a representation of an instance, find the optimal feasible solution.

Definition 4.2.1. ***Bin packing optimization problem***
Instance: A list of non-negative numbers $a_1,...,a_n \leq 1$
Task: Find a $k \in \mathbb{N}$ *and an assignment* $f: 1,...n \rightarrow 1,...,k$ *with* $\sum_{i:f(i)=j} a_i \leq 1$ *for all* $j \in 1,...,k$ *such that* k *is minimum.*

Second, there is the 'recognition version', also called the decision problem. This is in fact a question, which can be answered by 'yes' or 'no'.

Definition 4.2.2. ***Bin packing decision problem***
Instance: A list of non-negative numbers $a_1,...,a_n \leq 1$ *and a non-negative integer* K.
Task: Is there an assignment $f: 1,...n \rightarrow 1,...,K$ *with* $\sum_{i:f(i)=j} a_i \leq 1$ *for all* $j \in 1,...,K$*?*

Given both representations, Papadimitriou and Steiglitz [44] point out that the recognition version or decision problem is not harder than the original 'optimization version'. Hence, a proven complexity of the 'recognition version', also holds for the 'optimization version'. The aim is to classify the decision problem as NP-complete. First, the classes P and NP are introduced by the following definitions (van Iersel [45]).

Definition 4.2.3. *P is the class of decision problems that can be solved in polynomial time.*

Definition 4.2.4. *NP is the class of decision problems for which there exists a certificate for each yes-instance such that it can be verified in polynomial time whether a given certificate proves that a given instance is a yes-instance.*

To prove that a decision problem belongs to a certain class, reductions are used (van Iersel [45]).

Definition 4.2.5. *A reduction from a decision problem* $\sqcap_1$ *to a decision problem* $\sqcap_2$ *is a function that assigns to each instance* I *of* $\sqcap_1$ *an instance* $f(I)$ *of* $\sqcap_2$*, such that:*
1. there exists a polynomial-time algorithm computing f
2. for each instance I *of* $\sqcap_1$*:*

$$I \text{ is a yes-instance of } \sqcap_1 \Leftrightarrow f(I) \text{ is a yes-instance of } \sqcap_2$$

In addition, there is another subclass of problems, NPC, such problems are called NP-complete. Intuitively, NP-complete problems are the most difficult problems (van Iersel [45]).

Definition 4.2.6. *A decision problem is NP-complete if it is in* NP *and is NP-hard.*

Definition 4.2.7. *A decision problem* $\sqcap$ *is NP-hard if* $\sqcap' \propto \sqcap$ *for each* $\sqcap' \in NP$

Hence, to prove that the CSSD Planning Problem is an NP-hard problem, a reduction of any NP-complete problem has to be found. Similar as in Ozturk *et al.* [47], a reduction from the bin packing problem is used. The bin packing problem is NP-complete, as proven in Korte and Vygen [46]. To complete the definition of the bin packing problem, an Integer Linear Programming (ILP) model is given. In this problem, n is a known upper bound on the number of bins needed, equal to the number of jobs. (Korte and Vygen [46]).

Definition 4.2.8. ***Bin packing ILP formulation***

$$x_j = \begin{cases} 1, & \text{if bin } j \in 1,....,n \text{ is used} \\ 0, & \text{otherwise} \end{cases} \quad y_{ij} = \begin{cases} 1, & \text{if item } i \in 1,....,n \text{ is put in bin } j \in 1,....,n \\ 0, & \text{otherwise} \end{cases} \tag{4.52}$$

$$\min \quad \sum_{j=1}^{n} x_j \tag{4.53}$$

$$s.t. \sum_{i=1}^{n} a_i y_{ij} \leq 1 \qquad \forall j \in 1,...,n \tag{4.54}$$

$$\sum_{j=1}^{n} y_{ij} = 1 \qquad \forall i \in 1,....,n \tag{4.55}$$

$$\sum_{i=1}^{n} y_{ij} \leq M x_j \qquad \forall j \in 1,...,n \tag{4.56}$$

$$x_j \in \{0,1\} \qquad \forall j \in 1,...,n \tag{4.57}$$

$$y_{ij} \in \{0,1\} \qquad \forall j \in 1,...,n \qquad \forall i \in 1,....,n \tag{4.58}$$

$$\tag{4.59}$$

The CSSD Planning Problem can be reduced to a bin packing problem as follows. Let I_1 be an instance of the bin packing problem with item sizes $a_1,...,a_n$ and non-negative integer K. The capacity of each bin is 1. Binary variable x_j is 1 if bin j is used and binary variable y_{ij} is one if item i is placed in bin j. This is a 'yes'-instance if the objective value is at most K. Now, an instance I_2 of the CSSD Planning Problem can be constructed. In the case with one stage, one machine with capacity u_1^1 and processing time p_1^1, all jobs arriving at the same point in time, a planning horizon of one day with unlimited opening time, no lead times l_i, no set-up times s_i, no machine purchase costs c_1, batch costs c_2 which are equal to 1, no employee costs c_3 and c_4, and no surcharges r. Then, the capacity and job sizes can be rewritten as

$$u_1^1 := \frac{u_1^1}{u_1^1}, \tag{4.60}$$

and

$$z_i := \frac{z_i}{u_1^1}. \tag{4.61}$$

In this way, the capacity becomes equal to one, and the job sizes are scaled accordingly. The job sizes are given by $z_i = a_i \quad \forall i = 1,\ldots,n$. The objective function is the sum of the batch cost and should be at most $C = K$.

Theorem 4.2.1. *The recognition version of the CSSD Planning Problem is NP-complete.*

Proof. 1. Given which batches are assigned to the machine, it is possible to check in polynomial time if the sum is below C. Hence, the recognition version of CSSD Planning Problem is in NP.

2. $\Rightarrow$ Assume I_1 is a 'yes'-instance for the bin packing problem. Let $z_i = a_i \quad for i = 1,\ldots,n$. Let binary variable x_j be one if bin j is used and binary variable y_{ij} be 1 if job i is assigned to bin j. Then, $\sum_{j=1}^{n} x_j \leq K$, $\sum_{i=1}^{n} a_i y_{ij} \leq 1$ and $\sum_{j=1}^{n} y_{ij} = 1$ hold. Now, $S_{ib1}^1 = y_{ij}$, where S_{ib1}^1 is a binary variable that is equal to 1 if job i is assigned to batch b at machine 1 at stage 1. Then,

$$\sum_{b=1}^{n} S_{ib1}^1 = \sum_{j=1}^{n} y_{ij} = 1 \quad \forall i = 1,\ldots,n, \tag{4.62}$$

and

$$\sum_{i=1}^{n} z_i S_{ib1}^1 = \sum_{i=1}^{n} a_i y_{ij} \leq 1 = u \quad \forall j = b = 1,\ldots,n, \tag{4.63}$$

Additionally, $Z_{b1}^1 = x_j$, where Z_{b1}^1 is a binary variable that is equal to 1 if batch b is assigned to machine 1 at stage 1. Then,

$$\sum_{i=1}^{n} S_{ib1}^1 = \sum_{i=1}^{n} y_{ij} \leq M x_j = M Z_{b1}^1 \quad \forall b = j = 1,\ldots,n. \tag{4.64}$$

The objective function is,

$$\sum_{b=1}^{n} c_2 Z_{b1}^1 = \sum_{j=1}^{n} x_j \leq K = C. \tag{4.65}$$

Hence, the 'yes'-instance I_1 for the bin packing problem is reduced to a 'yes'-instance I_2 of the CSSD Planning Problem.

$\Leftarrow$ Assume I_2 is a yes-instance for the CSSD Planning Problem. Let $a_i = z_i \quad for i = 1,\dots,n$.Let binary variable S^1_{ib1} be 1 if job i is assigned to batch b at machine 1 at stage 1, and binary variable Z^1_{b1} be 1 if batch b is assigned to machine 1 at stage 1. Then, $\sum_{b=1}^n S^1_{ib1} = 1$, $\sum_{i=1}^n z_i S^1_{ib1} \leq u$, and $\sum_{i=1}^n S^1_{ib1} \leq MZ^1_{b1}$ hold. Now $y_{ij} = S^1_{ib1}$, where y_{ij} is a binary variable that is equal to 1 if item i is put in bin j. Then,

$$\sum_{j=1}^{n} y_{ij} = \sum_{b=1}^{n} S^1_{ib1} = 1 \quad \forall i = 1,\dots,n, \tag{4.66}$$

and

$$\sum_{i=1}^{n} a_i y_{ij} = \sum_{i=1} z_i S^1_{ib1} \leq u = 1 \quad \forall j = b = 1,\dots,n. \tag{4.67}$$

Additionally, $x_j = Z^1_{b1}$, where x_j is a binary variable that is equal to 1 if bin j is used. Then,

$$\sum_{i=1}^{n} y_{ij} = \sum_{i=1}^{n} S^1_{ib1} \leq MZ^1_{b1} = Mx_j \quad \forall j = b = 1,\dots,n. \tag{4.68}$$

The objective function is,

$$\sum_{j=1}^{n} x_j = \sum c_2 Z^1_{b1} \leq C = K. \tag{4.69}$$

Hence, the 'yes'-instance I_2 of the CSSD Planning Problem is reduced to a 'yes'-instance $I1$ for the bin packing problem.

□

To conclude, the recognition version of the CSSD Planning Problem is NP-complete. Since the CSSD Planning Problem is an optimization problem which is not in NP, the CSSD Planning Problem is NP-hard.

5

Solution approaches

Preliminary results show that the CSSD Planning Problem as described in Chapter 4 is difficult to solve. Although the model reflects the specific characteristics of the process at the CSSD, no good solution can be found for real-life size instances. Hence, in this chapter the problem is reformulated. The base of this reformulation is a decomposition based on the hierarchical levels in which capacity planning decisions can be divided. The framework as described in Section 2.6 is used to identify which capacity planning decisions have to be made on which level. First, in Section 5.1, the problem is simplified with the aim to determine the required number and type of machines. Second, in Section 5.2, the strategic model is extended to determine the amount of opening time. Lastly, in Section 5.3, the two-stage flow shop which considers capacity planning decisions on all hierarchical levels is reformulated as a four-stage flow shop.

5.1. Strategic model

In this section, a mixed integer linear program (MILP) is proposed which only considers capacity planning decisions at a strategic level. The required number and type of machines has to be determined, while taking into account the amount of opening time. Only the amount of opening time, and no specific opening and closing time, is taken into account. The solution of this problem can serve as a baseline or input to solve the CSSD Planning Problem. In Subsection 5.1.1, the model is formally introduced, and in Subsection 5.1.2, a linearization of the model is proposed. All relevant sets, variables, and parameters are introduced in the text and listed in the front matter of this thesis.

5.1.1. Formulation

In this subsection, first, the constraints are described, and second, the objective function is stated.

Constraints

Formally, there is a set I of instrument sets, also called jobs, that have to be sterilized by the CSSD. The process at the CSSD can be described as a set of stages, denoted by J, which each consist of a set of machines, denoted by H^j. Binary decision variables S^j_{ih} are introduced, which are equal to one if job $i \in I$ is processed at machine $h \in H^j$ at stage $j \in J$. Constraints (5.1) ensure that each job is assigned to exactly one machine at each stage.

$$\sum_{h \in H^j} S^j_{ih} = 1 \quad \forall i \in I, \quad \forall j \in J \tag{5.1}$$

The type and number of required machines is not known in advance, consequently, H^j represents a set of possible machines that can be purchased at stage $j \in J$. Each machine has a process time p^j_h and a capacity u^j_h. Binary decision variables P^j_h indicate if machine $h \in H^j$ at stage $j \in J$ is purchased. P^j_h is equal to one if machine $h \in H^j$ is purchased at stage $j \in J$, and zero otherwise. Constraints (5.2) ensure that if a job $i \in I$ is processed at machine $h \in H^j$ at stage $j \in J$, machine $h \in H^j$ is purchased.

$$\sum_{i \in I} S^j_{ih} \leq M P^j_h \quad \forall h \in H^j, \quad \forall j \in J \tag{5.2}$$

The model has a planning horizon of one week. This time horizon is divided into 7 days, denoted by set D. A job $i \in I$ can be processed from the release day, denoted by r_i, onwards. Constraints (5.3) ensure that each stage of processing a job is assigned to one day. Constraints (5.4) ensure that a job can only be processed after arriving at the CSSD.

$$\sum_{d \in D} Y_{id}^{j} = 1 \quad \forall i \in I, \quad \forall j \in J \tag{5.3}$$

$$r_i \leq \sum_{d \in D} Y_{id}^{1} d \quad \forall i \in I \tag{5.4}$$

As the CSSD is a flow shop environment, a job $i \in I$ first has to be processed at stage one, where after it can be processed at stage two. In addition, there are guidelines for the amount of time an instrument set can be kept before or in between stages. The maximum duration before disinfection is 24 hours, and the maximum duration in between disinfection and sterilization is 48 hours. For this formulation, this implies that a job $i \in I$ has to be processed at the first stage on the release day or the day after. Hereafter, the job has to be processed at the second stage within two days. Constraints (5.5) and (5.6) ensure that a job $i \in I$ can only be assigned to day $d \in D$ when both restrictions are fulfilled. Note that in term Y_{id}^2, the 2 stands for stage two and not the square of the term.

$$\sum_{d \in D} Y_{id}^{1} d \leq r_i + 1 \quad \forall i \in I \tag{5.5}$$

$$Y_{id}^{2} \leq \sum_{d_1 \geq d-2}^{d} Y_{id_1}^{1} \quad \forall i \in I, \quad \forall d \in D \tag{5.6}$$

Depending on the type of instrument set, each job $i \in I$ has a limited number of days in which the set has to be sterilized and transported back to the OR or outpatient clinic. The due date is defined as the release day plus lead time, which is denoted by l_i. For example, $l_i = 0$ indicates that a job has to be processed on the day of arrival, and $l_i = 3$ indicates that a job has be processed three days after arrival at the latest. Constraints (5.7) assure that a job is finished at the determined due date, which is the arrival day plus the number of days within it has to be sterilized.

$$\sum_{d \in D} Y_{id}^{2} d \leq r_i + l_i \quad \forall i \in I \tag{5.7}$$

For each day $d \in D$, the decision variables O_d represent the amount of opening time. As a job is only assigned to a specific day, it is not relevant to determine specific opening times m_d and n_d. In relation to the formulation in Chapter 4, the equation $O_d = n_d - m_d$ holds for each day $d \in D$. Apart from this relation, m_d and n_d could take any value during the day. Constraints (5.8) ensure that each weekday has the same amount of opening time. Since this relation does not hold for weekend days, Constraint (5.9) ensures that the amount of opening time each weekend day is also equal.

$$O_d = O_{d-1} \quad \forall d \in \{2,3,4,5\} \subset D \tag{5.8}$$

$$O_7 = O_6 \tag{5.9}$$

Each day $d \in D$, a machine $h \in H^j$ has a certain capacity depending on the process time, p_h^j, and the capacity, u_h^j, of the machine. Intuitively, it can be seen as the number of batches which are possible to process. The capacity of machine $h \in H^j$ at stage $j \in J$ on day $d \in D$ is defined as

$$\left\lfloor \frac{\gamma O_d}{p_h^j} \right\rfloor u_h^j. \tag{5.10}$$

Each job $i \in I$ has a size z_i^j at each stage $j \in J$. Constraints (5.11) ensure that the capacity of machine $h \in H^j$ at stage $j \in J$ is not exceeded on a day $d \in D$. A parameter γ is introduced to take into account the fact that the machines cannot be used continuously, as time is needed to execute setup processes and to form the batches before each stage. Furthermore, there could be machine failures or test batches which decrease the available time. A value for γ can be determined using the models in Chapter 4, or based on expert judgement. Note that Constraints (5.11) have two non-linear terms, $S^j_{ih}Y^j_{id}$ and $\left\lfloor \frac{\gamma O_d}{p^j_h} \right\rfloor$.

$$\sum_{i \in I} S^j_{ih} Y^j_{id} z^j_i \leq \left\lfloor \frac{\gamma O_d}{p^j_h} \right\rfloor u^j_h \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.11}$$

To take into account surcharges for working irregular hours, a different rate is used for opening hours that go over the regular hours. In case of a weekday, regular hours are from 07:00 until 20:00. Hence, the amount of opening time above 13 hours (780 minutes) is charged with a surcharge of 47%. In similar sense, this holds for opening time above 4 hours (240 minutes) on Saturday. For Sunday, for all opening hours a surcharge of 72% is paid. For each day $d \in \{1,2,3,4,5,6\} \subset D$, nonnegative variables Q_d represent the irregular hours as defined above. Constraints (5.12) ensure that for weekdays, if the amount of opening time is over 780 minutes, all time over 780 minutes is indicated as irregular opening time. Constraint (5.13) indicates the amount of irregular opening time on Saturday. Constraint (5.14) indicates the amount of irregular opening time on Sunday.

$$Q_d \geq O_d - 780 \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{5.12}$$

$$Q_6 \geq O_6 - 240 \tag{5.13}$$

$$Q_7 = O_7 \tag{5.14}$$

To take into account the amount of work employees can do at a day, the setup times of each job are used. Parameter v^j_d denotes the number employees at stage $j \in J$ on day $d \in D$. Constraints (5.15) ensure that the maximum time spend on the setup processes of instrument sets is smaller than the capacity of the employees at each stage $j \in J$ on each day $d \in D$.

$$\sum_{i \in I} Y^j_{id} s^j_i \leq v^j_d O_d \quad \forall j \in J, \quad \forall d \in D \tag{5.15}$$

OBJECTIVE

While satisfying all constraints, the objective is to minimize the total costs to obtain the required resources. The first term, denotes the machine purchase costs. The second term, denotes the employee costs during opening hours. The third an fourth term, indicate the employee costs during the irregular opening hours. r_2 and r_3 are defined as 47% and 72%, respectively. To be able to compare the results of this model with the models in Chapter 4, the fifth term gives an estimate of the batch costs. This is defined as the ceiling of the sum of all jobs assigned to a machine $h \in H^j$ at stage $j \in J$ on day $d \in D$, divided by the capacity of the machine. Note that the ceiling function is non-linear.

$$\min \sum_{h \in H^j} \sum_{j \in J} P^j_h c^j_{2h} + \sum_{j \in J} \sum_{d \in D} v^j_d c_3 O_d + \sum_{d \neq 7 \in D} r_2 v^j_d c_3 Q_d + r_3 v^j_7 c_3 Q_7 + \sum_{j \in J} \sum_{d \in D} \sum_{h \in H^j} \left\lceil \frac{\sum_{i \in I} S^j_{ih} Y^j_{id} z^j_i}{u^j_h} \right\rceil c^j_{1h} \tag{5.16}$$

5.1.2. LINEARIZATION

As already noted in the previous section, there are three non-linear terms within the formulation. First, Constraints (5.11) contain the terms $S^j_{ih}Y^j_{id}$ and $\left\lfloor \frac{\gamma O_d}{p^j_h} \right\rfloor$. These terms can be linearized by adding binary variables X^j_{ihd} and integer variables L^j_{hd}, respectively. Furthermore, Constraints (5.17), (5.18), and (5.19) are added to resemble the behaviour of the first quadratic term, and Constraints (5.20) are added to resemble the behaviour of the floor function.

$$X^j_{ihd} \leq S^j_{ih} \quad \forall i \in I, \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.17}$$

$$X^j_{ihd} \leq Y^j_{id} \quad \forall i \in I, \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.18}$$

$$X^j_{ihd} \geq S^j_{ih} + Y^j_{id} - 1 \quad \forall i \in I, \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.19}$$

$$L^j_{hd} \leq \frac{\gamma O_d}{p^j_h} \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.20}$$

Hereafter, Constraints (5.11) are transformed to Constraints (5.21).

$$\sum_{i \in I} X^j_{ihd} z^j_i \leq L^j_{hd} u^j_h \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.21}$$

Second, the last term of the objective function is non-linear. Integer variables K^j_{hd} and Constraints (5.22) are added to linearize the objective function, which is shown in Equation (5.23).

$$K^j_{hd} \geq \frac{\sum_{i \in I} X^j_{ihd} z^j_i}{u^j_h} \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.22}$$

$$\min \sum_{h^j \in H^j} \sum_{j \in J} P^j_h c^j_{2h} + \sum_{j \in J} \sum_{d \in D} v^j_d c_3 O_d + \sum_{d \neq 7 \in D} \sum_{j \in J} r_2 v^j_d c_3 Q_d + \sum_{j \in J} r_3 v^j_7 c_3 Q_7 + \sum_{j \in J} \sum_{d \in D} \sum_{h \in H^j} K^j_{hd} c^j_{1h} \tag{5.23}$$

5.2. TACTICAL MODEL

In this section, a MILP is proposed which considers capacity planning decisions at a strategic and tactical level. On a tactical level, the aim is to determine the specific opening and closing time of the CSSD. To determine these values, days are divided into multiple day parts. The specific opening hours can be determined by combining the opening hours of each day part. In Subsection 5.2.1, the model is formally introduced, and in Subsection 5.2.2, a linearization of the model is proposed. All relevant sets, variables, and parameters are introduced in the text and listed in the front matter of this thesis.

5.2.1. FORMULATION

The tactical formulation is an extension of the strategic model as presented in Subsection 5.1.1. Hereafter, this subsection first describes the constraints, and second, states the objective function. All constraints are presented, however, only differences in comparison to the notation in Subsection 5.1.1 are discussed.

CONSTRAINTS

Formally, the set G denotes the day parts, and parameter w the number of parts a day is divided in. For instance, given $w = 2$, the set G consists of $7w = 14$ elements. Note, with a higher value of w, in other words, more day parts, the problem tends to be more accurate to reality, partly taking into account release times. Table 5.1 indicates the time intervals for each considered number of day parts.

Day parts	Part 1	Part 2	Part 3	Part 4
1	00:00-00:00			
2	00:00-12:00	12:00-00:00		
3	00:00-08:00	08:00-16:00	16:00-00:00	
4	00:00-06:00	06:00-12:00	12:00-18:00	18:00-00:00

Table 5.1: Overview time intervals for each number of day parts.

Constraints (5.24) ensure that each job $i \in I$ is assigned to exactly one machine $h \in H^j$ at each stage $j \in J$. Constraints (5.25) ensure that if a job $i \in I$ is processed at machine $h \in H^j$ at stage $j \in J$, machine $h \in H^j$ is purchased.

$$\sum_{h \in H^j} S^j_{ih} = 1 \quad \forall i \in I, \quad \forall j \in J \tag{5.24}$$

$$\sum_{i \in I} S^j_{ih} \leq MP^j_h \quad \forall h \in H^j, \quad \forall j \in J \tag{5.25}$$

The considered planning horizon is a week, which consists of $7w$ day parts. A job $i \in I$ can be processed from the day part it arrives, denoted by $r_i \in G$. Constraints (5.26) ensure that each job $i \in I$ at each stage

$j \in J$ is assigned to one day part. Constraints (5.27) ensure that a job can only be processed after arrival at the CSSD.

$$\sum_{g \in G} Y_{ig}^{j} = 1 \quad \forall i \in I, \quad \forall j \in J \tag{5.26}$$

$$r_i \leq \sum_{g \in G} Y_{ig}^{1} g \quad \forall i \in I \tag{5.27}$$

As the CSSD is a flow shop environment, a job $i \in I$ first has to be processed at stage one, where after it can be processed at stage two. In addition, a job $i \in I$ has to be processed at the first stage within w day parts after arriving at the CSSD, and has to be finished at the second stage within $2w$ day parts after the end of the first stage. Constraints (5.28) and (5.29) ensure that a job $i \in I$ can only be assigned to day part $g \in G$ if both restrictions are fulfilled. Note that in term Y_{ig}^{2}, the 2 stands for stage two and not the square of the term.

$$\sum_{g \in G} Y_{ig}^{1} g \leq r_i + w \quad \forall i \in I \tag{5.28}$$

$$Y_{ig}^{2} \leq \sum_{g_1 \geq g-2w}^{g} Y_{ig_1}^{1} \quad \forall i \in I, \quad \forall g \in G \tag{5.29}$$

Constraints (5.30) ensure that each job $i \in I$ is finished before the determined due date, which is the arrival day part plus the number of day parts within which the job has to be sterilized, the lead time, denoted by l_i.

$$\sum_{g \in G} Y_{ig}^{2} g \leq r_i + l_i \quad \forall i \in I \tag{5.30}$$

For each day part $g \in G$, the decision variables O_g represent the amount of opening time. Constraints (5.31) ensure that the day parts have the same opening hours each weekday. Consequently, the total opening time is the same on each weekday. Constraints (5.32) ensure that the amount of opening time on weekend days is equal as well.

$$O_g = O_{g-w} \quad \forall g \in \{w+1, ..., 5w\} \subset G \tag{5.31}$$

$$O_g = O_{g-w} \quad \forall g \in \{6w+1, ..., 7w\} \subset G \tag{5.32}$$

In case $w > 2$, additional constraints are needed to define the opening hours. As the CSSD has continuous opening hours during the day, the considered day part has to have full opening hours if both adjacent day parts have hours in which the CSSD is open. Binary variables D_g are introduced to indicate if there are opening hours within day part $g \in G$. D_g is equal to one if O_g is larger than zero for day part $g \in G$, and zero otherwise. Constraints (5.33) assign a value to D_g.

$$D_g \geq \frac{O_g}{1440} \quad \forall g \in G \tag{5.33}$$

Constraints (5.34) ensure that if both adjacent day parts have hours in which the CSSD is open, the day part in between has full opening hours. These constraints are only introduced for day parts in the middle of a day, as there can be a break in opening hours between days.

$$O_g \geq \left(D_{g-1} + D_{g+1} - 1\right) \frac{1440}{w} \quad \forall g \in \{0w+2, \ldots, w-1, w+2, \ldots, 2w-1, \ldots\ldots, 6w+2, \ldots, 7w-1\} \subset G \tag{5.34}$$

Constraints (5.35) ensure that the capacity of machine $h \in H^j$ at stage $j \in J$ is not exceeded on interval $g \in G$. Note that these constraints contain two non-linear terms.

$$\sum_{i \in I} S_{ih}^{j} Y_{ig}^{j} z_i^{j} \leq \left\lfloor \frac{\gamma O_g}{p_h^{j}} \right\rfloor u_h^{j} \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall g \in G \tag{5.35}$$

To take into account surcharges for working irregular hours, a different rate is used for opening hours that go over the regular hours. The number of regular hours depends on the chosen number of day parts and the corresponding time intervals as indicated in Table 5.1. In case $w = 2$, Constraints (5.36) and (5.37) are added to determine the amount of irregular opening time on weekdays, and Constraints (5.38) and (5.39) are added to determine the amount of irregular opening time on Saturdays.

$$Q_g \geq O_g - 300 \quad \forall g \in \{1,3,\ldots,9\} \subset G \tag{5.36}$$

$$Q_g \geq O_g - 480 \quad \forall g\{2,4,\ldots,10\} \subset G \tag{5.37}$$

$$Q_{11} \geq O_{11} - 240 \tag{5.38}$$

$$Q_{12} = O_{12} \tag{5.39}$$

In case $w = 3$ and $w = 4$, similar constraints are added. In that case there are 3 and 4 constraints for each day, respectively. These constraints can be found in Appendix B.1.

To take into account the amount of work employees can do during a day part, the setup times of each job are used. Constraints (5.40) ensure that the time spend on the setup of an instrument set $i \in I$ is smaller than the capacity of the employees during the opening hours of the day part.

$$\sum_{i\in I} Y^j_{ig} s^j_i \leq v^j_g O_g \quad \forall j \in J, \quad \forall g \in G \tag{5.40}$$

OBJECTIVE

While satisfying all constraints, the objective is to minimize the total costs to obtain the required resources. The objective function is very similar to the objective function of the strategic model, only considering day parts instead of days.

$$\begin{aligned}\min \sum_{h\in H^j}\sum_{j\in J} P^j_h c^j_{2h} + \sum_{j\in J}\sum_{g\in G} v^j_g c_3 O_g + \sum_{0\leq g\leq 6w}\sum_{j\in J} r_2 v^j_g c_3 Q_g + \sum_{6w+1\leq g\leq 7w}\sum_{j\in J} r_3 v^j_g c_3 O_7 \\ + \sum_{j\in J}\sum_{g\in G}\sum_{h\in H^j}\left\lceil \frac{\sum_{i\in I} S^j_{ih} Y^j_{ig} z^j_i}{u^j_h}\right\rceil c^j_{1h}\end{aligned} \tag{5.41}$$

5.2.2. LINEARIZATION

Similar to the strategic model, there are three non-linear terms within the tactical model, two within the constraints, and one in the objective function. Binary variables X^j_{ihg}, integer variables L^j_{hg}, and integer variables K^j_{hg} are added in combination with Constraints (5.42), (5.43), (5.44), (5.45), and (5.46), which results in Constraints (5.47) and objective function (5.48).

$$X^j_{ihg} \leq S^j_{ih} \quad \forall i \in I, \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall g \in G \tag{5.42}$$

$$X^j_{ihg} \leq Y^j_{ig} \quad \forall i \in I, \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall g \in G \tag{5.43}$$

$$X^j_{ihg} \geq S^j_{ih} + Y^j_{ig} - 1 \quad \forall i \in I, \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall g \in G \tag{5.44}$$

$$L^j_{hg} \leq \frac{\gamma O_g}{p^j_h} \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall g \in G \tag{5.45}$$

$$K^j_{hg} \geq \left\lceil \frac{\sum_{i\in I} X^j_{ihg} z^j_i}{u^j_h} \right\rceil \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall g \in G \tag{5.46}$$

$$\sum_{i\in I} X^j_{ihg} z^j_i \leq L^j_{hg} u^j_h \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall g \in G \tag{5.47}$$

$$\min \sum_{h\in H^j}\sum_{j\in J} P_h^j c_{2h}^j + \sum_{j\in J}\sum_{g\in G} v_g^j c_3^j O_g + \sum_{0\le g\le 6w} r_2 v_g^j c_3 O_g + \sum_{6w+1\le g\le 7w} r_3 v_g^j c_3 O_7 + \sum_{j\in J}\sum_{g\in G}\sum_{h\in H^j} K_{hg}^j c_{1h}^j \tag{5.48}$$

5.3. OPERATIONAL MODEL

The model as described in Chapter 4, can be defined as an operational model considering capacity planning decisions at all hierarchical levels. On an operational level, the aim is to determine the assignment of an instrument set to a batch and an employee. In Subsection 5.3.1, a reformulation to a four-stage flow shop is described, and in Subsection 5.3.2, both the two-stage and the four-stage formulation are linearized. All relevant sets, variables, and parameters are introduced in the text and listed in the front matter of this thesis.

5.3.1. REFORMULATION

In the mathematical programming formulation in Section 4.1, multiple decision variables are introduced to keep track of the setup time for batches. In this subsection, a reformulation is proposed to avoid these variables and make the model better readable. Here, the problem is presented as a four stage hybrid flow shop. The four stages are: 'manually clean', 'disinfect' by the WD machines, 'check and assemble', and 'sterilize' by the autoclaves. As the formulation is similar to the model proposed in Chapter 4, only constraints, sets, parameters and decision variables which are changed are explained.

CONSTRAINTS

The notation of the reformulation is very similar to the model proposed in Chapter 4. Although all sets, parameters, and variables are stated, only significant differences are further elaborated. Similar as in Chapter 4, the sets I, J and D are introduced. The set of machines, H^j, and the set of batches, B^j, are now only introduced for stages two and four, the WD machines and autoclaves, respectively. All parameters related to machines, among which job size, z_i^j, machine capacity, u_h^j, processing time, p_h^j, machine purchasing costs, c_{1h}^j, and machine batch cost,c_{2h}^j, are introduced for only stages two and four as well. The set O_d^j is introduced, which represents the CSSD employees, the operators, at stage $j \in \{1,3\} \in J$, on day $d \in D$. The number of operators at stage $j \in J$ on day $d \in D$ is a fixed parameter v_d^j. Additionally, processing time s_i^j for job $i \in I$, equal to the setup time in Chapter 4, is added for stages one and three.

The decision variables t_i^j, m_d, n_d, q_d, and Y_{id}^j remain the same as in Chapter 4. The decision variables related to the machines, batches and setup times, t_{bh}^j, S_{ibh}^j, Z_{bh}^j, and P_h^j, are again only introduced for stages two and four. Binary decision variables A_{ik}^j and S_{iod}^j are added for stages one and three. S_{iod}^j is equal to one when job $i \in I$ is assigned to operator $o \in O_{id}^j$ at stage $j \in \{1,3\} \in J$ on day $d \in D$, and zero otherwise. A_{ik}^j is equal to one when job $k \in I$ is processed after job $i \in I$ at stage $j \in J$, and zero otherwise. All decision variables related to setup times, A_{id}^j and X_{id}^j, are not used in this formulation.

Constraints (5.49) ensure that each job is assigned to one batch and one machine at stages $j \in \{2,4\} \subset J$. Constraints (5.50) ensure that each job is assigned to one operator on one day at stages $j \in \{1,3\} \subset J$.

$$\sum_{b\in B^j}\sum_{h\in H^j} S_{ibh}^j = 1 \quad \forall i \in I, \quad \forall j \in \{2,4\} \subset J \tag{5.49}$$

$$\sum_{o\in O_d^j}\sum_{d\in D} S_{iod}^j = 1 \quad \forall i \in I, \quad \forall j \in \{1,3\} \subset J \tag{5.50}$$

Constraints (5.51) guarantee that each batch is assigned to at most one machine at stages $j \in \{2,4\} \subset J$. Constraints (5.52) and (5.53) ensure that if a batch is assigned to a machine, at least one job is assigned to the batch. Reversely, if a batch is not assigned to a machine, no jobs are assigned to the batch. Constraints (5.54) ensure that if a batch is processed at a machine $h \in H^J$ at stage $j \in \{2,4\} \subset J$, this machine is purchased. Constraints (5.55) ensure that the sum of the job sizes of each batch does not exceed the capacity of the assigned machine at the corresponding stage. Note that Constraints (5.53) and (5.55) can be merged as shown in (5.56). These constraints remain similar, only applied to stages two and four.

$$\sum_{h\in H^j} Z^j_{bh} \leq 1 \quad \forall b^j \in B^j, \quad \forall j \in \{2,4\} \subset J \tag{5.51}$$

$$\sum_{i\in I} S^j_{ibh} \geq Z^j_{bh} \quad \forall b^j \in B^j, \quad \forall h \in H^j, \quad \forall j \in \{2,4\} \subset J \tag{5.52}$$

$$\sum_{i\in I} S^j_{ibh} \leq M Z^j_{bh} \quad \forall b^j \in B^j, \quad \forall h \in H^j, \quad \forall j \in \{2,4\} \subset J \tag{5.53}$$

$$\sum_{b\in B^j} Z^j_{bh} \leq M P^j_h \quad \forall h \in H^j, \quad \forall j \in \{2,4\} \subset J \tag{5.54}$$

$$\sum_{i\in I} z^j_i S^j_{ibh} \leq u^j_h \quad \forall b^j \in B^j, \quad \forall h \in H^j, \quad \forall j \in \{2,4\} \subset J \tag{5.55}$$

$$\sum_{i\in I} z^j_i S^j_{ibh} \leq u^j_h Z^j_{bh} \quad \forall b^j \in B^j, \quad \forall h \in H^j, \quad \forall j \in \{2,4\} \subset J \tag{5.56}$$

Constraints (5.57) ensure that a job cannot be processed before the release date. This is dependent on the process time of job $i \in I$ at stage one. Constraints (5.58) ensure that a job is finished at stage four before the due date. Note that in the term t^4_i, the 4 stands for stage four and not to the power of 4.

$$t^1_i \geq r_i + s^1_i \quad \forall i \in I \tag{5.57}$$

$$t^4_i \leq r_i + l_i \quad \forall i \in I \tag{5.58}$$

In addition, there are guidelines for the amount of time an instrument set can be kept at a stage. Parameter e^j indicates the maximum time before or in between stage $j \in J$. Constraints (5.59) and (5.60) ensure that the maximum time between the release date and the start of stage two is e^1 minutes, and the maximum duration between completion time of the stages two and the start of stage four is e^2 minutes for each job $i \in I$. In other words, before disinfecting, the maximum elapsed time is e^1 minutes, and between disinfecting and sterilizing, the maximum elapsed time is e^2 minutes. The term $\sum_{h\in H^j}\sum_{b\in B^j} p^j_h S^j_{ibh}$ is used to indicate that the maximum amount of time is measured until the start of a machine at the next stage.

$$t^2_i - r_i - \sum_{h\in H^j}\sum_{b\in B^j} p^2_h S^2_{ibh} \leq e^1 \quad \forall i \in I \tag{5.59}$$

$$t^4_i - t^2_i - \sum_{h\in H^j}\sum_{b\in B^j} p^4_h S^4_{ibh} \leq e^2 \quad \forall i \in I \tag{5.60}$$

Constraints (5.61) and (5.62) define the batch completion time t^j_{bh} of batch $b \in B^J$ at machine $h \in H^j$ at stage $j = 2,4 \in J$. A machine can only process one batch at a time. Constraints (5.63) ensure that a batch cannot be scheduled earlier than the completion time of the previous batch at the same machine. These constraints remain similar, but only applied to stages two and four.

$$t^j_{bh} \geq t^j_i - M\left(1 - S^j_{ibh}\right) \quad \forall i \in I, \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in \{2,4\} \subset J \tag{5.61}$$

$$t^j_i \geq t^j_{bh} - M\left(1 - S^j_{ibh}\right) \quad \forall i \in I, \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in \{2,4\} \subset J \tag{5.62}$$

$$t^j_{bh} + M\left(1 - Z^j_{bh}\right) \geq t^j_{b'h} - M\left(1 - Z^j_{b'h}\right) + p^j_h \quad \forall h \in H^j, \quad \forall b, b' < b \in B^j, \quad \forall j \in \{2,4\} \subset J \tag{5.63}$$

Constraints (5.64) and (5.65) assign a value to Y^j_{id} given the completion time of a job. Constraints (5.66) ensure that a job is scheduled on exactly one day.

$$t^j_i + M\left(1 - Y^j_{id}\right) \geq m_d \quad \forall i \in I, \quad j \in J, \quad d \in D \tag{5.64}$$

$$t^j_i - M\left(1 - Y^j_{id}\right) \leq m_{d+1} \quad \forall i \in I, \quad j \in J, \quad d \in D \tag{5.65}$$

$$\sum_{d\in D} Y_{id}^j = 1 \quad \forall i \in I, \quad j \in J \tag{5.66}$$

In addition, for this formulation, constraints regarding the sequence of jobs processed by an operator have to be introduced for stages $j \in \{1,3\} \subset J$. Binary variables A_{ik}^j are introduced, which are equal to one if job $k \in I$ is processed after job $i \in I$ at stage $j \in \{1,3\} \subset J$, and zero otherwise. Constraints (5.67), (5.68), and (5.69) provide the order in which jobs are scheduled and ensure that a job cannot be scheduled earlier than the completion time of the previous job processed by the same operator at stages $j \in \{1,3\} \subset J$.

$$\begin{gathered} t_k^j + M\left(1 - A_{ik}^j\right) \geq t_i^j + s_i^j \\ \forall i,k \neq i \in I, \quad \forall j \in \{1,3\} \subset J \end{gathered} \tag{5.67}$$

$$\begin{gathered} A_{ik}^j + A_{ki}^j + M\left(1 - S_{iod}^j\right) + M\left(1 - S_{kod}^j\right) \geq 1 \\ \forall i,k > i \in I, \quad \forall d \in D, \quad \forall j \in \{1,3\} \subset J, \quad \forall o \in O_d^j \end{gathered} \tag{5.68}$$

$$\begin{gathered} A_{ik}^j + A_{ki}^j - M\left(1 - S_{iod}^j\right) - M\left(1 - S_{kod}^j\right) \leq 1 \\ \forall i,k > i \in I, \quad \forall d \in D, \quad \forall j \in \{1,3\} \subset J, \quad \forall o \in O_d^j \end{gathered} \tag{5.69}$$

As the CSSD Planning Problem is a flow shop, the jobs have to be processed at the stages in a fixed sequence. In other words, first the job has to processed at stage one, then stage two, stage three, and finally stage four. Two separate constraints are required to model the relation between the two different type of stages. Constraints (5.70) and (5.71) assure that for each job, the previous stage has to be finished before a new stage can start. Note that Constraints (5.71) are only introduced for the step between stages two and three, as Constraints (5.57) already ensure that a job cannot be processed at stage one before the release time.

$$t_i^j \geq t_i^{j-1} + \sum_{h\in H^j} \sum_{b\in B^j} p_h^j S_{ibh}^j \quad \forall i \in I, \quad \forall j \in \{2,4\} \subset J \tag{5.70}$$

$$t_i^3 \geq t_i^2 + s_i^3 \quad \forall i \in I \tag{5.71}$$

Constraints (5.72) and (5.73) ensure a job cannot be started before the opening time. Again, there are two constraints for the two types of stages.

$$t_i^j - \sum_{h\in H^j} \sum_{b\in B^j} p_h^j S_{ibh}^j + M\left(1 - Y_{id}^j\right) \geq m_d \quad \forall i \in I, \quad \forall j \in \{2,4\} \subset J, \quad d \in D \tag{5.72}$$

$$t_i^j - s_i^j + M\left(1 - Y_{id}^j\right) \geq m_d \quad \forall i \in I, \quad \forall j \in \{1,3\} \subset J, \quad d \in D \tag{5.73}$$

Constraints (5.74) determine the overtime each day. The overtime depends on the completion time of the last job in a batch at the machines or the last job processed by an operator.

$$q_d \geq t_i^j - n_d - M\left(1 - Y_{id}^j\right) \quad \forall i \in I, \quad \forall j \in J, \quad \forall d \in D \tag{5.74}$$

In addition, the surcharges for working irregular hours have to be taken into account. The formulation is exactly the same as for the two-stage flow shop formulation as described in Chapter 4. More specifically, the formulation can be found in Section 4.1 from Equation (4.36) onwards.

OBJECTIVE

While satisfying all constraints, the objective of the CSSD Planning Problem is to minimize the total costs to obtain the required resources. The total costs is the sum of the machine purchase costs, machine batch costs and employee costs. The first term denotes the machine purchase costs and the second term denotes the machine batch costs. The first two terms are only summed over stages two and four. The third term denotes the employee costs, only summed over stages one and three. The last term denotes the employee costs related to overtime.

$$\min \sum_{h^j\in H^j} \sum_{j\in\{2,4\}\subset J} P_h^j c_{2h}^j + \sum_{b^j\in B^j} \sum_{h^j\in H^j} \sum_{j\in\{2,4\}\subset J} Z_{bh}^j c_{1h}^j + \sum_{j\in\{1,3\}\subset J} \sum_{d\in D} \sum_{r\in R} V_{dr} v_d^j c_{3r} + \sum_{d\in D} q_d c_4 \tag{5.75}$$

5.3.2. LINEARIZATION

In this subsection, the linearization for the two-stage flow shop operational model is proposed. For the four-stage flow shop operational model, the same linearization applies for the constraints regarding the irregular hours from Constraints (5.82) onwards.

There are five non-linear terms in the two-stage model, namely $S^j_{ibh}\left(1-A^j_{id}\right)$, $N_{dp_1}\left(n_d+q_d\right)$, $M_{dp_4}m_d$, $N_{dp_2}\left(n_d+q_d\right)$, and $M_{dp_3}m_d$. In this subsection, a linearization, based on Hammer and Rudeanu [48], is proposed. First, binary decision variables F^j_{ibhd} are introduced, which are equal to one if job $i \in I$ in batch $b \in B$ at machine $h \in H^j$ at stage $j \in J$ is processed on day $d \in D$ and the setup is executed at the same day. Then, the Constraints (5.76), (5.77) and (5.78) are introduced.

$$F^j_{ibhd} \leq S^j_{ibh} \quad \forall i \in I, \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.76}$$

$$F^j_{ibhd} \leq \left(1-A^j_{id}\right) \quad \forall i \in I, \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.77}$$

$$F^j_{ibhd} \geq S^j_{ibh} - A^j_{id} \quad \forall i \in I, \quad \forall b \in B^j, \quad \forall h \in H^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.78}$$

Hence, Constraints (4.29) are transformed to Constraints (5.79), Constraints (4.31) are transformed to Constraints (5.80), and Constraints (4.32) are transformed to Constraints (5.81).

$$t^j_i \geq t^{j-1}_i + \frac{\sum_{k\in I}\sum_{h\in H^j} s^j_k F^j_{kbhd}}{v^j_d} + \sum_{h\in H^j}\sum_{b\in B^j} p^j_h S^j_{ibh} - M\left(1-\sum_{h\in H^j} S^j_{ibh}\right) - M\left(1-Y^j_{id}\right)$$
$$\forall i \in I, \quad \forall b \in B^j, \quad \forall j > 1 \in J, \quad \forall d \in D \tag{5.79}$$

$$t^j_i - \frac{\sum_{k\in I}\sum_{h\in H^j} s^j_k F^j_{kbhd}}{v^j_d} - \sum_{h\in H^j}\sum_{b\in B^j} p^j_h S^j_{ibh} + M\left(1-\sum_{h\in H^j} S^j_{ibh}\right) + M\left(1-Y^j_{id}\right) \geq m_d$$
$$\forall i \in I, \quad \forall b \in B^j, \quad \forall j \in J, \quad \forall d \in D \tag{5.80}$$

$$t^1_i \geq r_i + \sum_{h\in H^1}\sum_{b\in B^1} p^1_h S^1_{ibh} + \frac{\sum_{k\in I}\sum_{h\in H^1} s^1_k F^1_{kbhd}}{v^1_d} - M\left(1-\sum_{h\in H^1} S^1_{ibh}\right) - M\left(1-Y^1_{id}\right)$$
$$\forall i \in I, \quad \forall b \in B^1, \quad \forall d \in D \tag{5.81}$$

Next, to linearize Constraints (4.40), (4.41),(4.43), and (4.44), nonnegative decision variables G_{dp_1} and G_{dp_4} for $d \in \{1,2,3,4,5\} \subset D$, and G_{dp_2} and G_{dp_3} for $d = 6$ are introduced. Considering the bounds $0 \leq n_d + q_d \leq 1440(d+1)$, Constraints (5.82), (5.83), and (5.84) are added, and Constraints (4.40) can be transformed to Constraints (5.85).

$$G_{dp_1} \leq n_d + q_d \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{5.82}$$

$$G_{dp_1} \leq 1440(d+1)N_{dp_1} \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{5.83}$$

$$G_{dp_1} \geq \left(n_d+q_d\right) - 1440(d+1)\left(1-N_{dp_1}\right) \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{5.84}$$

$$W_{dp_1} \geq p_1 - m_d + G_{dp_1} - p_1 N_{dp_1} \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{5.85}$$

Considering the bounds $0 \leq m_d \leq 1440d$, Constraints (5.86), (5.87), and (5.88) are added, and Constraints (4.41) can be transformed to Constraints (5.89). In the same sense, the quadratic terms in Constraints (4.43) and (4.44) are linearized. All necessary constraints to linearize the model can be found in Appendix B.2.

$$G_{dp_4} \leq m_d \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{5.86}$$

$$G_{dp_4} \leq 1440 d M_{dp_4} \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{5.87}$$

$$G_{dp_4} \geq m_d - 1440 d \left(1 - M_{dp_4}\right) \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{5.88}$$

$$W_{dp_4} \geq (n_d + q_d) - p_4 - G_{dp_4} + p_4 M_{dp_4} \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{5.89}$$

5.4. OVERVIEW MODELS

In this section, an overview of the proposed models in this thesis is given, including the model proposed in Chapter 4. In addition, it is indicated which variables can be fixed to focus on capacity planning decisions on one specific hierarchical level. Figure 5.1 presents all models and capacity planning decisions which are included in the model. The three vertical boxes indicate the capacity planning decisions on a strategic, tactical and operational level. The three horizontal boxes indicate the strategic model as described in Section 5.1, the tactical model as described in Section 5.2, and the operational models, which contains both the two-stage as the four-stage flow shop formulation, described in Section 4.1 and Subsection 5.3.1, respectively. As depicted, the strategic model only takes capacity planning decisions on a strategic level into account. The tactical model takes capacity planning decisions on both a strategic and a tactical level into account. The operational models take capacity planning decisions on all levels into accounts. However, for the tactical and operational models, variables can be fixed to only take into account decisions on a tactical or operational level. For both the tactical and the operational models, the number of machines can be fixed. In addition, for the operational models, the acquired machines and the amount of opening time can be fixed. Furthermore, the assignment of jobs to machines can be fixed as well. Note that the results from a model on a higher hierarchical level can be used as input to fix these variables.

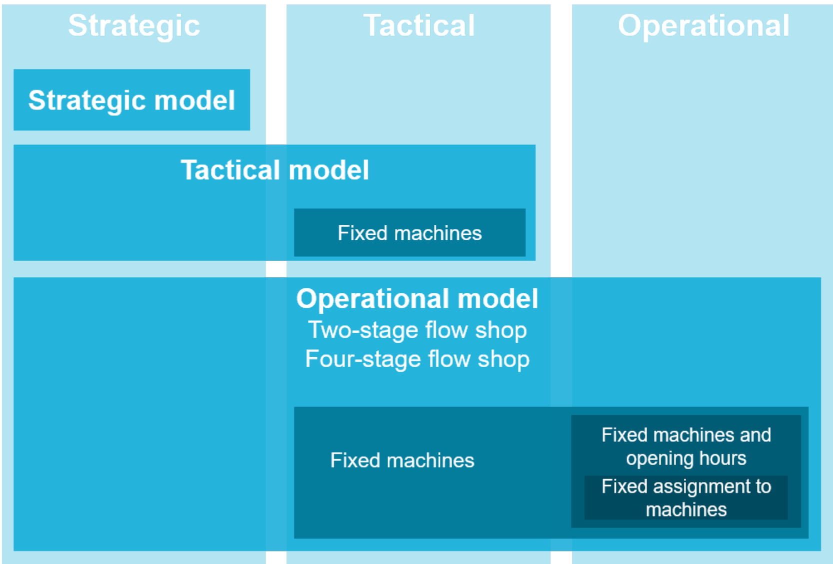


Figure 5.1: Overview of the proposed models.

Corresponding to the hierarchical level of a model, a time unit is used to schedule the jobs. For the strategic model, the considered time unit is days, for the tactical model day parts, and for the operation models minutes.

Given all model information, the following remarks are important to keep in mind:

- Only for the operational model, overtime is taken into account. This overtime is caused by emergency jobs and considerations such as release times on an operational level. Hence on a strategic and tactical level, the amount of opening time should be sufficient, as the aim is to avoid overtime.
- Overtime can only occur at the end of the day. If a job arrives during the night, there are two options: 1) the calculated overtime is very long, 2) the opening time of the CSSD is set very early. During overtime

the number of employees stays the same as during that day, even though, in reality, only two people stay to work in overtime.

- The setup time of a batch in the two-stage model is an approximation of the time that is needed. Instrument sets are not specifically assigned to an employee and the model implies that the process time for one job can be divided over multiple employees. The four-stage model states a better approximated time, as each job is assigned to a operator. Furthermore, the four-stage does not overestimate the batch setup time after opening hours, in between stages, and after the release times as is the case in the two-stage model.

6
Data analysis

In this chapter, a data analysis regarding the CSSD is presented. The aim is to give an impression of the complexity of the CSSD and to enumerate the required input data for the models presented in Chapter 4 and 5. Furthermore, all assumptions made while collecting the data are stated. As input for the models, data regarding the available machines, arriving instrument sets, and employee numbers is required. First, in Section 6.1, the instrument sets that arrive at the CSSD from the OR and the outpatient clinics are quantified. Second, in Section 6.2, the resources that are required to sterilize these instrument sets are enumerated. Lastly, as the operational models are difficult to solve, smaller artificial data sets are required in order to test their performance. Section 6.3 describes the method used to obtain these data sets. This data analysis is based on information from the IT system of the CSSD, T-DOC, the IT system of the OR, HIX, and expert judgement. The considered data from the IT systems is from March 2019 up to and including February 2020.

6.1. Instrument sets

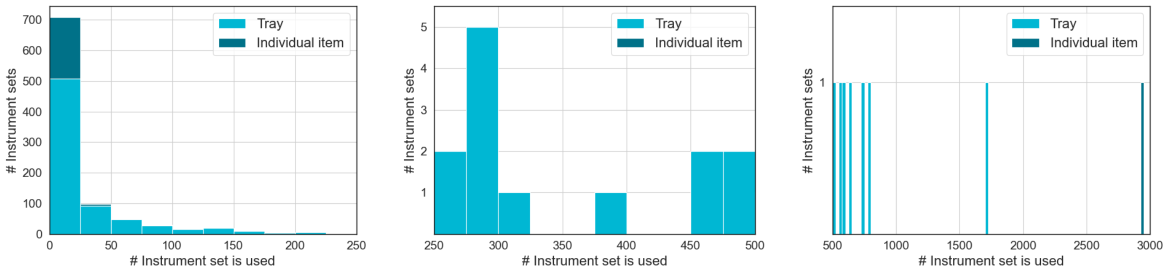
As previously described in Chapter 2, the instrument sets that arrive at the CSSD originate from the OR and the outpatient clinics. Within this thesis, the focus is on scheduling the instrument sets from the OR, as there is more data available and more complex instrument sets have to be sterilized. On the other hand, outpatient clinics are decentralized and fewer and more basic instrument sets are used. Each outpatient clinic has fixed arrangements with the CSSD, which can be reviewed, however, a pull approach is not yet feasible. This section is divided into two subsections. First, in Subsection 6.1.1, the input data from the OR is described, and second, in Subsection 6.1.2, the data of the outpatient clinics is presented.

6.1.1. Operating room

In the considered time period, 965 different instrument sets are used at the OR. From these sets, 469 are used during emergency surgeries, and 496 are only used during scheduled surgeries and never for an emergency surgery. Figure 6.1 presents three histograms of the number of instrument sets which are used a certain number of times, divided into three sub figures to improve the readability. The histograms are divided into occasionally, regularly, and frequently used instrument sets, which corresponds to intervals of 0-250, 250-500, and 500-3000 number of times the instrument set is used. It shows that most instrument sets are used only a few times a year. For example, 318 instrument sets are used a maximum of 5 times during the year. The 'Acute tray' is the most used tray, with a total usage of 1719 times, and the 'Mat Bad' is the most used individual item, with a total usage of 2945 times.

The arrival of instrument sets is partly a stochastic process. It depends on the scheduled surgeries for each week and the occurrence of emergency surgeries. To evaluate the performance of the models for different scenarios, three different instances based on specific weeks in the considered time horizon are created as follows:

- **Week 15, 2019**, is the peak week of the considered time horizon, where 855 instrument sets arrived from the OR.
- **Week 22, 2019**, is a week with a holiday, Ascension Day, on which there are no scheduled surgeries, where 656 instrument sets arrived from the OR.



(a) Occasionally used sets (b) Regularly used sets (c) Frequently used sets

Figure 6.1: Histograms showing the number of instrument sets per number of times an instrument set is used, for occasionally, regularly, and frequently used sets.

- **Week 43, 2019**, is a public school holiday week and the OR schedules only half of the OR blueprint that week, where 547 instrument sets arrived from the OR.

Figure 6.2 shows the number of arriving instrument sets each two hours for the three considered weeks. It clearly shows that week 22 contains a holiday and that the number of arriving sets is significantly lower in week 43 than in week 15. Furthermore, the surgeries during the weekend are mostly emergency surgeries. As the models in this thesis start on Monday morning 00:00 and finish on Sunday night at 00:00, it is crucial to check the beginning and end of each scenario. If an instrument set arrives 5 minutes before midnight on Sunday, this set will be processed on Monday morning. Hence, the instrument set is removed from the scenario as it would immediately lead to an infeasibility as it is not possible to finish the process before the model ends. On the other hand, instrument sets arriving late on the Sunday before the considered week should be added to the scenario on Monday morning.

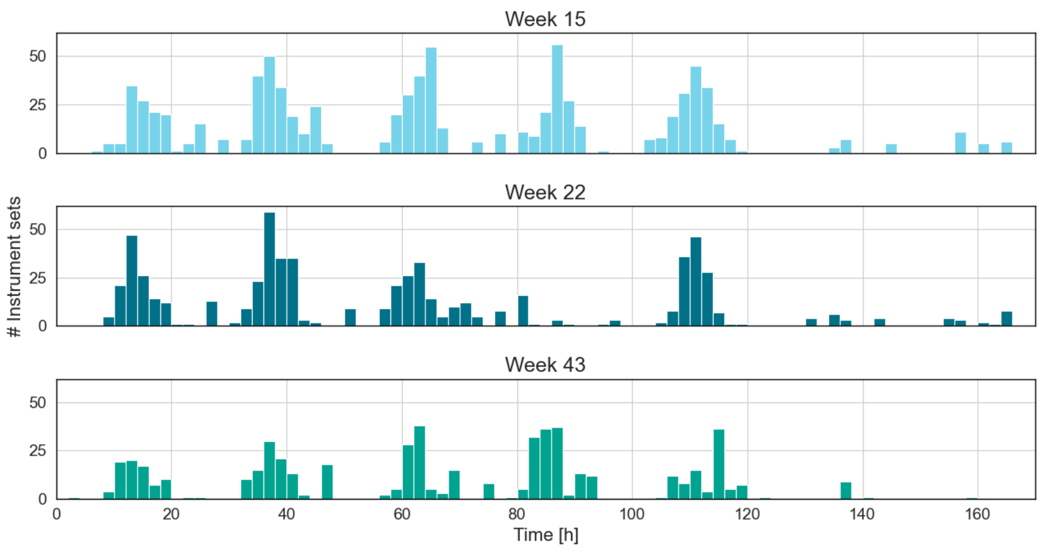


Figure 6.2: Number of arriving sets per interval of two hours, clearly showing the difference in arriving sets per scenario.

Table 6.1 gives an example of the information which is needed as input. For this subsection, the first three rows are of interest in Subsection 6.1.2, the data of the fourth row, regarding the outpatient clinics, is further explained. The data set is built upon the data set of the OR containing which instrument sets are used during a surgery. This data is relevant for the hospital as instrument sets can be backtracked to a specific patient if a contamination is found on a set. The end of a surgery is set as the release time of a job at the CSSD, which is given as the number of minutes passed after Monday morning 00:00. It is assumed that there is no transportation time between the OR and the CSSD.

From the release and lead times stated in Table 6.1, the subsequent times for the strategic and tactical model are derived using a ceiling function. For example, a release time of 956 translates to release day $\lceil \frac{956}{1440} \rceil =$ 1 in the strategic model and release day part $\left\lceil \frac{956}{\frac{1440}{2}} \right\rceil = 2$ within the tactical model. In a similar sense, all release times and lead times can be calculated from the basic data.

Job	Release time [min]	Lead time [min]	Size WD machine [DIN]	Size autoclave [DIN]	Time to clean [min]	Time to assemble [min]
BASIS NET I	956	1056	2	1	3	5
BASIS NET II	956	1200	2	1	3	5
ORTHO-ONCO SET	783	1200	0.25	1	3	5
Outpatient batch 1	2010	700	4	4	7	10

Table 6.1: Overview input data instrument sets from the OR.

An instrument has a size within the WD machines and a size within the autoclaves. The size of an instrument set is measured in DIN trays. A DIN tray is a basket with a surface size of 480 × 250 mm and a height of 100 or 60 mm. As described in Chapter 2, instruments from an instrument set are laid open in multiple baskets within the WD machines. Consequently, the size of an instrument set is larger in the WD machines than in the autoclaves. As there is no data available regarding the size of an instrument set within the WD machines, employees of the CSSD indicated the size of the, approximately, 500 most used instrument sets. For instrument sets for which no indication was given, a size of 1 DIN is assumed. Within the autoclaves, the instrument sets from the OR are already assembled and wrapped. After sterilization, they are ready for transport to the OR. Therefore, the sizes vary less and a size of 1 DIN is assumed for each instrument set originating from the OR. Note, as can be seen in the third row in Table 6.1, it can occur that the size of an instrument set is larger within the autoclaves than within the WD machines.

Before an instrument set is processed by a WD machine or autoclave, a setup process has to be executed, 'manual cleaning' and 'checking and assembling', respectively. The required time depends on the level of complexity of an instrument set. A set containing up to 100 instruments or a complex instrument set, such as the arms of the Da Vinci surgery robot, requires more time than an often used universal basic set consisting of 10 instruments. Moreover, the time to clean an instrument set depends on the extent to which the instrument set is used during a surgery, more specifically, the amount of contamination on the instruments. Finally, the time required varies per employee, depending on their skill and experience. Due to the current working routines, there is limited data available regarding the required time for the setup processes for each instrument set. After monitoring the process, a rough estimate has been made. For each instrument set, the duration of the cleaning setup process is set to 3 minutes and the duration of the assembling setup process is set to 5 minutes. Despite this rough estimate, it is important to take these setup times into account, as the workflow of instrument sets should be manageable for employees as well.

Lastly, for each instrument set, a lead time has to be determined. The release time plus the lead time indicates the time at which an instrument set has to be back in the OR storage. On an operational level, these lead times are based on the current stock level at the OR, the number of sets of a specific type, the scheduled surgeries and the preferred safety stock level at the OR based on the usage of the set during emergency surgeries. Consequently, the lead time can change over time in case an emergency surgery takes place, an additional instrument set is required for a surgery, or if there is more time required for a scheduled surgery due to unforeseen complications. These lead times form the basis for a pull approach workflow, which has not yet been implemented at the LUMC. As the research question of this thesis is a tactical and strategic question, the models only take into account a fixed lead time. Hence, based on the usage over the year and the number of sets, a lead time for each individual instrument set has to be determined. As basis for determining a lead time for each set, the decision tree in Figure 6.3 is used.

Commencing at the start of the tree, it has to be checked whether the available information on the used instrument sets within the CSSD IT tracking system T-DOC is correct. An example of incorrect information is when the name of an instrument set has been changed during the year. To avoid handling all exceptions, a general rule applies if the data from T-DOC is not complete or incorrect. If the instrument set is used more than 20 times during the considered time horizon, the deadline is 1440 minutes, which is the current agreement with the OR. If the instrument set is used less or equal to 20 times, the lead time is 4320 minutes, which is the maximum time allowed when taking into account the restriction that an instrument set has be

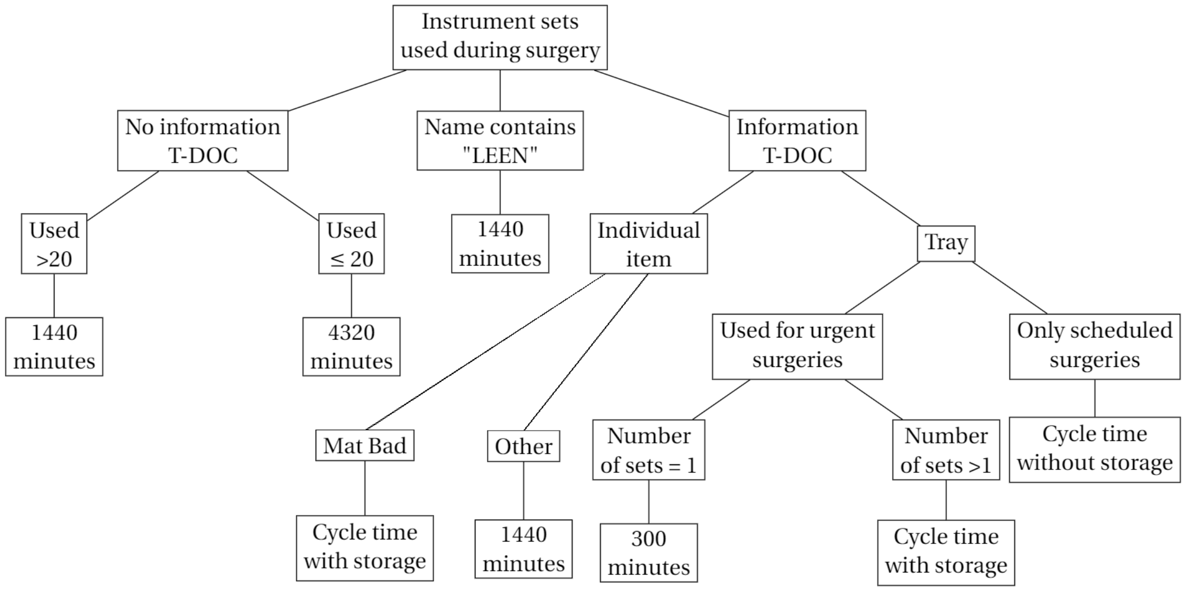


Figure 6.3: Decision tree to determine lead time per instrument set.

disinfected within 24 hours and has to be sterilized 48 hours after disinfection. Regularly, a special instrument set has to be borrowed from another hospital or supplier. Within T-DOC, these instrument sets are stored containing the string ‘LEEN’ within their name. As these instrument sets are brought to hospitals for specific scheduled surgeries, it is likely that they arrive one day ahead. After surgery, these instrument sets have to be returned to the supplier. Hence, the lead time is 1440 minutes. Sets for which information is available within T-DOC are divided into trays and individual items. There is less information available on the individual items as there is often no bar code on the instrument itself and it is often put into a tray after a surgery. Hence, for these instruments, the general rule of 1440 minutes applies. One exception has been made, namely a ‘Mat Bad’ is handled as a tray, since T-DOC contains correct information, each instrument has a unique serial number, and it is the most used instrument.

Lastly, for instrument sets packed in a tray, it is first checked if they are used for an emergency surgery. If the instrument sets are used for emergency surgeries, there has to be a safety stock level at the OR, which could lead to a shorter maximum process time at the CSSD. This specifically holds for instrument sets of which there is only one item available. If the instrument set is used during an emergency surgery and there is only one item, it has to be returned to the OR relatively fast and the lead time is set to 300 minutes (5 hours). The two remaining boxes are ‘Cycle time with storage’ and ‘Cycle time without storage’, which are explained in more detail below.

For instrument sets which are never used for an emergency surgery or which have more than one set available, a cycle time is calculated. The cycle time is a number that is calculated based on the interval times between surgeries and the number of available sets. There are two parts to the calculation. First, the so called number of rotating sets has to be determined. This number is defined as the number of sets which are available to cycle within the surgery schedule.

1. If an instrument set is not used during an emergency surgery, the number of rotating sets is equal to the number of available sets.

2. If the instrument set is used during an emergency surgery, the number of rotating sets is equal to the number of available sets minus the average daily usage of that instrument set. Intuitively, there will be a day of safety stock of the considered instrument set.

The second part consists of calculating the time interval between surgeries which use the same instrument sets. The number of rotating sets calculated above is used in this part.

1. For each instrument set, the start time of each surgery in which the set is used is selected. This results in a list of start times.

2. From the start time list, all time intervals between the number of rotating sets are calculated. An example, in case of 2 rotating sets, is shown in Figure 6.4. As these intervals are taken as lead times, for all executed surgeries there was an instrument set available.

3. As there are different surgery schedules, there is a range of intervals. The most safe option is to take the minimum of these intervals. To avoid taking very small cycle times due to extreme cases, the 5 percentile is taken from the list of intervals.

The calculated cycle time does not take into account practical limits. If the cycle time is smaller than 300 minutes, the lead time is set to 300 minutes. Whenever the cycle time is bigger than 4320 minutes, the lead time is set to 4320 minutes, as this is the maximum process considering the restriction of the sterilization process.

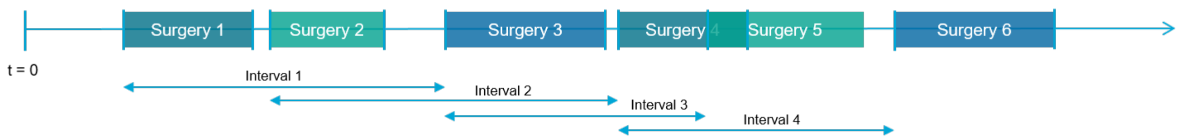


Figure 6.4: Example calculating intervals per instrument set.

As an example, for an 'Acute tray' the following calculation applies. There were 1719 surgeries for which an 'Acute tray' was required, while a total of 27 sets is available, and the set has an average daily usage of 2.3 trays. In addition, as the name already implies, an 'Acute tray' has been used for emergency surgeries. Hence, the time interval between each $\lfloor 27 - 2.3 \rfloor = 24$ surgeries for which an acute basket was required is calculated. From this list, the 5 percentile is taken, which results in a lead time of 4320 minutes.

6.1.2. OUTPATIENT CLINICS

Instrument sets from the outpatient clinics are not individually scanned on arrival at the CSSD and it is difficult to estimate the space required within the WD machines and autoclaves. The last entry in Table 6.1 shows an example of an instrument set batch from the outpatient clinics. There are fixed agreements with each outpatient clinic concerning the lead times. Instrument sets from the outpatient clinics arrive between 17:00 and 18:00 at the CSSD.

The lead time for instrument sets from the 'Ear-Nose-Throat (ENT) and 'Mouth care' outpatient clinics is 13:00 the next day, and for instrument sets arriving from other outpatient clinics, the lead time is 1440 minutes (24 hours). From expert judgement, the number of full WD machines arriving each day is estimated at 12-15 for all outpatient clinics combined. Considering the practical limit of 12 DIN of each WD machine, it is assumed that 150 DIN of instrument sets arrive each day from the outpatient clinics. This number is the same for both the WD machines and the autoclaves. The 150 DIN is split into smaller batches as can be seen in Table 6.1. Again, a rough estimation is made for the setup time, which is consistent for each outpatient clinic batch. The setup time of each batch is set to 7 minutes and 10 minutes for the WD machines and autoclaves, respectively.

6.2. RESOURCES

The required resources to sterilize instrument sets are WD machines, autoclaves, and staff hours. The number of employees available each day is an input parameter and will be discussed in Subsection 6.2.1. The different types of WD machines and autoclaves are described in Subsection 6.2.2.

6.2.1. EMPLOYEES

The total employee costs are based on the salaries, the openings hours of the CSSD, and the amount of overtime within the operational model. The gross salary per month of a CSSD employee at LUMC ranges between €2700- €2900 based on a 36 hours work week. As there are additional costs related to employees, a rough estimate of the salary is €27 per hour.

In addition to normal employee costs, there are allowances for working irregular hours. According to the collective labor agreement (LOAZ [42]) for university medical centers, the following allowances apply for the CSSD of LUMC:

- 47% for hours on weekdays between 00 : 00 and 07 : 00, and after 20 : 00, as well as for hours on Saturday between 00 : 00 and 08 : 00 and after 12 : 00.

- 72% for hours on Sundays or holidays.

The models presented in Chapters 4.1 and 5 only take into account the time in which an employee performs the primary processes, which are ‘manually clean’ and ‘assemble and check’ instrument sets. As part of the process will probably be automated in the future, time which is required for additional processes, such as loading the machines and arranging carts, is not taken into account. Within all models, it is assumed that during weekdays, 2 employees work on cleaning instrument sets and 4 employees work on assembling and checking them. During the weekend, 1 employee works on cleaning the instrument sets and 1 employee works on assembling them.

6.2.2. MACHINES

This section is based on the information retrieved from several suppliers, the report of Adank [1], and expert judgement. The purchase costs regarding machines include the actual machine, pumping system, housing of the machine and corresponding racks costs. Currently, the LUMC has only requested information on the possibilities from different suppliers, however, it is not yet decided which supplier and which specific machines. Hence, it is difficult to compare the exact prices. Consequently, only the general ratio between the different machines and employee costs is taken into account. The main focus is on the differences between machines of different sizes. Table 6.2 shows an overview of the considered types of WD machines and autoclaves.

The current WD machines at the CSSD have a theoretical capacity of 15 DIN and, as stated in Adank [1], cost €98.959 each. Hence, an amount of €106.667 is estimated for a WD machine with a capacity of 16 DIN. The considered machine sizes are all a multiplication of 4, so the increments in size between the machine types is even. Multiple characteristics play a role when estimating prices of smaller machines. The actual price of machines is in proportion with the number of DIN nets that can be processed. However, more smaller machines could take up more space than fewer larger machines and require more maintenance and complementary systems such as pumps. Thus, the price per DIN capacity increases as the machine gets smaller. A factor of 1.1 is used, in other words, for each DIN of capacity within the largest machine, €6.666 is payed, and for each DIN within a size smaller, €6.666 · 1.1 =€7.2600 is payed. On top of the purchase costs, maintenance costs of 15 % of the purchase costs per year are taken into account. For the maintenance costs, there are preventive and corrective maintenance costs. The first is given as a maintenance contract by the supplier and is known in advance. The second applies in case of a malfunction and is unknown in advance. The amounts which are stated in the table are the total sums for a period of 10 years. Considering a depreciation period of 10 years, the weekly depreciation rate is determined. Batch costs are taken into account to ensure no unlimited batches while scheduling the jobs. However, this is subordinate to the choice of machines and amount of opening time, hence a symbolic price is used. This price is scaled to the capacity of the different machines. The current autoclaves at the CSSD have a theoretical capacity of 21 DIN (Adank [1]), and cost €204.411 each. The prices for the different types of autoclaves are calculated in a similar way as for the WD machines.

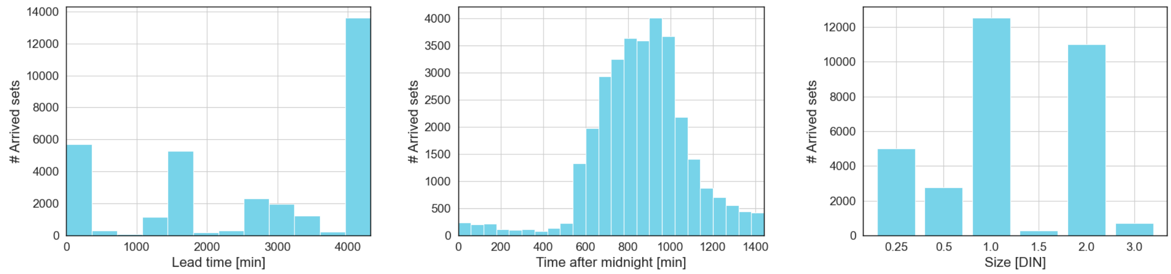
The prices in both tables are presented as if they are accurate, however, this is purely based on estimates and does not fully match real-life.

Set	Machine type	Capacity [DIN]	Process time [min]	Price	Maintenance	Depreciation amount	Batch cost
WD machines	1	8	60	€64.533	€96.800	€307	€5
	2	12	60	€88.000	€132.000	€419	€7.5
	3	16	60	€106.667	€160.000	€507	€10
Autoclaves	1	12	90	€138.286	€207.428	€680	€6
	2	16	90	€167.619	€251.428	€824	€8
	3	20	90	€190.476	€285.714	€936	€10

Table 6.2: Overview machine types

6.3. SMALL INSTANCES

As the operational models are difficult to solve, artificial small data sets are used to test the behaviour of these models. Even though instances based on data of the LUMC are created, the main purpose is to evaluate the performance of the models. These data sets are created using all data of weekdays within the considered time horizon. As the main focus is on scheduling the instrument sets from the OR, instrument sets arriving from the outpatient clinics are not taken into account. Within the models, it does not matter which exact instrument set is processed, as only three characteristics vary: the arrival time, the lead time, and the size within the WD machines. Figure 6.5 shows the distribution for all three characteristics.



(a) Histogram lead times (b) Histogram release times (c) Bar chart sizes within WD machines

Figure 6.5: Graphs showing the distribution of the three main characteristics of instrument sets.

Given the three considered characteristics and their distribution, two methods to create data sets are considered:

- Randomly select values for each of the three characteristics and combine these values to create an arriving instrument set. For this approach, it has to be assumed that the characteristics are independent from each other.
- Considering the release time as the most important characteristic, select arriving instrument sets from the data such that the distribution for the release times is correct. With this method, the combination of release time, lead time and size within the WD machines is preserved.

To check if the three characteristics are depended, three relations have to be checked: 'release time - size', 'lead time - size', and 'release time - lead time'. Figure 6.6 presents a stacked histogram of the arrival times, with each different size indicated by a different color. In Appendix C, Figures C.1 and C.2 present the histogram for each size separately. From the figures, it can be concluded that there are only minor differences between different sizes. For example, for instrument sets of size 0.5 and 1.5 DIN, two peaks during the day instead of one can be seen, and instrument sets of size 1.5 and 3.0 DIN are less likely to arrive during the night. However, there are no significant differences, especially considering that sizes that show the most significant differences are the least common sizes.

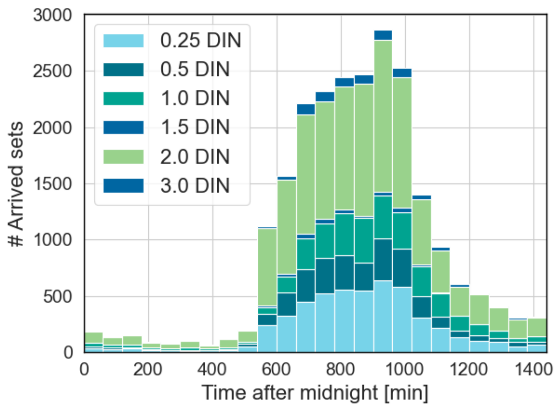


Figure 6.6: Stacked histogram of arrival times and the instrument set sizes in DIN.

Next, Figure 6.7 presents a scatter plot showing the size of an instrument set plotted against the lead time. Here, it is visible that there is a relation between the size of an instrument and the lead time, as only certain combinations occur. For instrument sets with a size of 1.0 DIN, the lead times appears evenly spread, however, for instrument sets of size 0.25, 0.5, 1.5 and 3.0 DIN, only certain lead times occur.

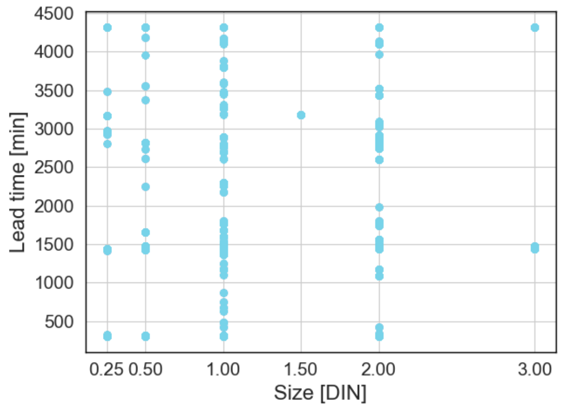


Figure 6.7: Scatter plot of size vs lead time.

Lastly, Figure 6.8 presents the relation between the arrival time and the lead time. Again there are some minor differences, for example, instrument sets with a shorter lead time arrive more in the middle of the day. Additional figures can be found in Appendix C.

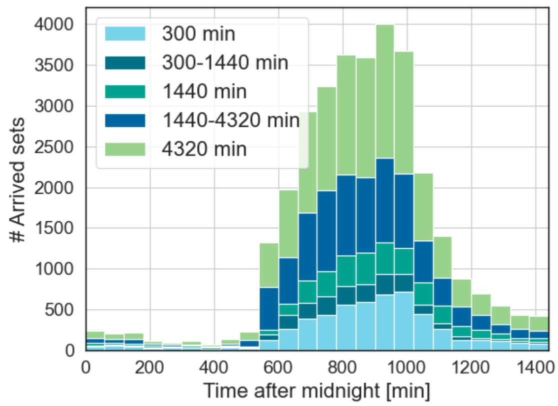


Figure 6.8: Stacked histogram of arrival times and lead time intervals.

From the presented figures, the three characteristics are not independent. Consequently, to create small data sets, arriving instrument sets have to be selected from the data set. The instrument sets which can be selected are those arriving at weekdays between 07:00 and 21:00. First, the percentage of jobs within each hourly time interval is determined. Next, considering the desired number of instrument sets for an instance, the number of instrument sets arriving within each interval is determined using these percentages. Note that in this way the distribution over the day remains the same for all instances of the same size. Next, for each interval, the number of instrument sets is randomly drawn from all arrived instrument sets during that hour on weekdays. After creating the instance, the distribution of the other two characteristics can be checked by creating the histograms as shown in Figure 6.5. It turns out that the instances have similar characteristics compared to the original data. In Appendix C, some additional figures of created instances are presented. There is some variation between the instances based on the sizes and the lead times, however, the main characteristics are preserved.

7

RESULTS

In this chapter, the computational results are presented. The results can be divided into three parts. First, in Section 7.1, the performance of each model is discussed individually. After evaluating the performance of the different models, in Section 7.2, the models are combined in a chain to explore the possibilities to construct an heuristic to obtain practical solutions. In Section 7.3, the solutions are evaluated based on their practical implications. Lastly, in Section 7.4, a concise summary of the findings of this chapter is stated.

All of the following results are obtained from models and algorithms coded in Python 3.6.11 and implemented using PuLP 1.6.8, an open source LP modeller which can call several solvers, including CPLEX and GUROBI, to solve integer linear problems. For this thesis, all problem instances are solved using the commercial CPLEX 12.8 solver. The experiments are run on 'The Distributed ASCI Supercomputer 5' (DAS-5), a six-cluster wide-area distributed system designed by the Advanced School for Computing and Imaging ([49], [50]).

7.1. MODEL PERFORMANCE

The performance of the models is compared considering computation time, solution values, objective function value, and optimality gap. The computation time is measured in ticks, a unit to measure work done in a deterministic way, as stated by IBM [41]. This time scale is chosen in order to compare experiments run on different nodes of DAS-5. Even though instances based on data of the LUMC are used, the main focus of this section is the performance of the models, instead of the practical solutions obtained for the LUMC.

First, the three models, strategic, tactical, and operational, are compared separately, in corresponding order. Each subsection describes the parameters which can be changed in the corresponding model. First, the results of the strategic model are stated. As already described in Chapter 6, both the strategic and tactical model are tested on three scenarios. The aim is to draw conclusions concerning the model performance based on the results of these scenarios. However, they remain unique instances and it can occur that a conclusion based on these results does not hold in general.

To obtain better solutions, after initial experiments, the node logs of CPLEX were studied. A concise overview of CPLEX and its parameter settings can be found in Section 3.2. In addition, for some models and instances, it appeared that memory saving strategies were required to avoid memory errors. While solving a MILP, it often occurs that the node logs and memory tree become very large, as was the case for the experiments run for this thesis. Taking into account that each node on the DAS-5 cluster has a limited default memory, the solution pool parameter and the maximum tree size have been used to limit the memory requirements. The solution pool has been set to zero and the maximum tree size is set to 60.000 MB. As these parameter settings could slightly alter the performance of the solver, it is explicitly stated when these settings are used. Despite these parameter settings, a small number of experiments still resulted in memory errors. For these experiments, the node log is used to evaluate the performance until the error occurred. In case the actual solution is required, after an initial run, the experiment is run again with a higher tolerated relative optimality gap.

7.1.1. STRATEGIC MODEL

Within the strategic model, the parameter γ can influence the performance of the model. This parameter indicates the fraction of time in which the machines can be used. In Table 7.1, the results are shown for different values of γ. Figure 7.1 shows these results graphically. The results are depicted as a line graph to indicate a trend, but can give a fall sense of linearity. This is due to the fact that the experiments are only done for $\gamma = 0.5$, $\gamma = 0.75$, and $\gamma = 1.0$. The deterministic time limit is set to 3×10^7 ticks, which roughly corresponds to a wall-clock time between 12 and 60 hours. Given the resulting optimality gap for all scenarios, it can be concluded that, even though all tactical and operational decisions are eliminated from the model, the problem instances are still difficult to solve. In addition, the model becomes more difficult to solve as γ becomes smaller. A higher value for γ can also be described as a higher price for opening time. Looking at the obtained solutions, it can be seen that for smaller values for γ, more machines are purchased and the opening time decreases. More machines mean there are more scheduling options which can explain the extra difficulty for a smaller γ value. In addition, it appears that especially the lower bound is worse in case of a smaller γ. Assuming that the objective function value becomes larger for a smaller γ, the lower bound only slightly or does not increases for a smaller γ. It can be said that the optimal solution for the instances with a higher value of γ represent a lower bound for the instances with a lower value of γ. Furthermore, from the results, it appears that for higher values of γ, 0.75 and 1.0, the optimality gap is similar for all scenarios. In other words, the number of arriving instrument sets and the distribution over the week does not significantly influence the difficulty of solving the instance. In contrast, for $\gamma = 0.5$, the optimality gap for scenario 'Week 15' is slightly larger than for scenario 'Week 43', and more clearly, the optimality gap for scenario 'Week 22' is much larger. This can be caused by the particular instance or can be connected to the inconsistent distribution of arriving instrument sets during that week.

Instance	γ	Objective function value [€]	Lower bound [€][%]	Optimality gap [%]
	0.5	20199	8910	55.9
Week 15	0.75	16681	8665	48.1
	1.0	14942	9011	39.7
	0.5	28199	7374	73.8
Week 22	0.75	14887	7805	47.6
	1.0	12593	7497	40.5
	0.5	17473	8129	53.5
Week 43	0.75	13809	7258	47.4
	1.0	12175	7312	39.9

Table 7.1: Results strategic model for different values of γ, with a deterministic time limit of 3×10^7 ticks.

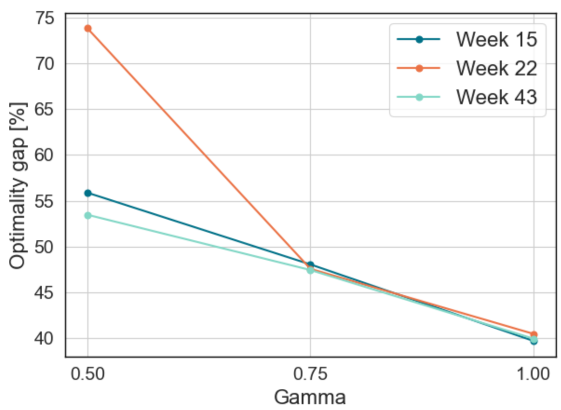


Figure 7.1: Results strategic model for different values of γ, with a deterministic time limit of 3×10^7 ticks.

After the first experiments, the aim is to improve the obtained solution and decrease the optimality gap by parameter tuning. After studying the node logs, the following findings can be listed:

- The best node improves slowly, which might indicate that the best integer solution is a relatively good solution, but that the algorithm has difficulties proving this. Parameters that could influence this behaviour are strong branching, probing and the emphasis of the algorithm.

- The algorithm spends a lot of time on the calculation of the root node. The algorithm quickly calculates the root relaxation, however, spends a lot of time at node 0. This behaviour is worse as the instance is larger or γ is smaller. Although, as stated by IBM [41], the computation at node 0 normally saves time in the overall branch & cut, two parameters can be tuned to decrease the time spent on the computation of node 0. First, the heuristic can be turned off for node 0, and, secondly, a less expensive variable selection strategy can be chosen, for example pseudo reduced costs.

- For some instances, the average node LP iteration count is more than 30%–50% of the root node iteration count. This is known as lack of node throughput (Klotz and Newman [51]) for which there are opportunities to improve solving a node by changing parameter settings. An example is a less expensive variable selection strategy, for example pseudo reduced costs.

The findings stated above sometimes require opposite solution approaches. The parameter settings which are considered are 'Strong branching', 'Probing', 'Aggressive cuts generation', 'Emphasis', 'Heuristic node 0', and 'Pseudo reduced costs'. These parameters are shortly described in Section 3.2. To start, a parameter setting was only implemented for one value of γ. These decisions were based on which instance showed the behaviour, as listed above, the most. The most promising parameters were tested for each value of γ, which are 'Strong branching', 'Probing' and 'Pseudo reduced costs'. In Table D.1, all results for each parameter setting, γ, and scenario are stated. The performance is compared to the default parameter setting of CPLEX. In Figure 7.2, the results are shown graphically. Note, again, the lines represent a trend and there is no proven linearity between the points in the graph. It can be seen that the parameter setting 'Pseudo reduced costs' decreases the optimality gap for almost all of the instances. On the other hand, the performance of the parameter settings 'Strong branching' and 'Probing' differs for the scenarios and values of γ. A parameter setting can be useful for a certain instance, but no general conclusions can be drawn.

Using Table D.1, more precisely, the objective function values and lower bounds, it can be seen that a combination of multiple runs can be useful. For example, scenario 'Week 15' and 'Week 43', with $\gamma = 1.0$, the highest lower bound is obtained using the 'Pseudo reduced costs' parameter, while the lowest objective function value is obtained using the 'Probing' parameter. For scenario 'Week 43', the optimality gap then becomes $\frac{11607-9658}{11607} = 16.8\%$.

Apart from attempting to improve the solution quality by parameter tuning, several experiments are conducted to explore which properties of the instances influence the solution quality. These experiments are only conducted for $\gamma = 1.0$ to show a proof of concept. The following experiments are conducted:

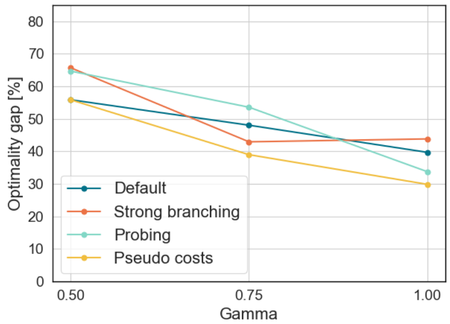
- Adding constraints to restrict the maximum number of jobs at one stage during a day. Although these constraints could eliminate integer feasible solutions from the solution space, it is highly unlikely that more than 300 instrument sets are processed at any of the two stages during one day in an optimal solution. Hence, Constraints (7.1) are added to restrict the maximum number of jobs processed at a stage on one day.

$$\sum_{i \in I} Y_{id}^{j} \leq 300 \quad \forall j \in J, \quad \forall d \in D \tag{7.1}$$

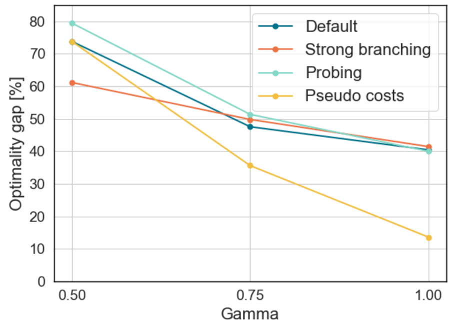
- Decreasing the size of the input machine set, by considering a set of 16 machines instead of a set of 25 machines.

- Shorter or longer lead times, by, for example, setting all lead times above 1440 to 1440 minutes. For the strategic model, this means that all instruments sets have to be processed on the day of arrival or the day after. On the contrary, all lead times can be set to 4320 minutes, the maximum duration at the CSSD for each instrument set.

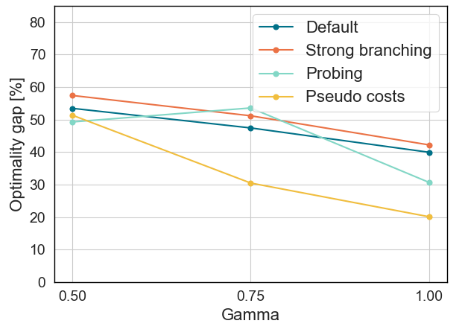
- Adding symmetry breaking constraints, since the model formulation in combination with the set of multiple machines of the same type, leads to a large number of symmetric solutions, which could cause a large computation time (van Essen [52]). For any solution in which two machines of the same type are purchased, an equivalent solution can be constructed by switching jobs processed on the same day between machines. To overcome this, the set T is introduced, which contains all the machine



(a) Week 15



(b) Week 22



(c) Week 43

Figure 7.2: Results strategic model for different CPLEX parameter settings and different values of γ, with a deterministic time limit of 3×10^7 ticks.

types. A subset $H_t^j \subset H^j$ is introduced, which indicates the set of machines at stage $j \in J$ of type $t \in T$. Constraints (7.2) ensure that for each machine type $t \in T$, the number of assigned jobs to a machines $h \in H_t^j$ decreases as the index of the machine increases.

$$\sum_{i \in I} S_{i(h-1)}^j \geq \sum_{i \in I} S_{ih}^j \quad \forall h \in H_t^j, \quad \forall t \in T, \quad \forall j \in J \tag{7.2}$$

Table 7.2 shows the results for each adjustment stated in the column 'Indicator'. It can be concluded that each adjustment decreases the difficulty of the problem as the optimality gap becomes smaller. Hence, a larger input set of machines and long lead times increase the difficulty to solve an instance. The addition of constraints that restrict the number of jobs is a promising option, as this does not change the practical solution and both the optimality gap and the objective function value decrease. Adding symmetry breaking constraints only leads to better results for scenario 'Week 43', however, the effect could increase if more machines of the same type are purchased. This could occur for lower values of γ.

Lastly, fixed opening hours or machines are considered to examine which decisions cause the difficulty in the model. Two fixed settings are chosen, opening time and machine purchases. The fixed variables are based on preliminary results that showed promising behaviour. The opening time is fixed to 360 minutes during week days and 240 minutes during weekend days. The purchased machines are 4 WD machines of 16 DIN capacity, and 4 autoclaves of 20 DIN capacity.

The results of the experiments with fixed variables are shown in Table 7.3. It can be seen that the problem can be solved up to relatively small optimality gaps. Note that the experiment with scenario 'Week 15' was infeasible with the considered fixed opening time. This is probably due to the total time required for the setup processes. It appears that finding the balance between the amount of opening time and the number and type of machines causes the difficulty to solve the model. The purchase of machines appears to be the most difficult choice, based on the slightly larger optimality gaps. Furthermore, it appears that the fixed number of machines is too many as the experiments with a fixed amount of opening time show lower objective function values.

Instance	Indicator	Objective function value [€]	Optimality gap [%]	Lower bound [€]
Week 15	Default	14942	39.7	9011
	Symmetry	14490	38.2	8962
	Restrict jobs	13635	36.6	8650
	Short lead times	14450	39.2	8779
	Long lead times	95864	91.3	8373
	Less machines	13088	28.6	9341
Week 22	Default	12593	40.5	7497
	Symmetry	12836	41.1	7567
	Restrict jobs	12029	39.0	7334
	Short lead times	12073	34.0	7964
	Long lead times	13439	46.3	7223
	Less machines	12094	31.8	8251
Week 43	Default	12175	40.0	7312
	Symmetry	11788	31.3	8089
	Restrict jobs	12293	41.1	7239
	Short lead times	11876	32.5	8013
	Long lead times	12494	47.4	6569
	Less machines	12319	34.6	8056

Table 7.2: Results strategic model for different adjustments as noted in the column 'Indicator', with $\gamma = 1.0$, and a deterministic time limit of 3×10^7 ticks.

Fixed variables	instance	Objective function value [€]	Optimality gap [%]	Lower bound [€]
Machines	Week 15	15255	2.7	14851
	Week 22	13903	0.2	13880
	Week 43	13506	0.1	13495
Opening time	Week 15	*	*	*
	Week 22	13829	2.2	13518
	Week 43	12998	1.2	12848

Table 7.3: Result strategic model with fixed variables determining the purchase of machines and the amount of opening time, with $\gamma = 0.75$, and a deterministic time limit of 3×10^7 ticks.

7.1.2. TACTICAL MODEL

The tactical model is an extension of the strategic model which takes into account day parts instead of full days. Besides γ, the number of day parts can influence the performance of the model. The main difference with the strategic model is the addition of extra constraints regarding opening hours in case the number of day parts is greater than or equal to 3. These constraints ensure that there are continuous opening hours during the day. To evaluate the model performance, each scenario is run with varying values for γ and number of day parts. In Table 7.4, the results for all scenarios are given for a varying values of γ, and in Table 7.5, the results are given for a varying number of day parts. The number of day parts ranges between 2 and 4. In addition, the results for different values of γ are graphically shown in Figure 7.3. Note that the tactical model with only one day part is exactly the same as the strategic model.

As can be seen in Table 7.4, the optimality gaps are large. Again, it appears that an instance is easier to solve as γ increases. However, scenario 'Week 15' shows a small increase in the optimality gap for $\gamma = 1.0$, which makes this statement less conclusive. Furthermore, the objective function values are much higher in comparison to the strategic model. Looking at the obtained solutions, it turns out that the model chooses to purchase all available machines, which leads to a high objective function value. It can be concluded that both the lower bound and the objective function value are not near the optimal solution. Looking at the node logs, the algorithm stays a long time on node 0, and does not iterate over many other nodes. The parameter setting 'Pseudo reduced costs' did not significantly change this behaviour.

Instance	Gamma	Day parts	Objective function value [€]	Lower bound [€]	Optimality gap [%]
	0.5	2	25710	7984	68.9
Week 15	0.75	2	22861	8079	64.7
	1.0	2	23299	8035	65.5
	0.5	2	23789	7003	70.6
Week 22	0.75	2	20447	7018	65.7
	1.0	2	18679	7015	62.4
	0.5	2	19558	6604	66.2
Week 43	0.75	2	17210	6524	62.1
	1.0	2	14127	6756	52.2

Table 7.4: Results tactical model for different values of γ, with 2 day parts, and a deterministic time limit of 3×10^7 ticks.

Instance	Gamma	Day parts	Objective function value [€]	Lower bound [€]	Optimality gap [%]
	0.75	2	22861	8079	64.7
Week 15	0.75	3	26857	12060	55.1
	0.75	4	25422	13830	45.6
	0.75	2	20447	7018	65.7
Week 22	0.75	3	28956	10866	62.5
	0.75	4	28387	15606	45.0
	0.75	2	17210	6524	62.1
Week 43	0.75	3	19558	11732	40.0
	0.75	4	28697	15967	44.4

Table 7.5: Results tactical model for different number of day parts, with $\gamma = 0.75$, and a deterministic time limit of 3×10^7 ticks.

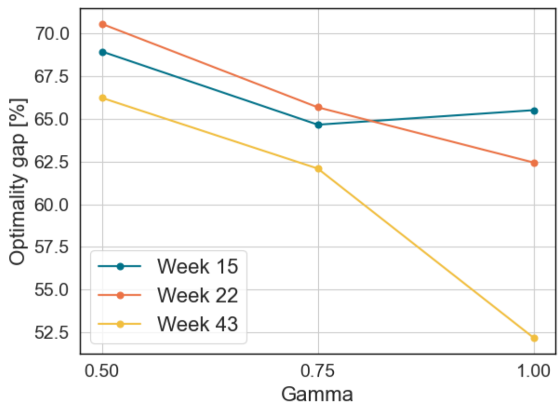


Figure 7.3: Results tactical model for different values for γ, with 2 day parts, and a deterministic time limit of 3×10^7 ticks.

Looking at Table 7.5, surprisingly, the optimality gap become smaller as the number of day parts increases. It was assumed that the problem would become more difficult as more day parts are taken into account. On the other hand, the problem is more restrained in case of more day parts. As can be seen from the results of the strategic model, when the opening hours are fixed, the problem is easier to solve. The additional constraints to ensure continuous opening hours could have similar effects. Taking into account the resemblance to the strategic model and due to time limitations, no further parameter settings or adjustments were tested for the tactical model.

7.1.3. OPERATIONAL MODELS

As already noted in Section 5.3, the operational model is difficult to solve for large instances. In this section, the computational results are shown to support this statement. As the instances of these models are difficult to solve, smaller instances, as described in Section 6.3, are used. The parameters that can influence the difficulty of the model are: model type, number of employees at each stage, the size of the machine set and the number of arriving jobs. The model type corresponds to the two-stage and four-stage flow shop formulation in Section 4.1 and Subsection 5.3.1, respectively. To enhance the readability of the tables, two-stage and four-stage are indicated by '2-stage' and '4-stage'. For the experiments, the size of the machine set is chosen based on the number of arriving sets. An instance with 15 arriving sets will obviously not use more than one machine at each stage. Hence, the machine set is kept very small. The different machines sets are called, 'Small', 'Medium', and 'Big', with 1, 2, and 3 machines of each type, respectively.

Preliminary results showed significant differences between instances with the same number of arriving instrument sets. Consequently, for each number of arriving instrument sets, five different instances were created. Table 7.6 shows a first overview of the results of experiments in which the model type and the number of employees is varied for instances with 15 arriving instrument sets. The column employees states the number of employees at stage 1 and stage 2, respectively.

Model type	Instance	# Employees	Objective function value [€]	Optimality gap [%]	Deterministic time [ticks]
2-stage	1	1,1	702	0	26807
2-stage	1	2,2	1198	0	5288
4-stage	1	1,1	685	0	14539
4-stage	1	2,2	1192	0	23127
2-stage	2	1,1	501	6.6	30063133
2-stage	2	2,2	733	3.6	30149279
4-stage	2	1,1	459	8.4	30155511
4-stage	2	2,2	721	9.0	30006198
2-stage	3	1,1	551	0	4098623
2-stage	3	2,2	871	0	5135913
4-stage	3	1,1	525	1.8	30079568
4-stage	3	2,2	852	1.3	30022109
2-stage	4	1,1	661	0	667232
2-stage	4	2,2	1089	0	553228
4-stage	4	1,1	636	0	482315
4-stage	4	2,2	1074	0.5	30006252
2-stage	5	1,1	647	0	1505111
2-stage	5	2,2	1065	0	53306
4-stage	5	1,1	629	0	54109
4-stage	5	2,2	1060	0	5045918

Table 7.6: Results operational model for different model types and number of employees, with 15 arriving instrument sets, and a deterministic time limit of 3×10^7 ticks.

Based on the results and looking more closely to the instances, the following preliminary conclusions can be drawn:

- There are significant differences between the different instances. For example, instance 1 is quickly solved, while on the contrary, even after running up to 15 hours, instance 2 cannot be solved to optimality. After evaluating the instances, it appears that the occurrence of instrument sets at the start of the day with a short lead time reduces the difficulty of the model. On the other hand, when the arriving instrument sets at the start of the day have a long lead time, the model is difficult to solve, which is the case for instance 2. This makes sense as the possible opening times are more restricted in case of instrument sets with short lead times at the start of the day. Note, the hypothesis is that differences between instances will decrease as the number of arriving sets is higher. In that case, the distribution of the different lead times is more evenly spread.

- In general, the two-stage model appears to perform better than the four-stage model. Looking at the optimality gaps, the results of the two-stage model are better or equal compared to the four-stage model. The number of ticks needed to obtain an optimal solution gives a more nuanced picture. Looking at the instances solved to optimality, in the case of 1 employee at each stage, the four-stage model requires less ticks than the two-stage model. In case of 2 employees at each stage, the opposite is valid. Surprisingly, with the two-stage model, the instances with 2 employees at each stage appear easier to solve than the instances with 1 employee at each stage.

- The differences in objective function values for the model types are relatively small. Consequently, the four-stage model gives a lower objective function value, which makes sense taking into consideration the overestimation of the batch setup time by the two-stage model. It appears that the best integer solution is relatively good for both models, even though there is an optimality gap.

Table D.2 shows the results for larger instances of 15, 25 and 50 arriving instrument sets. The column 'Instance' states the instance, which is written as 'number of arriving instrument sets - instance number'. The column 'Input resources' states the set of machines which is used. As can be seen in the table, for small instances, a set of only 6 machines is used, and for larger instances, a set of 12 machines is used. As most of the larger instances are not solved to optimality, the number of ticks is not shown. Note, all instances with size 25 and up are run with the memory saving parameter setting.

In Figures 7.4 and 7.5, the results are depicted using a scatter plot with a thin line to show the trend. Note that this line has no meaning and is added solely for readability of the graph. The numbers on the x-axis indicate the number of arriving instrument sets and the instance number, 1 to 5. Looking at the results, it can be seen that the earlier statements about the instances of size 15 do not all hold for larger instances.

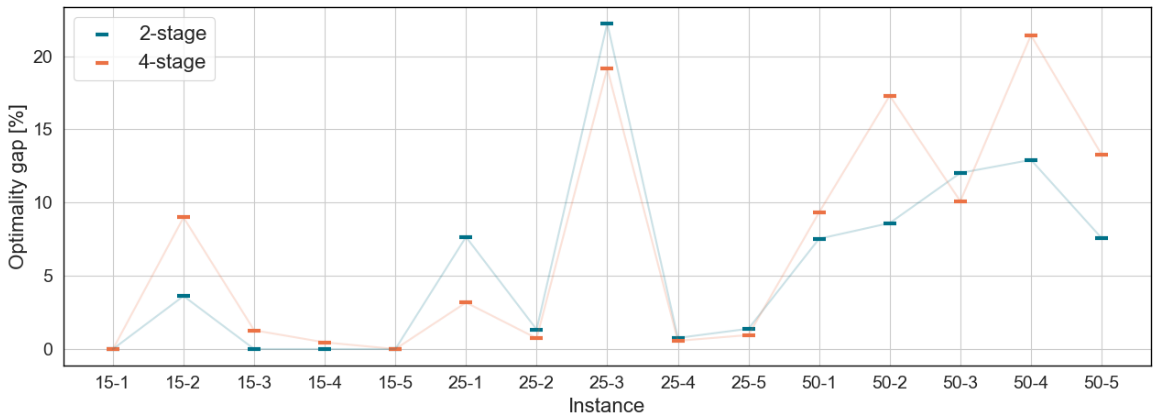


Figure 7.4: Results operational model for different model types and a varying number of arriving instrument sets, with 2 employees at each stage, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting for instances equal or larger than 25.

As can be seen in the figures, the difficulty of the instances increases with the number of arriving instrument sets. The objective function value for both model types remain similar up to instance '50-1', after which the differences get more significant. Considering the optimality gaps, the two-stage model outperforms the four-stage model. However, up to instance '50-1', the four-stage reports a lower objective function value. This is due to the model formulation, but also shows that the quality of the solutions from the four-stage model are quite good despite the often higher optimality gap than the two-stage model. Given the differences in objective function value, there is less certainty about the quality of the best found integer solution for the instances with 50 arriving instrument sets. In general, the two-stage model reports a lower objective function value and optimality gap.

Next, the performance of the models is tested for a period of 3 days to show the assignment of instrument sets to days. In Table D.3, the results are listed for instances with different number of arriving instrument sets. In Figure 7.6, these results are shown graphically. It can be seen that, for the smallest instances, the two-stage model outperforms the four-stage model. However, for instances with a total of 25 arriving instrument sets, the four-stage model consistently outperforms the two-stage model.

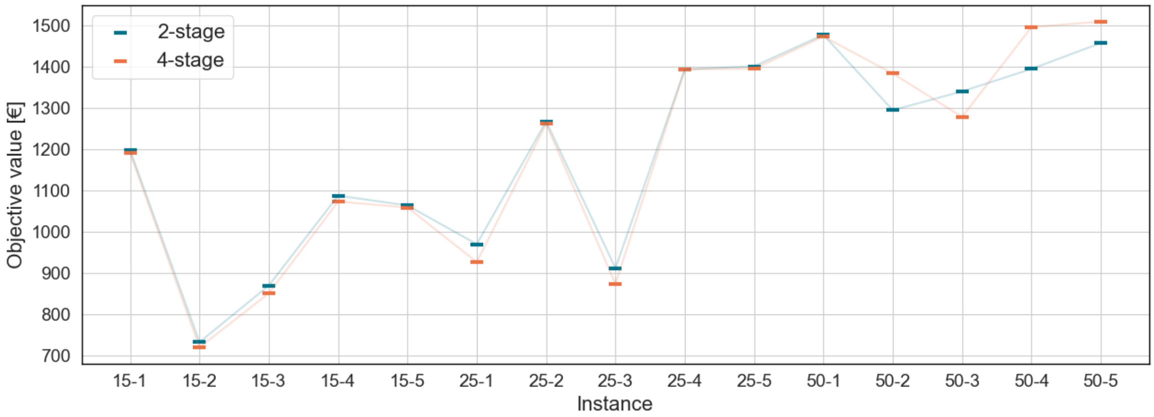


Figure 7.5: Results operational model for different model types and a varying number of arriving instrument sets, with 2 employees at each stage, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting for instances equal or larger than 25.

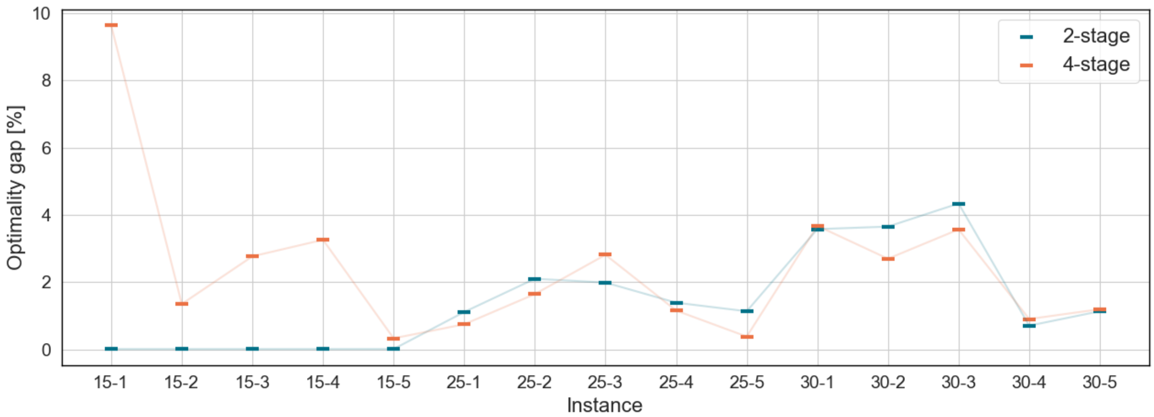


Figure 7.6: Results operational model for different model types and different numbers of arriving instrument sets during three days, with 2 employees at each stage, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting.

Apart from exploring the performance of the models using different instances, some additional options to enhance the performance were tested for several instances. The number of instances for which these options are tested are limited due to time constraints.

- Restrict choice of batch completion time, in the models, the batch completion time can take any value when the batch is not assigned to a machine. Hence, there is a large number of similar solutions. Additional constraints can be added to set batch completion times to zero when they are not assigned to a machine. In this way, these similar solutions are eliminated from the solution space. Constraints (7.3) are added to set the batch completion time to zero in case the batch is not assigned to a machine. The addition of these constraints is tested for instances '50-1' and '50-2'.

$$t_{bh}^{j} \leq M Z_{bh}^{j} \quad \forall b \in B, \quad \forall h \in H^{j}, \quad \forall j \in J \tag{7.3}$$

- After studying the node logs, and based on earlier results, parameter settings 'Pseudo reduced costs' and 'Probing' are used. It appears that the found solutions are quite good, hence, using the parameter setting 'Probing' could provide a better lower bound. On the other hand, the parameter setting 'Pseudo reduced costs' could increase the number of explored nodes in the branch-and-cut algorithm and improve the found solution. The addition of these constraints was tested for instance '50-1'.

In Table 7.7, the results are shown for both instances and the batch time constraints. These results have to be compared with the results in Table D.2. For both instances, the two-stage model performs worse with addition of the batch completion constraints. Both the optimality gap and the objective function value is worse in comparison to the experiments as denoted in Table D.2. For the four-stage model the addition of the constraints appears beneficial. The optimality gap and the objective function value become smaller.

Model type	Instance	Objective function value [€]	Optimality gap [%]	Lower Bound [€]
2-stage	50-1	1523	10.4	1364
4-stage	50-1	1408	5.2	1335
2-stage	50-2	1293	9.3	1172
4-stage	50-2	1279	10.5	1145
2-stage	50-2	1341	12.3	1180

Table 7.7: Results operational model for different model types and instances '50-1' and '50-2', with Constraints (7.3), with 2 employees at each stage, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting.

Model type	Instance	Indicator	Objective function value [€]	Optimality gap [%]	Lower Bound [€]
2-stage	50-1	Probing	1528	17.0	1268
4-stage	50-1	Probing	1536	13.3	1331
2-stage	50-1	Pseudo costs	1478	12.1	1300
4-stage	50-1	Pseudo costs	1444	7.7	1333

Table 7.8: Results operational model for different model types and instance '50-1', with 2 employees at each stage, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting.

In Table 7.8, the results for instance '50-1' with parameter settings 'Pseudo reduced costs' and 'Probing' is shown. These results have to be compared with the results in Table D.2. The parameter setting do not appear to be beneficial. Only the four-stage model with the parameter setting 'Probing' shows a lower objective function value and optimality gap in comparison to the default settings. Further research is required to investigate the influence of these parameter settings.

7.2. HEURISTIC APPROACHES

To improve the solution quality, the possibilities to form a chain of the models are explored. Solutions from one model can be used as input for a model on another hierarchical level. In Section 7.1, the focus was on evaluating the performance of the model, while in this section the actual solutions are discussed. It introduces the possibilities to use a chain of the models with the aim of finding practical solutions. By using a chain and decomposing the problem, the solution will differ from the theoretical optimal value. However, it could save computation time and yield practical solutions. In this section, all experiments are conducted using $\gamma = 0.75$ and 3 day parts for the strategic and tactical model. These parameters are chosen as they resemble real-life and are sufficient to prove the concept of a chain. In future research, additional parameter settings can be tested.

First, the solutions of the strategic model are evaluated as they can act as a starting solution for a chain. Table 7.9 presents a set of three solutions obtained from the experiments conducted in Subsection 7.1.1 with the lowest objective function values. Solution 4 is a manually devised solution, in addition to the solutions obtained from the strategic model. Multiple solutions are considered as the optimality gaps were large and no guarantees about the solution quality can be given. These solutions are from scenario 'Week 15'. The solutions of scenario 'Week 15' are chosen as it is certain that these are feasible for all other scenarios. Moreover, if the solutions of scenario 'Week 22' and 'Week 43' would be used, it is almost certain it would lead to infeasibilities for scenario 'Week 15'.

As can be seen in Table 7.9, the number and type of machines that are purchased fluctuate per solution. It appears that the decision which type of machine has to be purchased is not optimized yet. This can be explained by the large optimality gaps as presented in Section 7.1. By calculating the total capacity [DIN]

Resources	Part	Solution 1	Solution 2	Solution 3	Solution 4
Opening time	Week	400	400	480	-
	Weekend	345	240	480	-
Machines	WD machine (8 DIN)	2	1	1	0
	WD machine (12 DIN)	5	0	0	0
	WD machine (16 DIN)	0	4	4	4
	Autoclave (12 DIN)	0	4	4	0
	Autoclave (16 DIN)	1	1	0	0
	Autoclave (20 DIN)	4	2	2	4
Total capacity [DIN]	WD machines	76	72	72	64
	Autoclaves	96	104	88	80

Table 7.9: Set of best solutions retrieved from the strategic model, scenario 'Week 15' and $\gamma = 0.75$.

of the machines at each stage, the solutions appear more consistent. It can be seen that the second stage requires more capacity, probably due to the longer process time.

Given the results from the strategic problem, the number and type of required machines can be used as input for the tactical model. Table 7.10 shows the results of the tactical model where the number and type of machines is fixed according to the solutions presented in Table 7.9. In Table 7.10, the column 'Indicator' shows which solution is used. In comparison to earlier results, the quality of the solution is significantly better, as the optimality gaps are relatively small. For the larger scenarios; 'Week 15' and 'Week 22', the objective function value decreases and the lower bound increases significantly in comparison to the values stated in Table 7.5. For the smaller scenario, 'Week 43', the decrease in objective function value is less obvious and mostly the lower bound is improved. Furthermore, it can be noted that the amount of opening time only slightly changes given the fixed number and type of machines. It appears that this amount are mainly determined by the spread of release times in combination with short lead times.

Instance	Indicator	Objective function value [€]	Optimality gap [%]	Lower bound [€]	Opening time week [min]	Opening time weekend [min]
Week 15	fixed1 *	21366	1.3	21088	720	720
	fixed2	21825	2.6	21253	720	720
	fixed3	21006	2.5	20477	720	720
	fixed4	19848	0.1	19827	720	720
Week 22	fixed1	19838	0.3	19777	720	260
	fixed2	20345	0.4	20271	720	280
	fixed3	19479	0.1	19451	720	270
	fixed4	18388	0.2	18343	720	290
Week 43	fixed1	19574	0.2	19533	720	250
	fixed2	20058	4.7	19120	720	260
	fixed3	19258	3.3	18627	720	265
	fixed4	18145	0.2	18110	720	280

* Out of memory error, results obtained by setting a higher relative optimality gap

Table 7.10: Solutions tactical model where the number and type of machines is fixed according to the solutions as presented in Table 7.9, for different scenarios, with $\gamma = 0.75$, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting. *Set optimality gap.

After evaluating the first results, the question arises if the solutions can be improved further. Considering the increase in amount of opening time in comparison to the strategic model, the number of fixed machines is likely too high. Hence, it appears that the solutions which are obtained from the experiments with fixed machines can be improved. The solutions of the experiments with indicator 'fixed1' and 'fixed4' have the lowest objective function values, these are selected for further experiments. These solutions are used as a start solution for each scenario. In this case, the number and type of machines are not fixed, but only given as a start solution. By giving a relatively good start solution, the solution search space is decreased. It turns out the objective function value only slightly improves or remains the same and also no better lower bound was found. Even considering parameter settings 'Pseudo reduced costs' and 'Probing' did not help. The results can be found in Table D.4 in the appendix. The column 'Indicator' states which solutions are used as start solution, indicated as 'read1' for 'fixed1', and the parameter setting if applicable.

The main difference between the tactical and strategic model is the resulting amount of opening time. In comparison to reality, the amount of opening time from the strategic problem is very short. Currently, the CSSD is open for 16 hours during week days and 4 hours during weekend days. The amount of opening time which is shown in Table 7.9 are in that sense unrealistic. The opening time is more expensive than the purchase of machines, and thus the strategic model chooses to purchase more machines and limit the amount of opening time. In reality this amount is not feasible due to the inconsistent arrival of instrument sets in combination with short lead times. A higher value for γ can be considered, however, this actually results in a further increase in costs for the amount opening time and thus in a higher number of machines. This hypothesis is confirmed looking at the solutions for lower values of γ. To strengthen this statement, the addition of extra constraints to ensure a minimum amount of opening time is considered. Constraints (7.4) and (7.5) ensure a minimum of 12 opening hours during weekdays, and 6 opening hours during weekend days.

$$o_d \geq 720 \quad \forall d \in \{1,2,3,4,5\} \subset D \tag{7.4}$$

$$o_d \geq 360 \quad \forall d \in \{6,7\} \subset D \tag{7.5}$$

The results for each scenario with these additional constraints can be found in Table 7.11. First, the small optimality gaps have to be denoted. By adding a restriction for the opening time, the instances become easier to solve. These results match with the earlier findings with fixed opening times. To compare the results to the solutions stated in Table 7.9, the sum of the capacity of the WD machines and autoclaves is calculated. The required capacity is almost half of the capacity as stated in Table 7.9, which makes sense, as the amount of opening time is almost doubled. It can be concluded that the addition of the constraints to ensure a minimum amount of opening time are beneficial to obtain a practical solution.

Instance	Objective function value [€]	Optimality gap [%]	Lower bound [€]	Total capacity WD machines [DIN]	Total capacity autoclaves [DIN]
Week 15	16515	5.2	15649	44	48
Week 22	16523	8.6	15097	40	52
Week 43	15088	0.8	14967	32	40

Table 7.11: Result strategic model with a minimum amount of opening time, $\gamma = 0.75$, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting.

To evaluate the results of the strategic model with a minimum amount of opening time, the number and type of machines are used as input for tactical model. Within these experiments, the number and type of machines is, again, determined from scenario 'Week 15'. Hence, the other scenarios are evaluated using this solution. Table 7.12 shows the results for all scenarios with fixed machines based on the results of the strategic problem with a minimum amount of opening time. The small optimality gaps indicate a good solution and objective function value is the smallest of all experiments of the tactical model until now. It appears that the addition of the minimum amount of opening time and the chain structure yields practical solutions.

Instance	Objective function value [€]	Optimality gap [%]	Lower bound [€]	Opening time week [min]	Opening time weekend [min]
Week 15	17928	0.04	17925	720	720
Week 22	16626	0.02	16622	720	360
Week 43	16456	0.0	16456	720	360

Table 7.12: Result tactical model with fixed machines based on the results of 'Week 15' in Table 7.11, for all scenarios, with $\gamma = 0.75$, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting.

To strengthen the conclusions above, figure 7.7 shows a stacked bar chart of the resulting costs for several experiments. In this figure, the results of the strategic model, the strategic model with a minimum amount of opening time, and the tactical model with fixed machines. The first three bars represent the results of the strategic model with pseudo reduced costs. The next three bars represent the results of the strategic model with a minimum amount of opening time. The last three bars represent the results from the tactical model witch fixed machines based on the results from the strategic model, scenario ‘Week 15’ and a minimum amount of opening time. The figure shows that for the strategic model without a minimum amount of opening time, the total costs of machines and the total costs of employee hours are about the same amount. As expected, the model tries to balance these costs. In case of a minimum amount of opening time, the ratio changes and the total costs for employee hours are normative. A similar ratio can be seen for the tactical problem in which the machines are fixed based on the strategic model with a minimum amount of opening time. It can also be seen that the total costs of machines decreases as the amount of opening time increases. The total batch costs remain similar for all experiments. Lastly, the total costs for irregular hours are very small as no irregular hours during week days were required, and only two employees work during the weekend.

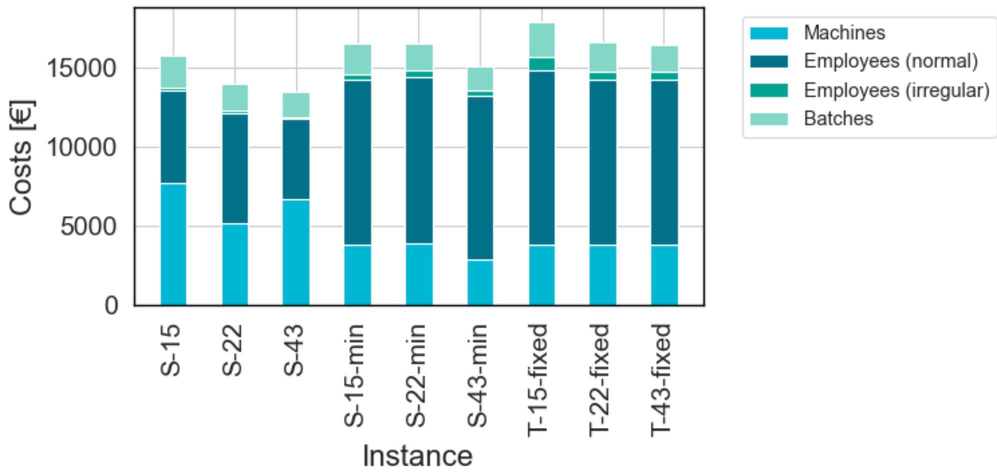


Figure 7.7: Resulting costs from instances as indicated on the x-axis.

Finally, the last step of the chain is the operational models. There are multiple variables within the operational models which can be fixed based on the results of the strategic and tactical model. First, instances with fixed machines and a fixed opening time are tried separately for instances ‘50-1’ and ‘50-2’. Table 7.13 shows the results of these experiments. The column ‘Indicator’ states which set of variables is fixed from the list below. The fixed machines are one WD machine with a capacity of 8 DIN, one autoclave of capacity 12 DIN, and the fixed opening time and closing time is 750 minutes and 1350 minutes for instance ‘50-1’, and 700 minutes and 1350 minutes for instance‘50-2’. These numbers are determined from earlier experiments These times indicate the time after midnight.

- Fixed 1: fixed machines and fixed opening and closing time
- Fixed 2: fixed machines
- Fixed 3: fixed opening and closing time

The results show that for the operational models, the case in which the the opening and closing time have to be determined is the most difficult. In all cases the instances with the indicator ‘fixed2’, the optimality gaps are large. Furthermore, the case in which the opening and closing time are fixed, the model provides a good solution and the lowest optimality gaps. These results show that the operational model can be used in a chain with a fixed opening and closing time, and fixed machines according to the results of the strategic and tactical model. The operational models can serve as verification of the scheduling of the instrument sets by the strategic and tactical model.

As a proof of concept, three day parts of a solved tactical instance are considered. Based on each day part, a new instance is created. The results of scenario ‘Week 22’ are used, as at the time, this instance yielded the best results. To avoid the start of the model, day parts 4, 5, and 6 (Tuesday) are considered.

The selected instrument sets for each instance, are the instrument sets assigned to that day part by the tactical model. As the two stages can be processed during different day parts, not all instrument sets have to

Model type	Instance	Indicator	Objective function value [€]	Optimality gap [%]	Lower bound [€]
2-stage	50-1	default	1478	7.5	1367
2-stage	50-1	fixed 1	1509	0.9	1496
2-stage	50-1	fixed 2	1464	6.6	1367
2-stage	50-1	fixed 3	1509	0.9	1496
4-stage	50-1	default	1474	9.3	1341
4-stage	50-1	fixed 1	1503	0.5	1495
4-stage	50-1	fixed 2	1435	4.7	1367
4-stage	50-1	fixed 3	1502	2.9	1460
2-stage	50-2	default	1296	8.6	1185
2-stage	50-2	fixed 1	1421	0.9	1408
2-stage	50-2	fixed 2	1414	16.3	1184
2-stage	50-2	fixed 3	1419	0.8	1408
4-stage	50-2	default	1384	17.3	1144
4-stage	50-2	fixed 1	1418	0.7	1408
4-stage	50-2	fixed 2	1376	14.0	1184
4-stage	50-2	fixed 3	1529	9.1	1390

Table 7.13: Results operational model for different model types, instances '50-1' and '50-2', with fixed variables, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting.

be processed on both staged during the considered day part. As the model as proposed in Chapter 4.1 does not take this possibility into account, the data is slightly altered. When an instrument set is only processed at the first stage, the size at the second stage is set to zero. When an instrument set is only processed at the second stage, the size at the first stage is set to zero. As the instrument sets for which these modifications are required do not represent outliers in terms of release time, this choice appears to be reasonable. In Table 7.14, the results are shown. The first three columns indicate the day part, the times of that day part, and the considered opening and closing time obtained from the tactical model. The third column indicates the number of instrument sets that have to be processed at each stage. Instrument sets that have to be processed on both stages are also summed individually to obtain these results. The results are the overtime and the optimality gap. The optimality gap is small considering the number of instrument sets within each instance. Note that the first day part is infeasible due to an instrument set arriving in the night, which has to be sterilized within 6 hours. The second and third day part are feasible, however show the occurrence of overtime due to instrument sets arriving just before the end of a day part.

Based on the small optimality gaps it can be concluded that the operational model can be used as a verification. However, the model should be altered to enable jobs which only have to be processed at one stage, and a workaround for jobs arriving just before the end of a day part has to be found.

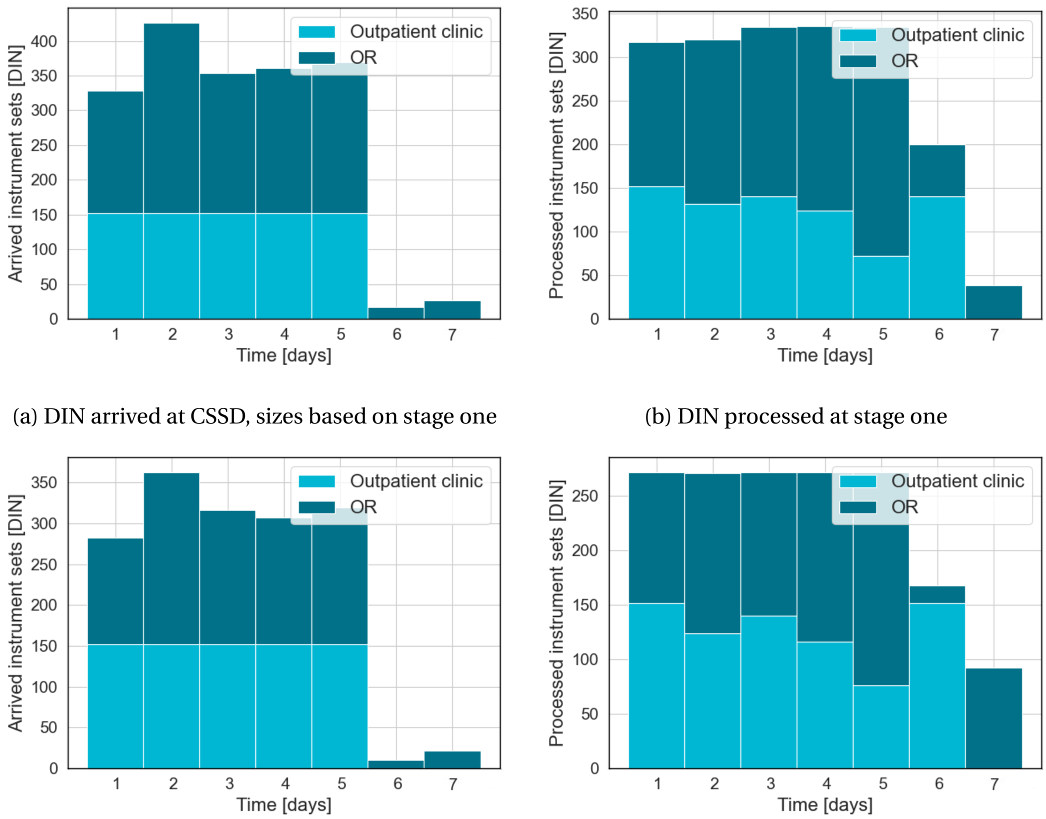
Day part	Time	Opening - closing time	# assigned instrument sets stage 1	# assigned instrument sets stage 2	Over time [min]	Optimality gap [%]
1	00:00 - 08:00	06:00 - 08:00	48	27	*	*
2	08:00 - 16:00	08:00 - 16:00	115	73	149.25	3.5
3	16:00 - 00:00	16:00 - 18:00	36	47	166	2.6

* Infeasible

Table 7.14: Results operational model with fixed instrument assignment, and a deterministic time limit of 3×107ticks, and memory save parameter setting.

7.3. SOLUTION CHARACTERISTICS

In addition to the analysis of the solutions based on the variables which directly impact the objective function value, in this section, the actual scheduling of instrument sets is considered. The aim is to show the number of instrument sets which are assigned to days or day parts. The results are shown for scenario 'Week 15'. As an instrument set has different sizes at stages one and two, the arrival data is plotted for both sizes. The sizes are indicated in terms of DIN baskets. First, the results from the strategic model are presented. Figures 7.8a and 7.8b show the number of DIN baskets arriving each day, and the number of DIN baskets processed, at stage one. Figures 7.8c and 7.8d show the number of DIN baskets arriving each day, and the number of DIN baskets processed, at stage two. The figures show that the instrument sets are evenly processed over the week. A significant number of the instrument sets are processed on Saturday. The number of instrument sets originating from the outpatient clinics is especially noticeable. This can be explained by the fact that there are only two employees present at the CSSD on Saturday, and the setup time for instrument sets from the outpatient clinics is less than for instrument sets originating from the OR.



(a) DIN arrived at CSSD, sizes based on stage one

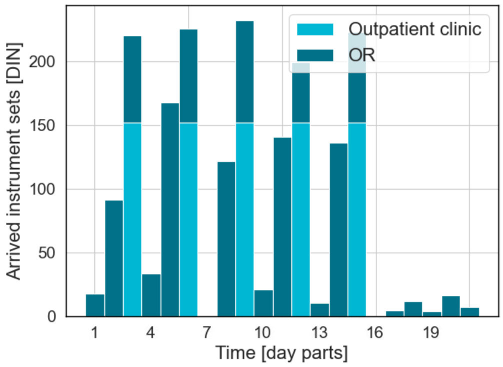
(b) DIN processed at stage one

(c) DIN arrived at CSSD, size based on stage two

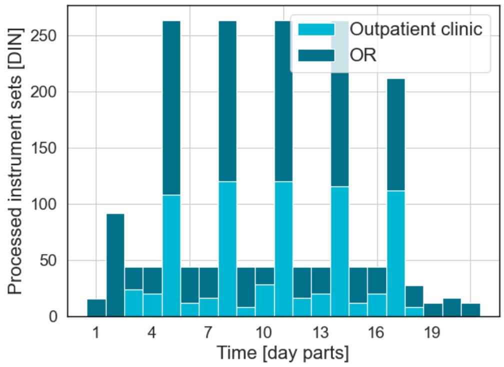
(d) DIN processed at stage two

Figure 7.8: Results from the strategic model, scheduling of instrument sets over days, for stages one and two.

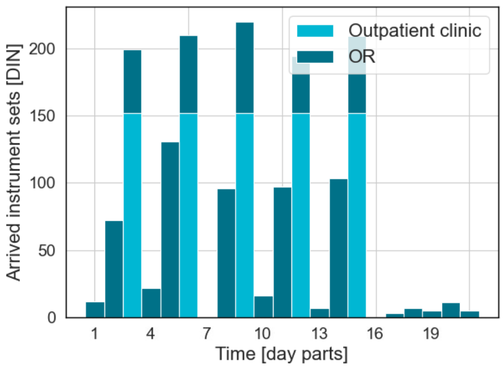
Second, to look more closely into the required amount of opening time, the solutions of the tactical model are presented. Figures 7.9a and 7.9b show the number of DIN baskets arriving each day and the number of DIN baskets processed, at stage one. Figures 7.9c and 7.9d show the same metrics at stage two. The figures show that most of the instrument sets are processed during regular hours on week days. Note that the figures show a low number of instrument sets processed on Monday. This can be explained by the fact that most of the instrument sets arrive during the afternoon and evening. Hence, according to the tactical model, these cannot be processed on Monday. Here the tactical model shows the added characteristic of release times in comparison to the strategic model.



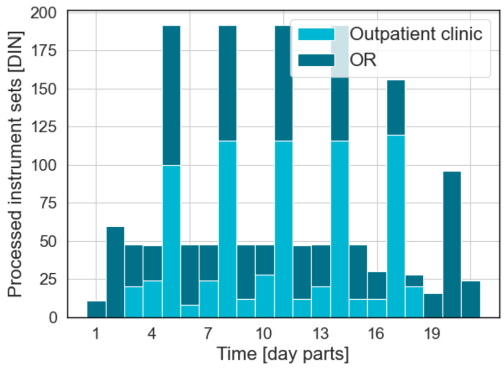
(a) DIN arrived at CSSD, sizes based on stage one



(b) DIN processed at stage one



(c) DIN arrived at CSSD, size based on stage two



(d) DIN processed at stage two

Figure 7.9: Results from the tactical model, scheduling of instrument sets over days, for stages one and two.

7.4. SUMMARY

In this chapter, the results of all the conducted experiments are enumerated. It has been concluded that the branch-and-cut algorithm of CPLEX is not efficient for the models without any restrictions or fixed variables. However, if restrictions are added or a chain is formed, the branch-and-cut algorithm can be used. The main findings for each model level are:

- For the strategic model, the parameter setting 'Pseudo reduced costs', restricting the number of processed instrument sets each day at any stage, and decreasing the size of the machine set provide the largest decrease in optimality gap. The model proves to more difficult to solve for a lower value of γ.
- The tactical model becomes more difficult to solve for lower values of γ and a lower number of day parts.
- The operational model can only be solved for small instances. The performance varies for different instances based on the combination of release times and lead times. The four-stage model provides a more accurate and lower objective function value, however, it is, in comparison to the two-stage model, more difficult to solve for instances of one day. On the other hand, the four-stage appears to be better suited for instances of multiple days. By adding constraints to restrict the batch completion time, the performance of the four-stage model improves.

The balance between the amount of opening time and the number of machines appears to cause the computational complexity of the models. All models show significantly better results when the amount of opening time or the number of machines are fixed. Furthermore, the number and type of machines appear to be a more difficult to determine than the amount of opening time. The results of the models with fixed variables and the construction of a chain of models show promising results. The best results for practical application were obtained by setting a minimum amount of opening time in the strategic model, and using the resulting machines in the tactical model. The results show that the processing of instrument sets is spread over the week. The operational models are not suitable yet to implement in a chain structure.

As there is a large amount of parameter settings, model configurations, and possibilities to create an heuristic approach, only part of the options are explored. Based on the current conducted experiments, the following remarks can be considered for future research:

- Test the models and the proposed chain of models for more scenarios. Currently, the conclusions are based on the performance of three scenarios. These scenarios are chosen to represent a range of options. However, more experiments are required to evaluate whether these conclusions can be generalized.
- The numbers of machines is a rigid capacity, hence, it has to be the same for all scenarios. Currently, only a fixed number of machines, based on the results of 'Week 15' is considered. In future research, the required number of machines has to be evaluated for different scenarios, as it should be the optimal number of machines for all scenarios, and not only for scenario 'Week 15'.
- Combinations of parameter settings and restriction, or another structure to form a chain of models might be efficient.
- The big-M term can lead to weak lower bounds. CPLEX recommends to implement indicator constraints obtain more numerically robust and accurate solutions. This option can be explored for the operational models.

8

Conclusion

In this chapter, the conclusions from this thesis are discussed in Section 8.1. Furthermore, the main research question: *'How can the number of required resources for a sterilization process within a hospital be quantified?'*, is answered. In Section 8.2, the obtained results and the limitations of this thesis are discussed. Finally, in Section 8.3, recommendations for the LUMC and suggestions for future research are stated.

8.1. Conclusions

The objective of this thesis is to quantify the required resources for the sterilization of instrument sets at a CSSD within a hospital. The CSSD at the LUMC acts as a case study. To determine the required resources, an optimization problem is defined and formally introduced. To solve real-life size instances, a decomposition of the model, based on the three hierarchical capacity planning decision levels, strategic, tactical, and operational, is proposed.

In Chapter 2, the position of the CSSD within the hospital and the main steps of the process are described. In addition, a framework is proposed to identify the capacity planning decisions on the three hierarchical levels. The CSSD can be characterized by highly specialized manual labor and two stages of batching machines. In Chapter 3, a concise literature study regarding the CSSD is presented. This thesis contributes to current research by proposing a framework for the capacity planning decisions at a CSSD, by extending existing models by taking specific characteristics of the CSSD into account, and considering a new objective function, namely minimizing the total costs. In Chapter 4, the problem is formally introduced as a two-stage flow shop with setup processes, which is proven to be NP-hard. In Chapter 5, a reformulation of this problem is proposed by decomposing the capacity planning decisions on a strategic, tactical, and operational level. The demand for sterile instrument sets by the outpatient clinics and the OR is determined using historical data from the LUMC and expert judgement. In Chapter 6, all required data and assumptions made to obtain this data are enumerated. The main focus is on scheduling the instrument sets arriving from the OR, for which a method to calculate the lead time per instrument set is proposed. Finally, Chapter 7 presents the results of all conducted experiments. First, the individual model performance is discussed, where after heuristic approaches are explored by creating a chain of the models. It can be concluded that the difficulty of the strategic and tactical model are mainly caused by the trade-off between the number of machines and amount of opening time. When the number of machines or amount of opening time is restricted, practical solutions can be obtained. Hence, the heuristic approach to create a chain of the models is a promising method which can be further investigated in future research. The operational models can be used to verify the results from the strategic and tactical model, and evaluate the feasibility of a daily schedule. Although the two-stage and four-stage formulations show small differences in objective function value, both can be used for these purposes. Currently, this application is not implemented yet, as some alterations in the models are required.

By combining the findings of these chapters, the main research question can be answered. The models presented in this thesis are capable of providing insights into the required resources at the CSSD. These insights concern the total required machine capacity at each stage and the amount of opening time during week and weekend days. Based on the computational complexity of the individual models, on of the two important variables, the amount of opening time and the number of machines, have to be restricted to obtain practical solutions. To determine these restrictions, a chain of models is required. The most promising method is a chain of the strategic model with a minimum amount of opening time, where after the resulting number of machines is used as input for the tactical model. The strategic model is required to determine the number of machines and the tactical model ensures that the spread of release times of instrument sets is taken into account. Together, a total required capacity of machines at each stage and the amount of opening time can be determined. The type of machines is not yet determined, as characteristics on an operational level also have to be taken into account. The operational models are capable of solving small instances. However, further research is required to obtain practical solutions, and implement the operational models as part of a chain. The results show that the costs to sterilize all instrument sets are mainly determined by the amount of opening time, which is the most expensive resource. The amount of opening time is determined by the spread of arrival times of instrument sets. Ensuring an evenly distributed workload and providing a lead time per instrument set can reduce the amount of opening time. However, the arrival of instrument sets during irregular hours with short lead times prevents a further decrease in the amount of opening time.

The results of this thesis contribute to quantifying the required resources for a sterilization process within a hospital. However, to obtain more practical results, future research research is required. In the next sections, a discussion about the limitations of this thesis and recommendations are presented.

8.2. Discussion

While conducting this research, several assumptions, which could influence the performance of the models and the obtained results, were made. Below, the assumptions that have, presumably, the most impact are discussed.

The price of the machines is determined based on a combination of the price of the current machines, information requested from suppliers, and maintenance costs. Based on the information of the suppliers, there are machines of numerous different sizes. As the exact prices were not known, in this thesis, an assumed ratio between the price per DIN of capacity for smaller machines in comparison to larger machines is used. Even if the exact prices per machine were known, some additional remarks have to be made. Indeed, multiple smaller machines could require more space than one larger machine. In addition, multiple smaller machines can require more resources such as pumps or racks. Both characteristics result in an higher cost. However, it is currently not possible to quantify the increase in cost per DIN of capacity. Before deciding upon the purchase of new machines, this has to be further investigated.

The reduction of peak workloads is based on the calculated lead times per instrument set. It appears that a significant amount of the instrument sets do not have to be returned to the OR the next day, which is currentlyreflected in the lead times. Hence, the workload can be spread more evenly over the week. The lead times are calculated using the number of items of each instrument set. However, the tray composition, which includes the number of items, has not yet been optimized. It is possible that, currently, more items are available than actually required to meet the demand of the OR. In that case, the lead time is equal to the maximum duration at the CSSD. Whenever the tray composition is changed, the lead times should be reconsidered.

Overtime is only taken into account within the operational models. The LUMC indicates it wants to minimize the overtime to improve employee satisfaction. However, solely based from cost perspective, overtime is not made more expensive or restricted in number. From a practical point of view, it is clear that overtime is not desired. Hence, it should be determined to what extent the overtime should be penalized.

The tactical and strategic model have a planning horizon of one week. Since the start of the models is at the end of the weekend, the practical implication will be limited. However, it has to be noted that there will be inconsistencies at the start and the end of the planning horizon of the model. On Monday, the CSSD is empty, while in reality, instrument sets which still have to be processed from the previous day could be present. Furthermore, within the models, all instrument sets arriving on Sunday are processed the same day. In fact, these instrument sets could also be processed at the start of the following week. A rolling time horizon could be considered to overcome these problems.

As already noted, the amount of opening time represents a large portion of the total costs. From the solutions of the strategic problem, it can be concluded that opening the CSSD for 6 hours in combinations with more machines, appears more cost-efficient than longer opening hours with fewer machine. However, this short opening time is in practice not feasible, and additional constraints regarding the opening time have to be taken into account. The tactical model with 3 day parts results in more opening time, but no major differences were noticed for different scenarios. Hence, there is little room to optimize the amount of opening time due to these restrictions and the ratio of costs between machines and opening hours. This problem can be partly solved by the addition of parameter γ. However, this parameter implicitly makes increasing the opening time even more expensive in comparison to the machines. Furthermore, the cost of opening time is determined by the number of employees during that day. Hence, the cost ratio between the machine purchase and the amount of opening time can significantly change when less employees are scheduled.

8.3. RECOMMENDATIONS

The recommendations are divided into two parts. First, the recommendations for the LUMC are stated, and second, suggestions for future research are discussed.

RECOMMENDATIONS LUMC

- The results show that instrument sets that arrive during weekdays are mainly processed on weekdays and Saturday. To spread the workload, instrument sets that arrive on Friday afternoon and evening are processed on Saturday. Looking at the results from the tactical model and the costs of opening hours on Saturday, it is recommended to open the CSSD on Saturday morning between 08:00 and 12:00. The results are not conclusive about the total amount of opening time on Saturday, hence, these opening hours are a minimum and additional opening hours after 12:00 could be required. On the other hand, employees can be reluctant to work on Saturday and it is important the the practical feasibility is properly evaluated.

- While optimizing the required resources, the tray composition should be reviewed. The lead time is determined using the number of items of each instrument set. In case the lead time of instrument sets decreases, the peak and low demand will increase and more resources are required to process these fluctuations in demand.

- The willingness to avoid working during overtime needs to be quantified. Currently, solely based on the cost perspective, overtime is not more expensive or restricted. However, in practice, the hospital indicates it wants to minimize the overtime to improve employee satisfaction.

- Instrument sets from the outpatient clinics represent a large portion of the arriving instrument sets expressed in DIN trays. Currently, the focus is on scheduling the instrument sets originating from the OR. It can be beneficial to review the agreements concerning the lead times with the outpatient clinics as well.

SUGGESTIONS FOR FUTURE RESEARCH

- The implementation of a metaheuristic or hybrid algorithm needs to be investigated. Based on Chapter 3, it can be concluded that the most promising solution methods to solve a multi-stage flow shop are metaheuristics and hybrid algorithms. By improving the performance of the operational models, more operational characteristics of the CSSD can be taken into account.

- Extent the operational models to take the current stock level at the OR into account. Currently, fixed lead times per instrument set are used. By adding the stock level at the OR storage to the model, more realistic lead times based on the stock level can be determined. Note that the lead times will vary over time as the stock at the OR storage changes.

- As the amount of opening time is mainly defined by the arrival time of instrument sets in combination with their lead time, there are limited opportunities to optimize or decrease the amount of opening time and the corresponding costs. In case of a fixed amount of opening time, the number of employees on different parts of a day can vary in order to decrease the costs. A future research topic could be to determine working shifts at the CSSD, the number of shifts during a week, the start and finish time of each shift, or the number of employees during a shift.

- Taking uncertainties of processes within a hospital into account. Processes within a hospital have a non-deterministic behavior, for a CSSD, uncertain processes or events include: emergency surgeries or surgeries which require additional instrument sets, the failure of machines, and the uncertain time requirements of the manual setup processes. Furthermore, the greater the variability in a system, the greater the capacity required to meet a given service standard (Hall [37]). In this thesis, the model properties and some initial solution approaches are explored, so the next step is to incorporate these uncertainties.

Bibliography

[1] M. W. Adank, *Meerjarenplan Centrale Sterilisatie Dienst Leids Universitair Medisch Centrum*, Tech. Rep. (TU Delft, LUMC, 2016).

[2] J. van de Klundert, P. Muls, and M. Schadd, *Optimizing sterilization logistics in hospitals,* Health Care Management Science **11**, 23 (2008).

[3] A. Saif and S. Elhedhli, *Sterilization network design,* EURO Journal on Transportation and Logistics **8**, 91 (2019).

[4] A. Rossi, A. Puppato, and M. Lanzetta, *Heuristics for scheduling a two-stage hybrid flow shop with parallel batching machines: Application at a hospital sterilisation plant,* International Journal of Production Research **51**, 2363 (2013).

[5] A. G. Leeftink, R. J. Boucherie, E. W. Hans, M. A. Verdaasdonk, I. M. Vliegen, and P. J. van Diest, *Batch scheduling in the histopathology laboratory,* Flexible Services and Manufacturing Journal **30**, 171 (2018).

[6] P. J. Hulshof, N. Kortbeek, R. J. Boucherie, E. W. Hans, and P. J. Bakker, *Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS,* Health Systems **1**, 129 (2012).

[7] E. Keseler, *The Hospital Logistics of Designing the Central Sterile Processing Department - From the inside and out*, Tech. Rep. June (2019).

[8] M. van Blijswijk, *Improving the efficiency of the delivery of surgical instruments at the Leiden University Medical Center*, Ph.D. thesis, TU Delft (2015).

[9] W. M. P. van der Aalst, *Process mining : discovery, conformance and enhancement of business processes* (Springer Berlin Heidelberg, 2011).

[10] C. Combi, B. Oliboni, A. Zardini, and F. Zerbato, *Seamless Design of Decision-Intensive Care Pathways,* in *Proceedings - 2016 IEEE International Conference on Healthcare Informatics, ICHI 2016* (Institute of Electrical and Electronics Engineers Inc., 2016) pp. 35–45.

[11] BPM Platform for Process Modeling - Signavio Process Manager, *https://www.signavio.com/products/process-manager/* (2020).

[12] Medische Automatisering - Boikon B.V., *https://www.boikon.nl/technologieen/medische-automatisering/* (2020).

[13] T. Schneider, *Integral Capacity Management & Planning in Hospitals*, Ph.D. thesis, University of Twente, Enschede, The Netherlands (2020).

[14] V. p. PG-16, *VCCN richtlijn 11 Centrale Sterilisatie Afdeling - Richtlijn voor ontwerp, bouw en opstart,* Tech. Rep. (2019).

[15] K. Moons, G. Waeyenbergh, and L. Pintelon, *Measuring the logistics performance of internal hospital supply chains – A literature study,* Omega (United Kingdom) **82**, 205 (2019).

[16] E. Ahmadi, D. T. Masel, A. Y. Metcalf, and K. Schuller, *Inventory management of surgical supplies and sterile instruments in hospitals: a literature review,* (2019).

[17] T. Dollevoet, J. T. van Essen, and K. M. Glorie, *Solution methods for the tray optimization problem,* European Journal of Operational Research **271**, 1070 (2018).

[18] E. Huynh, S. Klouche, C. Martinet, F. Le Mercier, T. Bauer, and A. Lecoeur, *Can the number of surgery delays and postponements due to unavailable instrumentation be reduced? Evaluating the benefits of enhanced collaboration between the sterilization and orthopedic surgery units,* Orthopaedics and Traumatology: Surgery and Research **105**, 563 (2019).

[19] J. V. Brooks, J. A. Williams, and K. Gorbenko, *The work of sterile processing departments: An exploratory study using qualitative interviews and a quantitative process database,* American Journal of Infection Control **47**, 816 (2019).

[20] H. Al Hasan, C. Guéret, D. Lemoine, and D. Rivreau, *Surgical case scheduling with sterilising activity constraints,* International Journal of Production Research **57**, 2984 (2019).

[21] O. Ozturk, *A bi-criteria optimization model for medical device sterilization,* Annals of Operations Research (2019), 10.1007/s10479-019-03296-x.

[22] A. Rossi, A. Pandolfi, and M. Lanzetta, *Dynamic set-up rules for hybrid flow shop scheduling with parallel batching machines,* International Journal of Production Research **52**, 3842 (2014).

[23] M. Di Mascolo and A. Gouin, *A generic simulation model to assess the performance of sterilization services in health establishments,* Health Care Management Science **16**, 45 (2013).

[24] M. Lanzetta, A. Rossi, and A. Puppato, *Modelling activity times by hybrid synthetic method,* Production Planning and Control **27**, 909 (2016).

[25] O. Ozturk, M. L. Espinouse, M. D. Mascolo, and A. Gouin, *Makespan minimisation on parallel batch processing machines with non-identical job sizes and release dates,* International Journal of Production Research **50**, 6022 (2012).

[26] O. Ozturk, M. Di Mascolo, M.-L. Espinouse, A. Gouin, and M. D. Mascolo, *A semi-online algorthm for optimizing the pre-disinfection duration of medical devices in a hospital sterilization service,* (2012).

[27] E. M. González-Neira, J. R. Montoya-Torres, and D. Barrera, *Flow-shop scheduling problem under uncertainties: Review and trends,* International Journal of Industrial Engineering Computations **8**, 399 (2017).

[28] M. D. F. Morais, T. J. P. Boiko, L. D. S. Coelho, R. P. Da Rocha, and P. R. PAraíso, *Multicriteria Hybrid Flow Shop Scheduling Problem: Literature Review, Analysis, and Future Research,* Independent Journal of Management & Production **5**, 1004 (2014).

[29] T. S. Lee and Y. T. Loong, *A review of scheduling problem and resolution methods in flexible flow shop,* International Journal of Industrial Engineering Computations **10**, 67 (2019).

[30] Y. Li and Z. Dai, *A two-stage flow-shop scheduling problem with incompatible job families and limited waiting time,* Engineering Optimization **52**, 484 (2020).

[31] M. Abedi, H. Seidgar, H. Fazlollahtabar, and R. Bijani, *Bi-objective optimisation for scheduling the identical parallel batch-processing machines with arbitrary job sizes, unequal job release times and capacity limits,* International Journal of Production Research **53**, 1680 (2015).

[32] Y. Tan, L. Mönch, and J. W. Fowler, *A hybrid scheduling approach for a two-stage flexible flow shop with batch processing machines,* Journal of Scheduling **21**, 209 (2018).

[33] S. Lu, X. Liu, J. Pei, M. T. Thai, and P. M. Pardalos, *A hybrid ABC-TS algorithm for the unrelated parallel-batching machines scheduling problem with deteriorating jobs and maintenance activity,* Applied Soft Computing Journal **66**, 168 (2018).

[34] S. Wang, X. Wang, and L. Yu, *Two-stage no-wait hybrid flow-shop scheduling with sequence-dependent setup times,* International Journal of Systems Science: Operations and Logistics **2674** (2019), 10.1080/23302674.2019.1575997.

[35] M. Liu, X. Yang, J. Zhang, and C. Chu, *Scheduling a tempered glass manufacturing system: a three-stage hybrid flow shop model,* International Journal of Production Research **55**, 6084 (2017).

[36] B. Shahidi-Zadeh, R. Tavakkoli-Moghaddam, A. Taheri-Moghadam, and I. Rastgar, *Solving a bi-objective unrelated parallel batch processing machines scheduling problem: A comparison study,* Computers and Operations Research **88**, 71 (2017).

[37] R. Hall, *Handbook of Healthcare System Scheduling* (Springer, 2012) p. 867.

[38] D. E. Tamir, N. D. Rishe, and A. Kandel, *Studies in Fuzziness and Soft Computing Fifty Years of Fuzzy Logic and its Applications*, Tech. Rep. (2015).

[39] A. Sadati, R. T. Moghaddam, B. Naderi, and M. Mohammadi, *A bi-objective model for a scheduling problem of unrelated parallel batch processing machines with fuzzy parameters by two fuzzy multi-objective meta-heuristics,* Iranian Journal of Fuzzy Systems **16**, 21 (2019).

[40] A. Shapiro, D. Dentcheva, and A. Ruszczyński, *Lectures on Stochastic Programming* (2009).

[41] IBM, *IBM ILOG CPLEX Optimization Studio CPLEX User's Manual*, Tech. Rep. (2017).

[42] LOAZ, *Cao universitair medische centra 2018-2020,* (2019).

[43] R. L. Graham, E. L. Lawler, J. K. Lenstra, and A. H. Kan, *Optimization and approximation in deterministic sequencing and scheduling: A survey,* Annals of Discrete Mathematics **5**, 287 (1979).

[44] C. H. Papadimitriou and K. Steiglitz, *Combinatorial Optimization: Algorithms and Complexity.* (1998).

[45] L. van Iersel, *AM2020 Optimization*, Tech. Rep. January (TU Delft, 2020).

[46] B. Korte and J. Vygen, *Combinatorial Optimization Theory and Algorithms* (Springer, 2018).

[47] O. Ozturk, M. A. Begen, and G. S. Zaric, *A branch and bound based heuristic for makespan minimization of washing operations in hospital sterilization services,* European Journal of Operational Research **239**, 214 (2014).

[48] P. L. Hammer and S. Rudeanu, *Boolean Methods in Operations Research and Related Areas*, Ökonometrie und Unternehmensforschung / Econometrics and Operations Research, Vol. 7 (Springer Berlin Heidelberg, Berlin, Heidelberg, 1968).

[49] DAS-5: Distributed ASCI Supercomputer 5, *https://www.cs.vu.nl/das5/about.shtml* (2020).

[50] H. Bal, D. Epema, C. De Laat, R. Van Nieuwpoort, J. Romein, F. Seinstra, C. Snoek, and H. Wijshoff, *A Medium-Scale Distributed System for Computer Science Research: Infrastructure for the Long Term,* Computer **49**, 54 (2016).

[51] E. Klotz and A. M. Newman, *Practical guidelines for solving difficult mixed integer linear programs,* (2013).

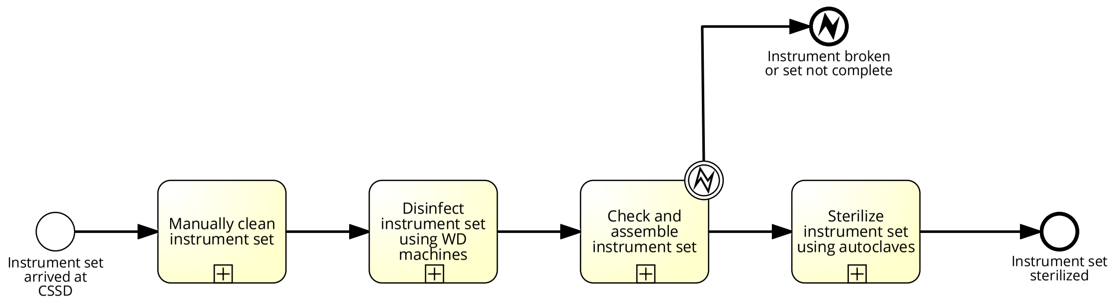
[52] J. T. van Essen, *Flowing through hospitals Johanna Theresia van Essen*, Ph.D. thesis (2013).

A

BMPN MODELS

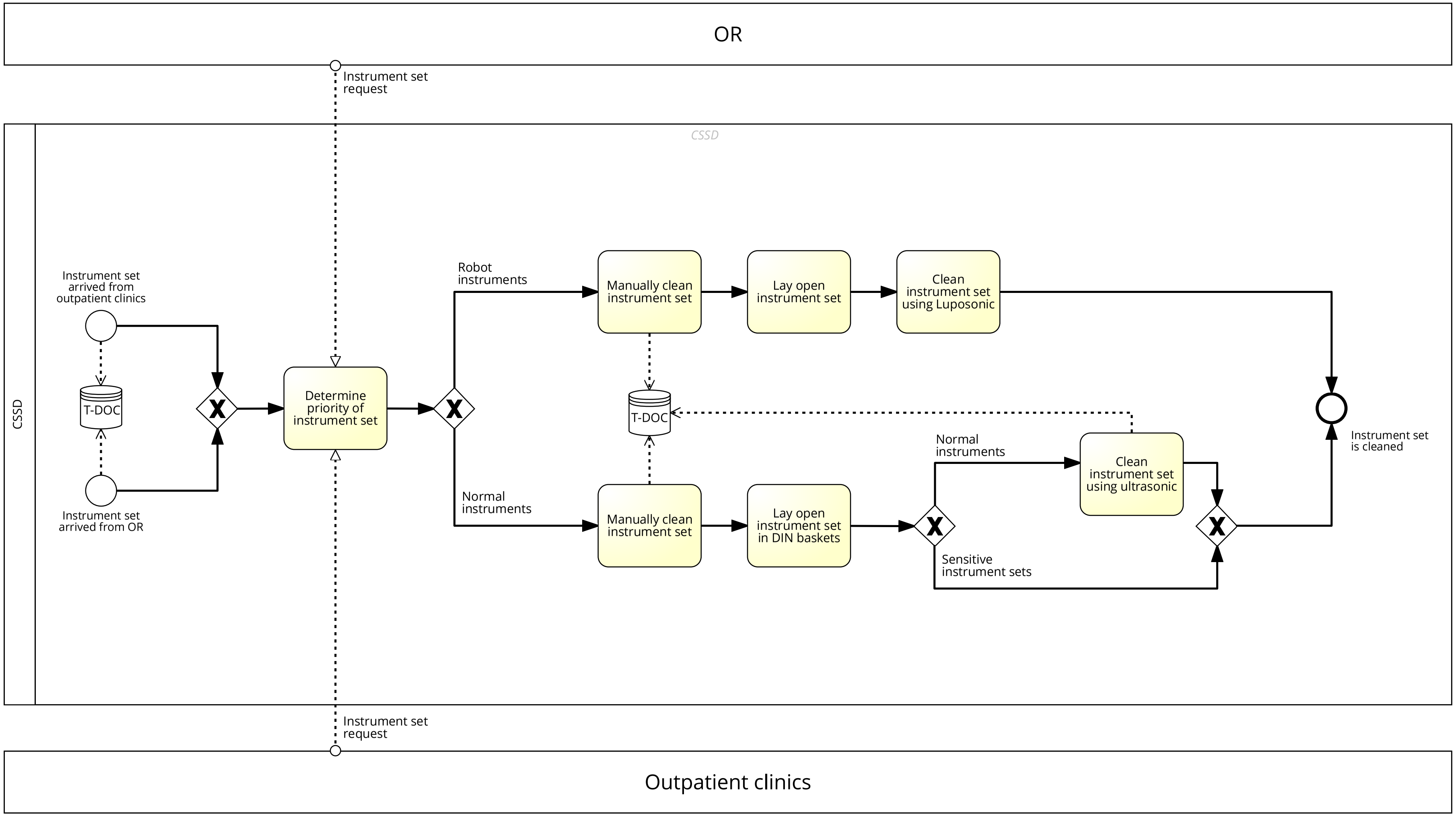
This chapter provides all BPMN models as described in Chapter 2.3 and created with Signavio Process Manager [11].

CSSD

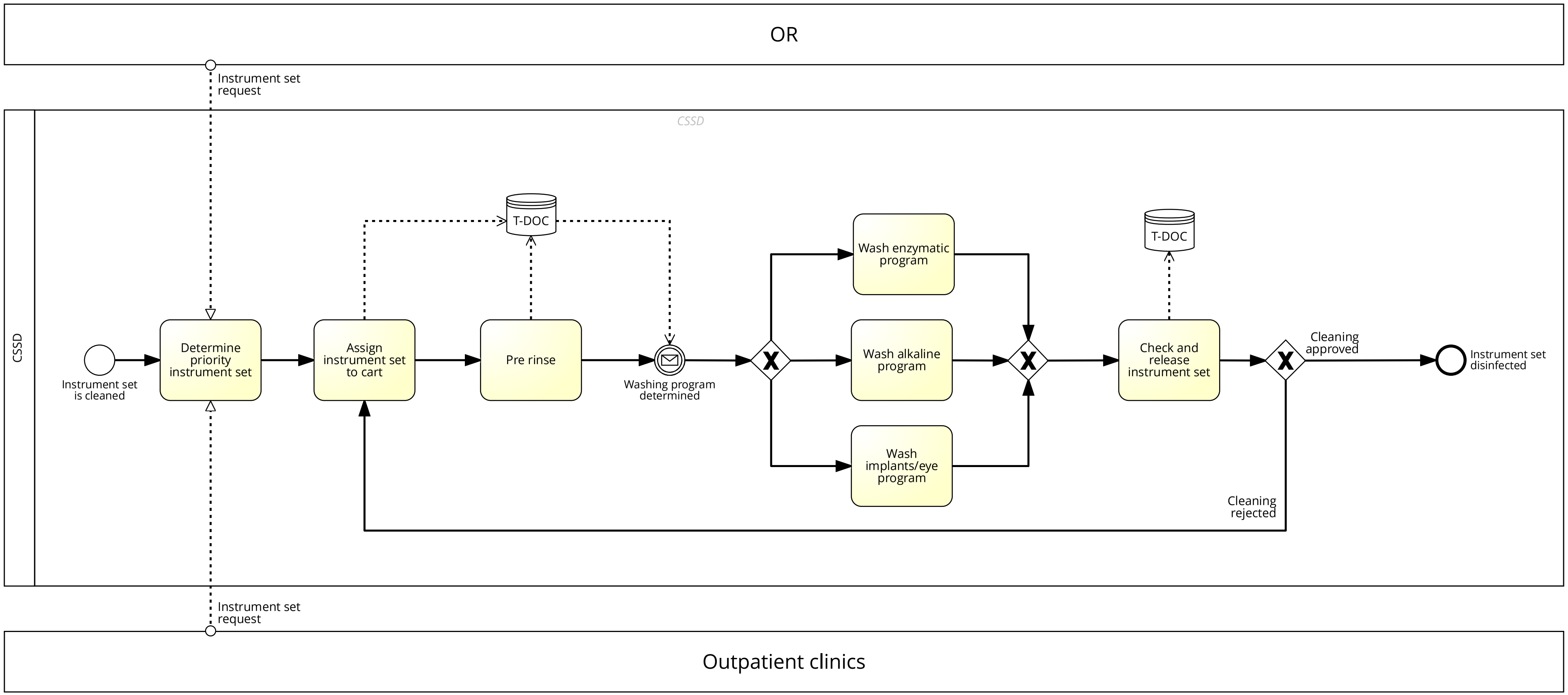


Instrument set arrived at CSSD
Manually clean instrument set
Disinfect instrument set using WD machines
Check and assemble instrument set
Instrument broken or set not complete
Sterilize instrument set using autoclaves
Instrument set sterilized

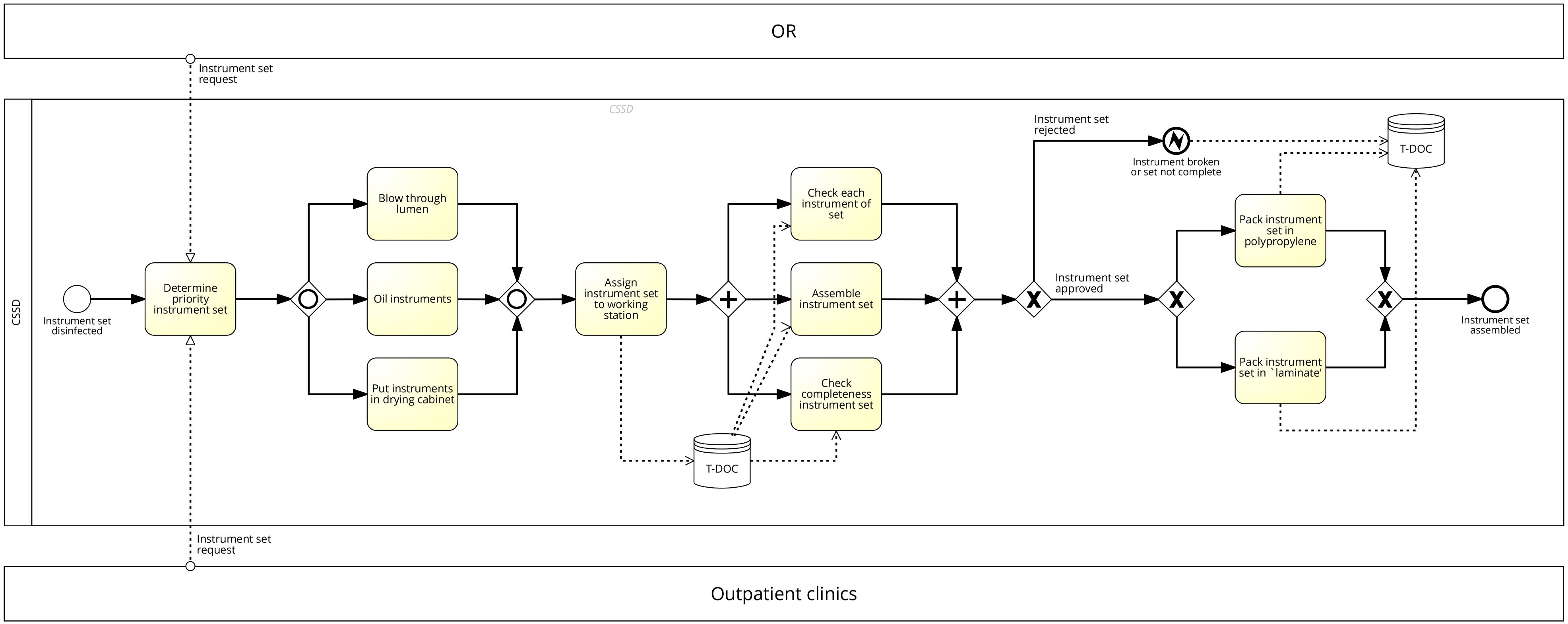
Manually clean instrument set



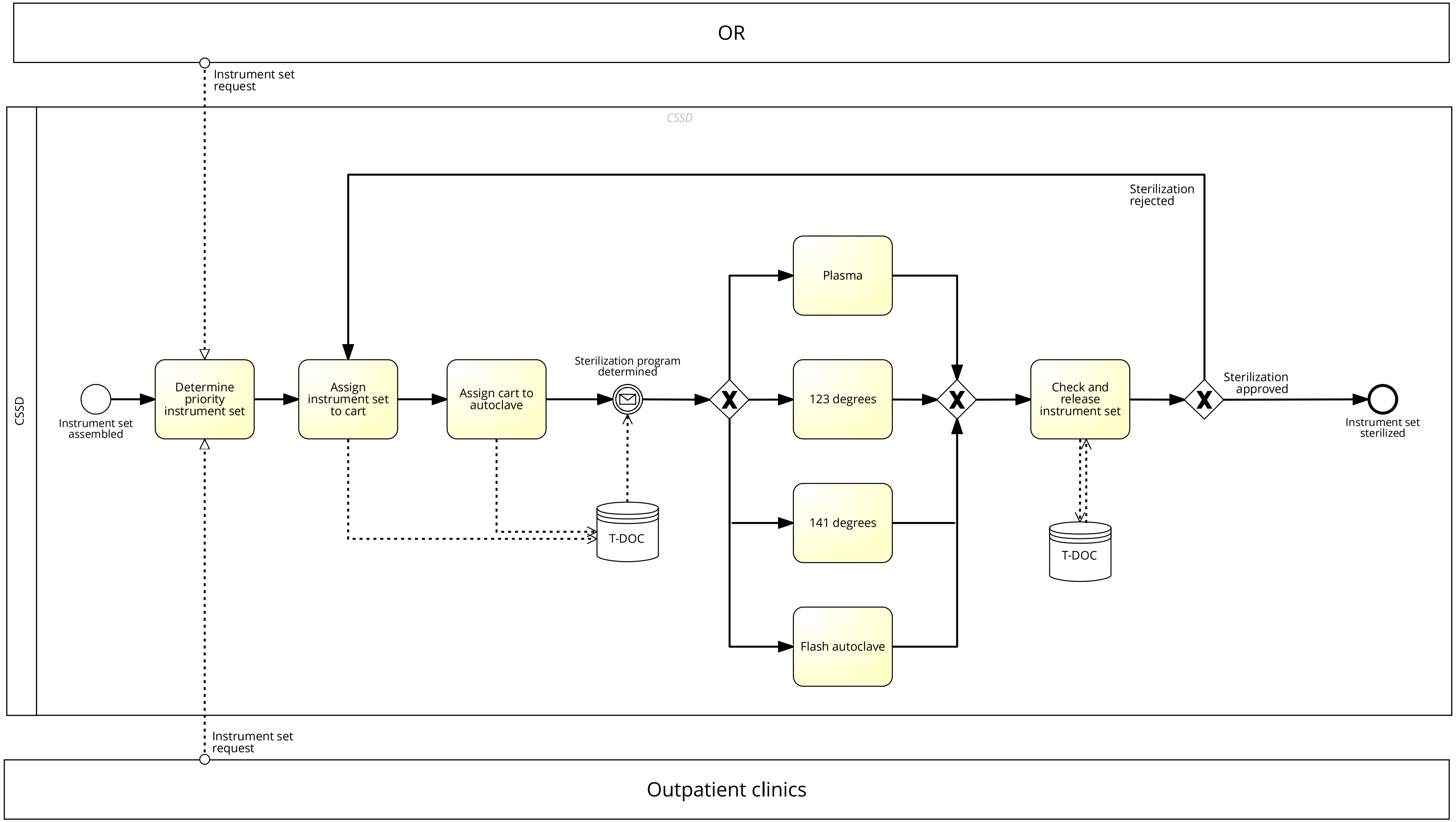
Disinfect instrument set using WD machines



Check and assemble instrument set



Sterilize instrument set using autoclaves



B

ADDITIONAL CONSTRAINTS

B.1. TACTICAL MODEL

In case $w = 3$, Constraints (B.1), (B.2), and (B.3) are added to determine the amount of irregular hours on weekdays, and Constraints (B.4), (B.5), and (B.6) are added to determine the amount of irregular hours on Saturdays.

$$Q_g \geq O_g - 60 \quad \forall g \in \{1, 4, \ldots, 13\} \subset G \tag{B.1}$$

$$Q_g = 0 \quad \forall g\{2, 5, \ldots, 14\} \subset G \tag{B.2}$$

$$Q_g \geq O_g - 240 \quad \forall g\{3, 6, \ldots, 15\} \subset G \tag{B.3}$$

$$Q_{16} = O_{16} \tag{B.4}$$

$$Q_{17} \geq O_{17} - 240 \tag{B.5}$$

$$Q_{18} = O_{18} \tag{B.6}$$

In case $w = 4$, Constraints (B.7), (B.8), (B.9), and (B.10) are added to determine the amount of irregular hours on weekdays, and Constraints (B.11), (B.12), (B.13), and (B.14) are added to determine the amount of irregular hours on Saturdays.

$$Q_g = O_g \quad \forall g \in \{1, 5, \ldots, 17\} \subset G \tag{B.7}$$

$$Q_g \geq O_g - 300 \quad \forall g\{2, 6, \ldots, 18\} \subset G \tag{B.8}$$

$$Q_g = 0 \quad \forall g\{3, 7, \ldots, 19\} \subset G \tag{B.9}$$

$$Q_g \geq O_g - 120 \quad \forall g\{4, 8, \ldots, 20\} \subset G \tag{B.10}$$

$$Q_{21} = O_{21} \tag{B.11}$$

$$Q_{22} \geq O_{22} - 240 \tag{B.12}$$

$$Q_{23} = O_{23} \tag{B.13}$$

$$Q_{24} = O_{24} \tag{B.14}$$

B.2. LINEARIZATION OPERATIONAL MODEL

To linearize Constraints(B.15) and (B.16), nonnegative decision variables G_{dp_2} and G_{dp_3} are introduced for $d = 6$.

$$W_{dp_2} \geq p_2 - m_d - N_{dp_2}\left(p_2 - \left(n_d + q_d\right)\right) \quad \forall d \in \{6\} \subset D \tag{B.15}$$

$$W_{dp_3} \geq \left(n_d + q_d\right) - p_3 - M_{dp_3}\left(m_d - p_3\right) \quad \forall d \in \{6\} \subset D \tag{B.16}$$

Considering the bounds $0 \leq \left(n_d + q_d\right) \leq 1440(d+1)$, Constraints (B.17), (B.18), and (B.19) are added, and Constraints (B.15) can be transformed to Constraints (B.20).

$$G_{dp_2} \leq n_d + q_d \quad \forall d \in \{6\} \subset D \tag{B.17}$$

$$G_{dp_2} \leq 1440(d+1)N_{dp_2} \quad \forall d \in \{6\} \subset D \tag{B.18}$$

$$G_{dp_2} \geq \left(n_d + q_d\right) - 1440(d+1)\left(1 - N_{dp_2}\right) \quad \forall d \in \{6\} \subset D \tag{B.19}$$

$$W_{dp_2} \geq p_1 - m_d + G_{dp_2} - p_2 N_{dp_2} \quad \forall d \in \{6\} \subset D \tag{B.20}$$

Considering the bounds $0 \leq m_d \leq 1440d$, Constraints (B.21), (B.22), and (B.23) are added, and Constraints (B.16) can be transformed to Constraints (B.24).

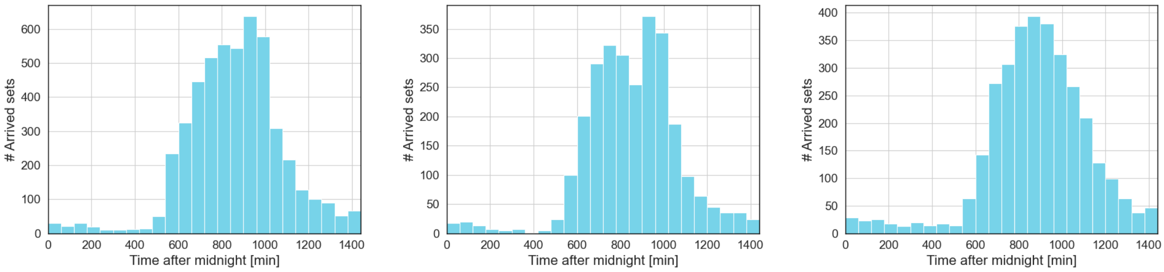
$$G_{dp_3} \leq m_d \quad \forall d \in \{6\} \subset D \tag{B.21}$$

$$G_{dp_3} \leq 1440d M_{dp_3} \quad \forall d \in \{6\} \subset D \tag{B.22}$$

$$G_{dp_3} \geq m_d - 1440d\left(1 - M_{dp_3}\right) \quad \forall d \in \{6\} \subset D \tag{B.23}$$

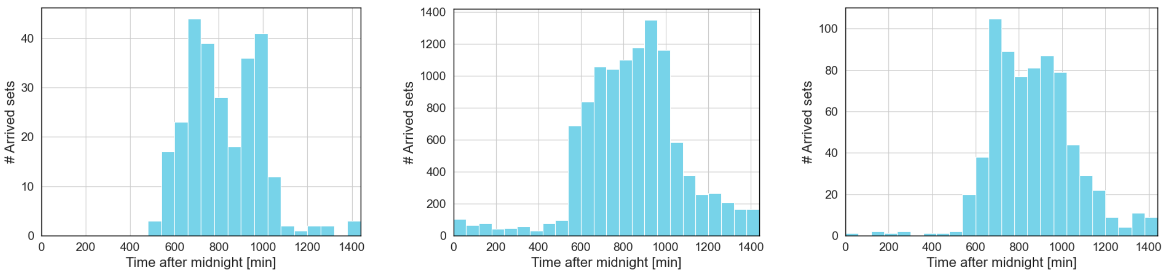
$$W_{dp_3} \geq (n_d + q_d) - p_3 - G_{dp_3} + p_3 M_{dp_3} \quad \forall d \in \{6\} \subset D \tag{B.24}$$

C
ADDITIONAL FIGURES



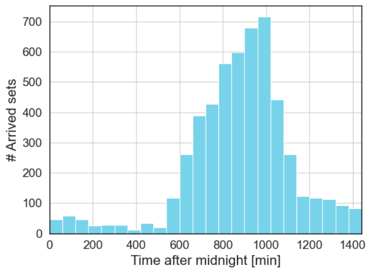
(a) 0.25 DIN (b) 0.5 DIN (c) 1.0 DIN

Figure C.1: Arrival pattern over a weekday for instrument sets of size 0.25, 0.5, and 1.0 DIN.

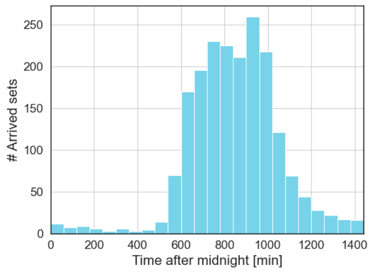


(a) 1.5 DIN (b) 2.0 DIN (c) 3.0 DIN

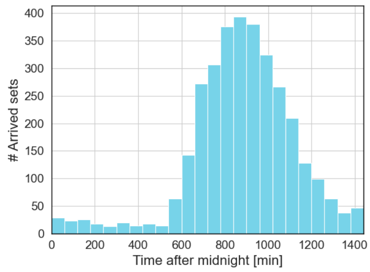
Figure C.2: Arrival pattern over a weekday for instrument sets of size 1.5, 2.0, and 3.0 DIN.



(a) 0.25 DIN

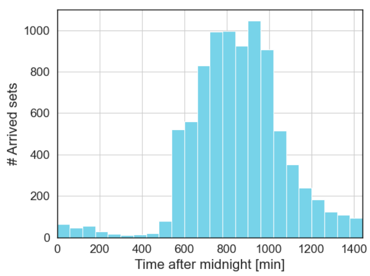


(b) 0.5 DIN

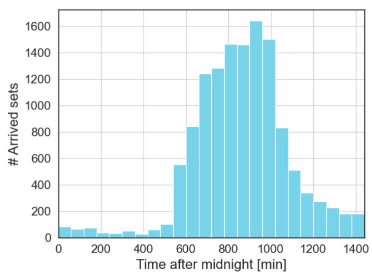


(c) 1.0 DIN

Figure C.3: Arrival pattern over a weekday for instrument sets with lead time intervals '300', '300-1440', and '1440' minutes.



(a) 0.25 DIN



(b) 0.5 DIN

Figure C.4: Arrival pattern over a weekday for instrument sets with lead time intervals '1440-4320' and '4320' minutes.

D

ADDITIONAL RESULTS

This chapter provides additional tables with results of the experiments as conducted in Chapter 7.

Instance	γ	Parameter setting	Objective function value [€]	Lower bound [€]	Optimality gap [%]
Week 15	0.5	Probing	24471	8635	64.7
	0.5	Pseudo costs	20199	8910	55.9
	0.5	Strong branching	25021	8568	65.8
	0.75	Probing	18784	8718	53.6
	0.75	Pseudo costs	15753	9612	39.0
	0.75	Strong branching	15935	9092	42.9
	1.0	Probing	13442	8908	33.7
	1.0	Pseudo costs	13903	9754	29.8
	1.0	Strong branching	15411	8657	43.8
Week 22	0.5	Probing	40806	8371	79.5
	0.5	Pseudo costs	28199	7374	73.8
	0.5	Strong branching	19198	7449	61.2
	0.75	Probing	15128	7356	51.4
	0.75	Pseudo costs	14034	9035	35.6
	0.75	Strong branching	14990	7522	49.8
	1.0	Probing	12841	7704	40.0
	1.0	Pseudo costs	12422	10732	13.6
	1.0	Strong branching	12840	7516	41.5
Week 43	0.5	Probing	16301	8267	49.3
	0.5	Pseudo costs	17060	8294	51.4
	0.5	Strong branching	19138	8146	57.4
	0.75	Probing	14666	6807	53.6
	0.75	Pseudo costs	13474	9367	30.5
	0.75	Strong branching	14330	6996	51.2
	1.0	Probing	11607	8048	30.7
	1.0	Pseudo costs	12088	9658	20.1
	1.0	Strong branching	11905	6880	42.2

Table D.1: Results strategic model for different CPLEX parameter settings and different values of γ, with a deterministic time limit of 3×10^7 ticks.

Model type	Instance	# instrument sets	Input resources	Objective function value [€]	Optimality gap [%]	Lower bound [€]
2-stage	1	15	small	1198	0	1198
4-stage	1	15	small	1192	0	1192
2-stage	2	15	small	733	3.6	707
4-stage	2	15	small	721	9.0	656
2-stage	3	15	small	871	0	870
4-stage	3	15	small	852	1.3	841
2-stage	4	15	small	1089	0	1088
4-stage	4	15	small	1074	0.5	1069
2-stage	5	15	small	1065	0	1065
4-stage	5	15	small	1060	0	1060
2-stage	1	25	medium	971	7.7	897
4-stage	1	25	medium	928	3.2	898
2-stage	2	25	medium	1268	1.3	1251
4-stage	2	25	medium	1262	0.7	1253
2-stage	3	25	medium	913	22.2	710
4-stage	3	25	medium	875	19.2	707
2-stage	4	25	medium	1395	0.8	1384
4-stage	4	25	medium	1395	0.6	1387
2-stage	5	25	medium	1402	1.4	1382
4-stage	5	25	medium	1396	1.0	1383
2-stage	1	50	medium	1478	7.5	1367
4-stage	1	50	medium	1474	9.3	1336
2-stage	2	50	medium	1296	8.6	1184
4-stage	2	50	medium	1384	17.3	1145
2-stage	3	50	medium	1341	12.0	1180
4-stage	3	50	medium	1279	10.1	1150
2-stage	4	50	medium	1396	12.9	1215
4-stage	4	50	medium	1497	21.4	1176
2-stage	5	50	medium	1458	7.6	1348
4-stage	5	50	medium	1510	13.3	1310

Table D.2: Results operational model for different model types and a varying number of arriving instrument sets, with 2 employees at each stage, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting for instances equal or larger than 25.

Model type	Instance	# instrument sets	Objective function value [€]	Optimality gap [%]	Lower bound [€]
2-stage	1	15	1620	0.0	1620
4-stage	1	15	1596	9.6	1442
2-stage	2	15	1613	0.0	1613
4-stage*	2	15	1606	1.4	1584
2-stage	3	15	1344	0.0	1343
4-stage	3	15	1352	2.8	1314
2-stage	4	15	1404	0.0	1404
4-stage	4	15	1411	3.3	1365
2-stage	5	15	1522	0.0	1521
4-stage	5	15	1519	0.3	1514
2-stage	1	25	2691	1.1	2661
4-stage	1	25	2680	0.7	2660
2-stage	2	25	2167	2.1	2121
4-stage	2	25	2156	1.6	2120
2-stage	3	25	1799	2.0	1763
4-stage	3	25	1794	2.8	1744
2-stage	4	25	2453	1.4	2419
4-stage	4	25	2450	1.2	2421
2-stage	5	25	2645	1.1	2615
4-stage	5	25	2624	0.4	2614
2-stage	1	30	2213	3.6	2134
4-stage	1	30	2204	3.7	2123
2-stage	2	30	2129	3.7	2051
4-stage	2	30	2086	2.7	2030
2-stage	3	30	2339	4.3	2238
4-stage	3	30	2316	3.6	2234
2-stage	4	30	3289	0.7	3266
4-stage	4	30	3279	0.9	3250
2-stage	5	30	3083	1.1	3048
4-stage	5	30	3073	1.2	3036

* Out of memory error, results obtained from node log

Table D.3: Results operational model for different model types and different numbers of arriving instrument sets during three days, with 2 employees at each stage, medium machine set, a deterministic time limit of 3×10^7 ticks, and memory save parameter setting.

Instance	Indicator	Objective function value [€]	Optimality gap [%]	Lowerbound [€]
Week 15	fixed1*	21366	1.3	21082
	read1	21356	41.7	12443
	read1 & pseudo costs	21356	41.7	12443
	read1 & probing	21358	47.6	11182
	fixed4	19848	0.1	19827
	read4	19848	38.6	12183
Week 22	fixed1	19838	0.3	19777
	read1	19818	40.4	11804
	read1 & pseudo costs	19818	40.4	11804
	fixed4	18388	0.2	18343
	read4	18388	40.1	11014
Week 43	fixed1	19574	0.2	19533
	read1	19563	40.0	11735
	read1 & pseudo costs	19563	40.0	11735
	read1 & probing	19559	37.3	12254
	fixed4	18145	0.2	18110
	read4	18145	37.1	11416

Table D.4: Results tactical model for different start solutions and CPLEX parameter settings, with $\gamma = 0.75$, a deterministic time limit of 3×10^7 and the memory save parameter setting. *Results obtained by setting a higher tolerated relative optimality gap.