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Solving the Master Surgery Scheduling Problem to improve waiting list management at the cardiothoracic surgery department of the MUMC+

van der Sande, Luka A.

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Operations, Planning, Accounting & Control (OPAC) group

Solving the Master Surgery Scheduling Problem to improve waiting list management at the cardiothoracic surgery department of the MUMC+

Master thesis

Luka Annemarie van der Sande - 1237207

Supervisors:

dr. ir. N.P. Dellaert, TU/e

dr. P.M.E. van Gorp, TU/e

ir. Charles Debats EngD, MUMC+

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Abstract

The tactical level of surgery planning is concerned with the allocation of operating time to surgical groups, which is represented in a Master Surgery Schedule (MSS). The optimization problem related to this schedule is called the Master Surgery Scheduling Problem (MSSP). Most papers in the literature emphasize the importance of resource utilization in the MSSP, whereas only a limited number of studies have been identified that consider waiting list characteristics as well. The addition of waiting list characteristics in the MSSP has become more important since the COVID-19 pandemic has disrupted the supply and demand of healthcare. Accordingly, we propose an optimization-simulation approach that enhances a previous model with waiting list characteristics. The new and previous models were compared in various demand and supply scenarios. The numerical study was based on hospital data of the Maastricht University Medical Centre+ (MUMC+). The results of this study indicate that adjusting the target patient throughput based on the waiting list length and flexible resource capacity leads to fewer required resources and more patients being planned within their urgency term. Additionally, a dynamic MSS results in fewer tardy patients compared to a constant MSS. Therefore, we recommend that future research and practices in this field incorporate waiting list characteristics into the MSSP to improve waiting list management of elective surgeries.

Keywords: Master Surgery Schedule; Waiting list; Optimization; Simulation; Tactical planning;

Preface

This master's thesis is the final step in completing my Master's Degree in Operations Management and Logistics at Eindhoven University of Technology (TU/e). The project was conducted within the Integral Capacity Management (ICM) team of the Maastricht University Medical Centre (MUMC+). The completion of my master's degree marks the end of my life as a student in Eindhoven. Overall I have really enjoyed the past five years and therefore I'm very grateful. I would like to use this Preface to thank several people.

Firstly, I would like to thank my mentor Nico Dellaert from the TU/e for his time, support, and inspiration. Throughout my studies in Eindhoven, I followed multiple courses given by Nico on healthcare operations management. These courses and Nico's enthusiasm have inspired me to do my graduation project in this field and continue in this direction after my graduation. Additionally, I'm very grateful for his guidance throughout this project. Furthermore, I would like to thank my second supervisor, Pieter van Gorp, for his valuable insights. His knowledge from another perspective has made me look at my project more critically. Next, I would like to thank the OPAC group for providing a good workplace at Atlas 4 to cooperate with fellow students. This group of students, the thesis circle, has supported me through the ups and downs of this project and I could not have done it without them.

The completion of this project can be attributed not only to my guidance at the TU/e but also to the support of the MUMC+. Especially, I would like to thank Charles Debats for teaching me so much about capacity management. Our brainstorming sessions have really helped in completing this project. Furthermore, I would like to thank Nol and Esther for managing the ICM department so well and for inspiring me to continue my career in ICM. I'm also grateful to the rest of the ICM team, the surgeons of the cardiothoracic surgery department, and the employees of the heart and vascular centre for sharing their knowledge with me.

Finally, I would like to thank my family, boyfriend, best friend, my university friend group the "Appeltaartjes", friends from high school and all my other friends for their unconditional support during this project and my academic career. I feel very grateful that you are always there for me.

Luka van der Sande,

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Contents

1 Introduction

The importance of managing hospital services is increasing because of the interests of many stakeholders involved. These interests include, among others, cost reduction, resource utilization, patient throughput and waiting time (Razali et al., 2022). Managing the major unit of the hospital, the operating theatre (OT) is hard due to these sometimes conflicting interests. The OT is a combination of multiple operating rooms (OR). The research on this topic is called operating room planning and scheduling and consists of three planning levels, which are strategic, tactical, and operational planning. On the strategic level, the number and type of surgeries and the number of resources over a longer time period are determined. On the tactical level, the allocation of resources to surgical groups over a month or quartile is regulated. On the operational level, individual patients are assigned to specific resources. The various planning levels use one another as input (Zhu, Fan, Yang, Pei, & Pardalos, 2019). This paper focuses on the tactical planning level, which includes the Master Surgery Scheduling Problem (MSSP). The MSSP aims to assign operating time to surgical groups.

Optimization of the MSSP is essential to comply with the stakeholders' interests, and in accordance with the quadruple aim (Bodenheimer & Sinsky, 2014), we discuss those interests. Firstly, ensuring acceptable waiting times is important for improving the health of the population since long waiting times result in decreased quality of life and increased mortality rates (Nehme, Puchkova, & Parlikad, 2022). Secondly, enhancing the patient experience of care is considered in this paper by examining patient opinions instead of assuming a preference for short waiting times. Thirdly, we aim to reduce costs by optimizing resource utilization and capacity allocation. Improving the MSS of the OT has the potential for significant cost reductions as the OT expenditures are estimated to be 40 percent of the hospital revenue (Abdelrasol, Harraz, & Eltawil, 2014). Finally, we intend to improve the work life of surgeons by designing a cyclical schedule and the possibility to restrict surgery days and to improve the working conditions of nurses by smoothing bed occupancy.

Recent articles on the optimization of the MSSP frequently focus on patient throughput, costs, and the utilization of resources. In contrast, only a limited amount of papers could be identified that also took the waiting list or waiting time into account when solving the MSSP. The literature presents various ways to address the MSSP while considering waiting list characteristics.

The first differentiation is based on the solution approach. Oliveira, Visintin, Santos, and Marques (2021) and other papers on this topic proposed an optimization-simulation approach to evaluate the effects of the master surgery schedule (MSS) on the waiting list. Dellaert, Cayiroglu, and Jeunet (2016) used a complex power method to calculate the steady-state probabilities of the waiting list length as a result of the MSS. Their research did not consider the waiting list during the optimization of the MSS, only during the evaluation. Other papers have proposed optimization models that include waiting list characteristics to solve the MSSP but did not incorporate a simulation or other waiting list evaluation methods (Aringhieri, Duma, Landa, & Mancini, 2022; Makboul, Kharraja, Abbassi, & Alaoui, 2022).

Another categorization between research papers is based on the resources involved. Various researchers included both the OT and up-and-downstream resources, such as the intensive care unit (ICU), medium care unit (MCU) and post anaesthesia care unit (PACU) in contrast to Agnetis et al. (2012), who only included the OT. Vanberkel et al. (2011) claimed that downstream resources should be considered when optimizing the MSS because of the sensitivity of those resources related to the OT.

A third distinction is based on patient characteristics in terms of homogeneity of the procedure and urgency. Patient categories can be formed based on resource usage, urgency level, or surgical speciality. Adan, Bekkers, Dellaert, Vissers, and Yu (2009) distinguished patients based on the surgery duration and the length of stay (LOS) in the ICU. Tànfani and Testi (2010) classified patients on LOS, ward type, priority, and urgency-related groups (URG).

Furthermore, a distinction within these patient categories can be made between emergency and elective patients. Some papers did consider both groups and others only the elective patients. The approach in dealing with emergency patients also varies. The paper of Tànfani and Testi (2010) took the emergency patients into account by assuming that the hospital had additional ORs dedicated to emergency patients. In contradiction with the assumption that a special OT is reserved for emergency patients, Bovim, Christiansen, Gullhav, Range, and Hellemo (2020) solved the MSSP considering both elective and emergency patients. Some operating rooms were only dedicated to elective patients and some were flexible. Agnetis et al. (2012) and other researchers reserved extra capacity for emergency patients.

Finally, various methods for dealing with uncertainty have been proposed in the literature on the MSSP. Most papers include uncertainty in some of their variables. Dellaert et al. (2016) used a probabilistic length of stay (LOS) in the IC and MC. Banditori, Cappanera, and Visintin (2013) randomly generated surgery durations. Van Oostrum et al. (2008) assumed a lognormal distribution for surgery durations. Some other papers took uncertainty into account in the research method. For example, Makboul et al. (2022) used robust optimization to deal with uncertainty in surgery duration and IC bed availability.

Our paper aims to improve waiting list management by providing a new approach to the MSSP to improve the practicality of the problem for hospitals. Therefore, we propose an optimization-simulation approach to test various scenarios. In this approach, the OT, IC, and MC utilization are included. Uncertainty is incorporated in the LOS in the IC and MC. Furthermore, whereas the MSSP only considers the planning of elective patients, capacity is reserved for emergency patients. Patients are grouped by procedure, resource needs, and surgeon attributes.

We applied this approach to the cardiothoracic surgery department (CTC) of the Maastricht University Medical Centre (MUMC+) by performing a numerical study. The MUMC+ is the largest and only academic hospital in the south of the Netherlands with around 700 beds, 20 active ORs, and 22 thousand admissions per year (Maastricht UMC+, 2022). During the COVID-19 pandemic, the waiting list for cardiothoracic surgery at the MUMC+ increased by around 50 percent compared to the pre-pandemic situation. As a result, waiting times increased and patients had to wait longer than their urgency term, which may cause a decrease in health. The impact of the pandemic was not only experienced by the MUMC+ but was observed worldwide. The COVID-19 pandemic resulted in an increase in waiting list lengths for elective surgeries worldwide because of the allocation of scarce resources to COVID-19 patients, thereby reducing the capacity for elective surgery patients (Nehme et al., 2022). The MUMC+ has successfully reduced the waiting list of the CTC department to a pre-pandemic level. However, treating patients within their urgency term is sometimes still challenging and should therefore be considered in the MSSP.

The contribution of this paper to the literature is threefold.

Firstly, this paper enhances the literature on the MSSP by incorporating waiting list characteristics in solving and analysing the MSSP. Only a limited amount of papers could be identified that incorporate this important aspect.

Secondly, as suggested by Testi and Tànfani (2009), we performed a demand and supply analysis by testing the models with various numerical scenarios. In these scenarios, we compare our model with the model of Adan et al. (2009), which only focuses on resource utilization. Furthermore, a simulation was built that compares the situation of frequent optimization of the MSS based on the proposed model with a constant MSS that was based on a steady-state waiting list.

Finally, we have captured the effects of surgical staff availability on the model outcomes as suggested by Oliveira et al. (2021).

The rest of this paper is structured as follows: Chapter 2 describes the research methods used and the design of a numerical study. The computational results are shown in Chapter 3. In Chapter 4, the results, limitations, and practical implications are discussed. Finally, Chapter 5 provides the conclusion.

2 Method

We used multiple research methods to combine waiting list management with the MSSP. This chapter elaborates on these methods, which are an optimization model, a Markov model, a simulation model, and a numerical study. The optimization model is an adjusted version of the mixed integer linear programming (MILP) model of Adan et al. (2009) and designs an MSS. The MSS could then be evaluated by describing the waiting list as a Markov model or by using a simulation model. A Markov model assumes that demand is stationary, meaning that it does not change over time. However, this assumption was not valid for the past years since the COVID-19 pandemic caused a global disruption in healthcare. Therefore, a simulation model was used in addition to the Markov model. The simulation model was used to compare the new optimization model with the MILP of Adan et al. (2009) and the MSS that resulted from the Markov model in a numerical study.

2.1 Optimization model

We propose a mixed-integer programming (MIP) optimization model to solve the MSSP. The optimization model aims to develop an MSS to create sufficient slots for patients from a patient category $c \in N$ in recurring cycles of length T while reserving capacity for emergency patients and ensuring high utilization of the resources without wasting capacity. Each patient category c has its own resource characteristics, which are the operation duration o_c, pre-operative days at the MC po_c, and a LOS distribution for the MC and IC $L_{ic,c,j}$ and $L_{mc,c,j}$. Equation 1 and 2 describe how the probability that a patient is still at the IC or MC j days after surgery can be calculated.

$$p_{IC,c,j} = P\left(L_{IC,c} > j\right) \tag{1}$$

$$p_{MC,c,j} = P\left(L_{IC,c} + L_{MC,c} > j \mid L_{IC,c} \leq j\right) \tag{2}$$

The decision variables $X_{c,t}$ and $Y_{c,t}$ in this model intend to determine an MSS for the number of target and non-target patients for each patient category per day t. These decision variables are included in the objective function with the aim of approximating the input variables R_c and E_c. Penalty costs PC_C are attached to planning fewer target patients than R_c and a bonus factor BF_c is provided to planning non-target patients of E_c. The category differentiation is based on the surgical procedure and resource requirements, whereas the differentiation between target and non-target patients is based on urgency.

The target patients, denoted by R_c, are the patients who should be planned within the cycle length T based on their urgency and current waiting time. These target patients include patients who are on the waiting list and have a due date within the planning cycle when the new planning is created, as well as the expected urgent patients who are not yet on the waiting list. Urgent patients are patients who can wait for at most two weeks.

The variable E_c represents the additional patients on the waiting list, who can wait longer than the time horizon but can be planned if possible. This group represents the non-target patients. The non-target patients refer to those patients who are on the waiting list and have a due date outside the planning cycle when the new planning is created plus the number of expected elective patients who are not yet on the waiting list. Elective patients can wait for at most 12 weeks. Elective patients become target patients when the due date is within the planning cycle.

Table 1: Input parameters and variables

Input parameters	
T	Cycle length in days
N	Number of patient categories
RS	Resource set = OT, IC, MC
R_c	Target patient throughput of category c
E_c	Additional number of patients on the waiting list of patient category c, i.e. non-target patients
$C_{r,t}$	Maximum capacity of resource r on day d
TR	Target utilization rate to reserve capacity for emergency patients
o_c	Operation duration of a patient of category c in hours
po_c	Number of pre-operative days at the MC unit of a patient of category c
$p_{IC,c,j}$	Probability that a patient of category c is at the IC j days after surgery, $j = 0, 1, 2, ..., L_{IC}^{max}$
$L_{IC,c,j}$	Probability that a patient of category c stays at the IC for j days, $j = 0, 1, 2, ..., L_{IC}^{max}$
L_{IC}^{max}	Maximum length of stay in the IC over all categories
$p_{MC,c,j}$	Probability that a patient of category c is at the MC j days after surgery, $j = 0, 1, 2, ..., L_{MC+IC}^{max}$
$L_{MC,c,j}$	Probability that a patient of category c stays at the MC for j days, $j = 0, 1, 2, ..., L_{MC}^{max}$
L_{MC}^{max}	Maximum length of stay in the MC over all categories
W_r	Relative weight of resource r
PC_c	Penalty costs of a target patient of category c
BF_c	Bonus factor for a non-target patient of category c
Variables	
$X_{c,t}$	Number of target patients of category c planned on day d
$Y_{c,t}$	Number of non-target patients of category c planned on day d
$OU_{r,t}$	Over-utilization of resource r on day d
BC_r, d	Booked capacity of resource r on day d
$U_{r,t}$	Target utilization of resource r on day d

The MSS results in the resource utilization of resource r in the resource set R, which consists of the OT, IC, and MC. Each resource has a maximum capacity, denoted by $C_{r,t}$. We can choose to allocate a part of this capacity to another surgical specialism during the planning cycle. The capacity dedicated to our specialism is called the booked capacity $BC_{r,t}$. The resource utilization cannot exceed this booked capacity.

The booked capacity is partially reserved for emergency patients. We want to reserve capacity for emergency patients as they are the main reason for surgery cancellations at the MUMC+. The results from a focus group discussion demonstrated that most elective patients prefer the certainty of their surgery date over waiting time. Appendix C further elaborates on this focus group.

The other part of the booked capacity is aimed at the planning of urgent and elective patients and is called target utilization. The target utilization is the proportion TR of the booked capacity. The utilization can exceed the target capacity, but this over-utilization $OU_{r,t}$ is penalized by the weight W_r because non-emergency patients use the reserved capacity for emergency patients. All variables are shown in Table 1. The remaining part of this section further describes the optimization model by outlining the objective and constraints.

2.1.1 Objective

The objective of this optimization model, as shown in Equation 3, is to (1) minimize the over-utilization of the resources, (2) minimize the booked capacity, (3) minimize the number of penalized patients for not being planned, and (4) maximize the number of extra patients planned. The hospital can determine the resource weights W_r, penalty costs PC_c, and bonus factors BF_C according to their priorities and preferences. These values can be adjusted easily if priorities change.

$$Minimize \sum_{r\in RS}\sum_{t=1}^{T}\Big(W_r \cdot OU_{r,t} + BC_{r,t}\Big) + \sum_{c=1}^{N}\Big(PC_c\big(R_c - \sum_{t=1}^{T} X_{c,t}\big)^{+} - BF_c\sum_{t=0}^{T} Y_{c,t}\Big) \tag{3}$$

2.1.2 Throughput constraints

The sum of the target and non-target patients planned cannot exceed the number of target patient throughput (Equation 4) and the additional number of patients on the waiting list (Equation 5), respectively. Non-target patients of a category c can only be planned if all target patients are already planned, as described in Equation 6.

$$\sum_{t=1}^{T} X_{c,t} \leq R_c \quad c = 1, ..., N \tag{4}$$

$$\sum_{t=1}^{T} Y_{c,t} \leq E_c \quad c = 1, ..., N \tag{5}$$

$$\sum_{t=1}^{T} Y_{c,t} \leq \left(\sum_{t=1}^{T}(X_{c,t} + Y_{c,t}) - R_c\right)^{+} \quad c = 1, ..., N \tag{6}$$

$$X_{c,t} \geq 0, \quad Y_{c,t} \geq 0, \quad X_{c,t}, Y_{c,t} \in \mathbb{Z}$$

2.1.3 Resource utilization constraints

The resource utilization constraints are defined to calculate the over-utilization of each resource in the resource set. The utilization of the OT (Equation 7) is defined as a multiplication of the operation duration times the number of planned patients, both target and non-target. The surgery duration depends on the patient category and is defined as a deterministic parameter. Probabilistic values would not make a difference since this results in an expected value. Furthermore, variations in the actual surgery duration would not change the number of patients that can be planned in advance, only the realised utilization of the OT.

The utilization of the IC and MC are defined as expected utilization, which is similar to the definition in the MILP of Adan et al. (2009). The probabilistic constraints deal with uncertainty by multiplying the planned patients with a probability of length of stay. This gives a more accurate representation of the stochastic use of these resources.

The utilization of the IC is defined as the sum of patients that had surgery before and are therefore still in the IC. The probabilistic constraint takes into account that there is a certain probability that the patient is still in the IC j days after the surgery, which is represented by $P_{IC,c,j}$.

The utilization of the MC is defined similarly but also takes into account the pre-operative days and the number of days after surgery that the patient occupies an IC bed. The over-utilization is calculated by taking the positive part of the difference between the utilization and the target utilization for each day in the time horizon. As we consider cyclical planning, patients whose surgery took place j days before the start of the cycle, still occupy a bed in the current cycle. This is taken into account in constraints 8 and 9. The subscript t in $X_{c,t}$ and $Y_{c,t}$ should be subtracted from T if the value becomes zero or negative: so day 0 is the same as day T, day -1 is the same as T-1 and so on.

$$OU_{OT,t} = \left(\sum_{c=1}^{N} o_c * (X_{c,t} + Y_{c,t}) - U_{OT,d}\right)^{+} \quad t = 1, ..., T \tag{7}$$

$$OU_{IC,t} = \left(\sum_{c=1}^{N} \sum_{j=0}^{L_{IC}^{max}} p_{IC,c,j} * (X_{c,d-j} + Y_{c,d-j}) - U_{IC,d}\right)^{+} \quad t = 1, ..., T \tag{8}$$

$$OU_{MC,t} = \left(\sum_{c=1}^{N} \sum_{s=1}^{po_c} (X_{c,d+s} + Y_{c,d+s}) + \sum_{c=1}^{N} \sum_{j=0}^{L_{MC}^{max}} p_{MC,c,j}(X_{c,d-j} + Y_{c,d-j}) - U_{MC,d}\right)^{+} \quad t = 1, ..., T \tag{9}$$

2.1.4 Capacity constraints

The target utilization is defined in Equation 10 as the booked capacity times the target utilization rate TR. The over-utilization plus the target utilization cannot exceed the booked capacity (Equation 11). The booked capacity cannot exceed the maximum capacity (Equation 12) and should be an integer since only whole beds are possible. Furthermore, the booked capacity should remain constant on week and weekend days during the time horizon, which is achieved by Equations 13 and 14.

$$U_{r,t} = TR * BC_{r,t} \quad r \in RS, \quad t = 1, ..., T \tag{10}$$

$$U_{r,t} + OU_{r,t} \leq BC_{r,t} \quad r \in RS, \quad t = 1, ..., T \tag{11}$$

$$BC_{r,t} \leq C_{r,t} \quad r \in RS, \quad t = 1, ..., T \tag{12}$$

$$BC_{r,t} = BC_{r,t'} \quad t \in weekdays \quad t' = t + 1, ..., T \in weekdays \tag{13}$$

$$BC_{r,t} = BC_{r,t'} \quad t \in weekenddays \quad t' = t' + 1, ..., T \in weekenddays \tag{14}$$

$$BC_{r,t} \in \mathbb{Z}$$

2.2 Markov model

The second research method used in this paper is a Markov model. This model aims to evaluate the effects of an MSS on the waiting list length by modelling the waiting list as a Markov chain. In this model, each state is represented by the number of patients of category c on the waiting list and stationary demand is assumed. The state transitions occur based on daily arrivals and the planning of patients. The MSS affects the removal of patients from the waiting list and therefore this method can be used to assess the performance of the MSS. A queue length distribution can be found by adopting the power method to reach a steady-state waiting list length as introduced by Dellaert et al. (2016).

The queue length distributions result from steady-state probabilities and are used to determine whether, in the long run, the capacity is enough to cover the average demand and how many patient slots are required to reach the steady state. We used iterative vector calculations for every patient category separately. Each calculation results in a vector of the probabilities of a specific queue length. Two calculation steps were performed for each day.

The first step corresponds with the patients who are planned according to the MSS and are therefore removed from the waiting list. During the second step of the day, new patients arrive and consequently, the waiting list increases. The arrivals are assumed to follow a Poisson distribution with rate λ_c. The tactical plan is repeated every T days and the waiting list length probabilities are calculated repeatedly to reach the steady state probabilities of the waiting list length. The two steps are represented in the waiting list vectors $W_{c,d}^{BS}$, which is the waiting list before the surgeries are planned, and $W_{c,d}^{NS}$, which is the waiting list vector after the surgeries are planned. Equations 15 and 16 refer to the vector calculations. i and j represent the index of the number of patients on the waiting list.

$$WL^{BS}_{c,d} = \begin{bmatrix} Q^{BS}_{c,d}(0) & Q^{BS}_{c,d}(1) & Q^{BS}_{c,d}(2) & ... & Q^{BS}_{c,d}(i) & ... & Q^{BS}_{c,d}(I) \end{bmatrix}$$

$$Q^{NS}_{c,d}(j) = \begin{cases} \sum_{i=0}^{X_{c,d+L}} Q^{BS}_{c,d}(i) & \text{if } j = 0 \\ Q^{BS}_{c,d}(j + X_{c,d+L}), & \text{if } j > 0 \end{cases} \tag{15}$$

$$Q^{BS}_{c,d}(i) = \begin{cases} \sum_{j=0}^{i} Q^{NS}_{c,d-1}(j) * P_c(i-j)) & \text{if } i < WL_{max} \\ \sum_{j=0}^{i} \Big(Q^{NS}_{c,d-1}(j) * (1 - \sum_{a=0}^{i-j-1} P_c(a)) \Big) & \text{if } i = WL_{max} \end{cases} \tag{16}$$

Repeatedly calculating the waiting list vector eventually leads to a steady state probability for every category and day within the time horizon. The expected waiting list length per day and category can be calculated with equation 17. The average waiting list length per category over the time horizon is calculated by adding up all the expected waiting list lengths divided by the time horizon, as shown in Equation 18.

$$E[WLL_{c,d}] = \sum_{i=0}^{I} Q^{BS}_{c,d}(i) * i \tag{17}$$

$$E[L_c] = \frac{\sum_{d=1}^{T} E[WLX_{c,d}]}{T} \tag{18}$$

Little's law (Equation 19) is used to calculate the average waiting time of each patient category. Little's law claims that under steady-state conditions, the average number of patients in the system L equals the arrival rate λ multiplied by the average waiting time in the system W. The average time in the system is defined as the time in the queue plus the service time (Little & Graves, 2008). Rewriting this formula implies that the expected waiting time per patient category can be calculated by dividing the expected waiting list length by the arrival rate, as displayed in Equation 20. Another implication of Little's law is to define a target waiting list length if the arrival rate and target waiting time are known. The target waiting list length for which patients are planned within their urgency term is calculated by multiplying the arrival rate by their urgency term, which is shown in Equation 21.

$$L = \lambda * W \tag{19}$$

$$E[WT_c] = E[L_c]/\lambda_c \tag{20}$$

$$TL = \lambda_c * TWT_c \tag{21}$$

2.2.1 Algorithm

Algorithm 1 (see Appendix D) was used to design an MSS that ensures sufficient waiting time based on the steady-state probabilities within the maximal capacity. Therefore, the algorithm starts with an initial target number of patients to plan for each category. This number is defined by the average daily arrival rate multiplied by the cycle length, which is then rounded down to the nearest integer value. Therefore, the algorithm starts with a number of slots that is certainly too low to reach a steady-state waiting list length.

In each iteration, a new MSS is optimized according to the optimization model. Subsequently, we determine whether the capacity is sufficient and whether the average waiting list length is below the target waiting list length. If there is sufficient capacity, one patient is added to the target patient throughput R_c of each category for which the average waiting list length is longer than the target waiting list length. The iterations stop when there is either not enough capacity to plan more patients or if the average waiting list length is sufficient for each patient category.

Furthermore, the resource utilization that follows from the schedule shows the required capacity and the optimized MSS shows how to plan these patients accordingly.

2.3 Simulation model

We introduce the next research method, the simulation model, to perform a demand and supply analysis. The assumption of stationary demand for the Markov model was not valid for the past years, since the COVID-19 pandemic caused a global disruption of care. A simulation model is considered to be a more realistic approach for predicting the performance of an MSS in a non-stationary situation compared to the Markov modelling approach. The simulation model is used to evaluate the proposed optimization model, compare it with other models, and test the effects of seasonality. The combination of the optimization and simulation model is called an optimization-simulation approach and is visualized in Figure 2.

This section explains the solution approach by introducing additional variables, which are shown in Table 2, and by outlining how the optimization-simulation model works.

We start by describing the additional variables for the simulation model. Firstly, the simulation model introduces two types of waiting lists, which are denoted by WLX and WLY.

WLX is the "must-do" waiting list and this list should be empty at the end of the planning cycle because the patients on this list should be planned within the planning cycle. The urgent patients who arrive within the planning cycle are added to this waiting list. Operational surgery scheduling should ensure that these patients are scheduled on time. This tactical simulation model only keeps track of the length of the waiting list and the cancelled surgery slots.

WLY is the "can-do" waiting list and patients from this list can be planned for surgery, but should not necessarily be planned. Elective patients who arrive during the planning cycle are added to this waiting list because their surgery can be planned in the next planning cycle.

The simulation model uses an optimized MSS for a certain optimization period, which is denoted by T. This optimized schedule is then repeated Q times since hospitals prefer repetition in their schedule and the computational time for the optimization is less. After a time period of T times Q (TQ) days a new planning cycle starts, for which a new MSS is optimized. The number of planning cycles within the simulation is denoted by H and indexed by h. These indexes are useful for changing demand rates and capacity throughout the year. An overview of these time indicators is shown in Figure 1. The number of repetitions Q should be chosen such that the urgency term of the elective patients is within TQ. The red bars indicate the moments where a new MSS is generated. Other variables are the daily arrival rates of both the urgent and elective patients, which are λx and λy, respectively.

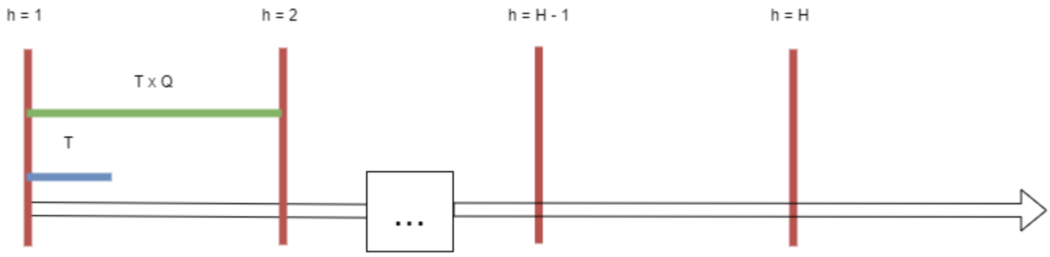


Figure 1: Time indicators simulation model

Initialization

The next step is to describe how the optimization-simulation approach works. To determine the performance of our optimization model, we simulate future demand arrivals and check the performance measures for the simulated demand. After TQ days, we recalculate the MSS based on the simulated queues. All the patients on the waiting list start on the must-do waiting list WLX_c because all patients should be planned within TQ. The can-do waiting list WLY_c starts at zero.

The optimization model requires a target throughput and additional patients. The target throughput R_c equals the must-do waiting list divided by the number of repetitions Q plus the number of expected urgent patient arrivals during T. The waiting list is divided by Q since the patients should be planned within a time period of TQ and the MSS is optimized for a time period of length T. The new E_c is the number of expected arrivals of elective patients during T. The numbers are rounded up to the next integer. The determination of the target patient throughput and the additional number of patients occurs every planning cycle of length TQ. Based on these variables an MSS schedule is optimized, which is the first step in the approach. The simulation model then consists of two steps during each simulation day, which are patient planning and patient arrival.

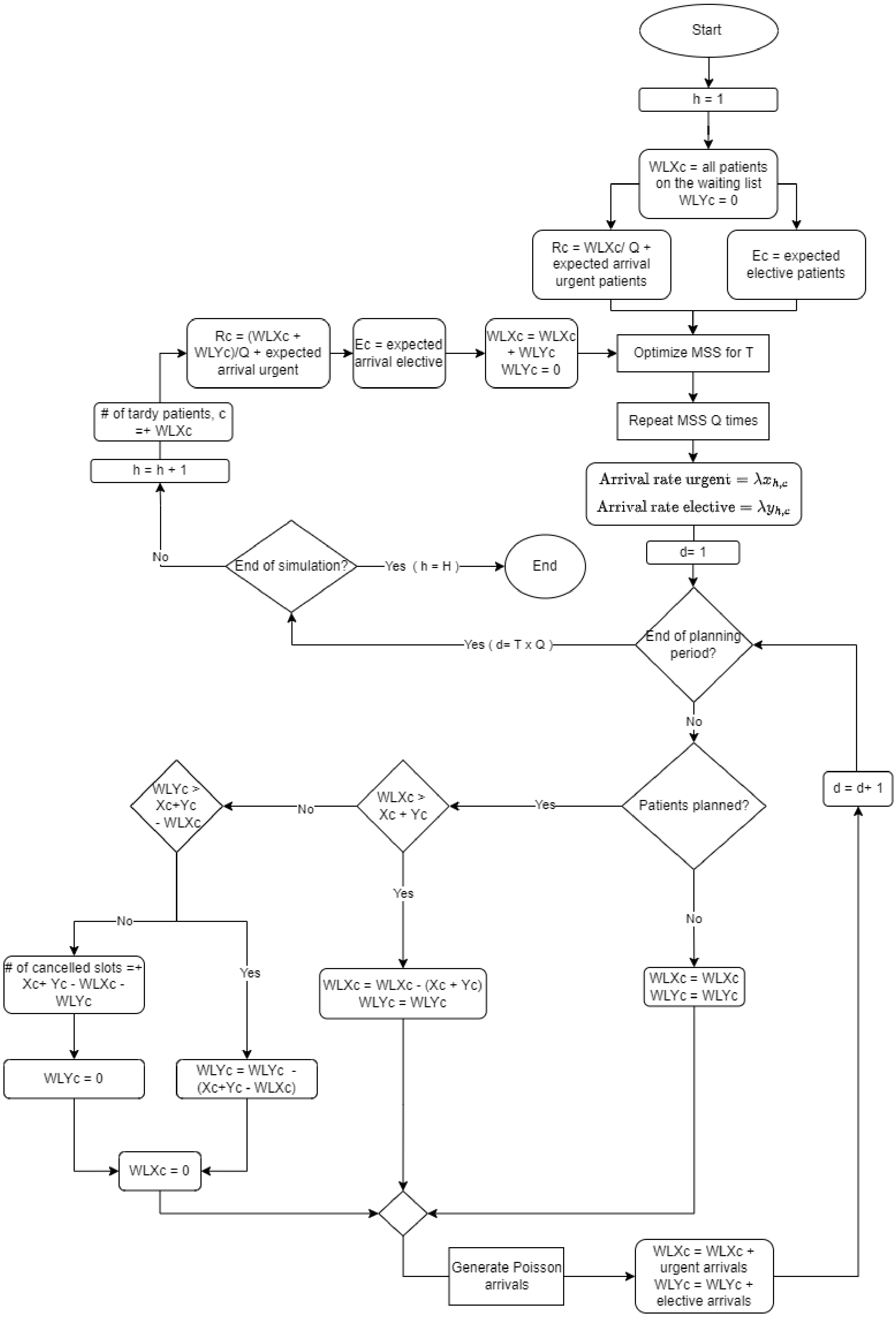


Figure 2: Optimization-simulation approach

Patient planning
The first step in the simulation is to check whether patients are planned according to the schedule and remove them from the waiting list. If no surgeries are planned, both waiting lists remain the same. When surgeries are planned, the must-do waiting list is decreased first with the planned patients. If there are not enough patients on the must-do waiting list, the patients are removed from the can-do waiting list. In case the number of planned surgery slots exceeds the number of patients on both waiting lists, surgery slots are cancelled and both waiting lists become empty. The number of cancellations is recorded in the simulation.

Patient arrival
The second step in the simulation is the arrival of new patients. In accordance with Dellaert et al. (2016), we assume a daily Poisson arrival distribution to generate multiple simulations easily. Furthermore, the Poisson distribution was tested in a goodness-of-fit test. The outcomes indicate that a Poisson arrival distribution holds for most patient categories. The urgent arrivals are added to the must-do waiting list and the elective arrivals are added to the can-do waiting list. This continues until the end of the planning cycle is reached. Then the number of tardy patients is determined by counting each patient still on the must-do waiting list. There are often some tardy patients since urgent patients can still arrive at the end of the cycle on the must-do waiting list, leaving limited time to plan them.

The new target patient throughput is determined at the end of every planning cycle of length TQ by adding up the must-do and can-do waiting list and the number of expected urgent patients for the next TQ days. These patients should be planned within a time period of TQ. However, the input variable in the optimization model for the required number of patients, denoted by R_c, is this number divided by Q, since the MSS is optimized for a time period of length T. The new E_c is the number of expected arrivals of elective patients during T. The determination of the target patient throughput and the additional number of patients occurs every planning cycle of length TQ.

The must-do waiting list now equals the previous must-do waiting list plus the can-do waiting list because those patients should be planned in the next planning cycle. The can-do waiting list becomes equal to zero.

Then a new MSS is optimized and this cycle repeats itself until the end of the simulation. This simulation model keeps track of the waiting list length, number of cancelled slots and tardy patients per cycle. Furthermore, when surgery slots are cancelled, the planned utilization of the resources is adjusted downwards, which is called the expected utilization.

Table 2: Simulation variables

Variables	Description
d	Index of time in days
T	Length of optimization period in days
Q	Number of repetitions of optimized schedule
H	Number of planning cycles
h	Index of the planning cycle
WLX_c	must-do waiting list of category c
WLY_c	can-do waiting list of category c
R_c	Target patient throughput
E_c	Additional patients
$\lambda x_{h,c}$	Daily arrival rate of urgent patients of category c during h
$\lambda y_{h,c}$	Daily arrival rate of elective patients of category c during h

2.4 Numerical study

The models are tested in a numerical study utilizing input data collected from the cardiothoracic surgery (CTC) department of the Maastricht University Medical Centre (MUMC+). The input data related to patient category features are based on surgical data recorded from 2021 and capacity data is based on past experiences. Individual patients are organized into patient categories based on resource utilization and procedure type in accordance with cardiothoracic surgeons. Each patient category c has its own resource characteristics, which are the operation duration o_c, pre-operative days at the MC po_c (Table 3), and a LOS distribution for the MC and IC $L_{ic,c,j}$ and $L_{mc,c,j}$ (Appendix A). Furthermore, the penalty costs and the bonus factors for each category are stated in Table 3. Finally, the number of patients currently on the waiting list is represented as the start waiting list in Table 3. Table 4 shows the maximum resource capacity and the weights for the over-utilization of resources. The patient and resource weights are chosen by trial and error.

The optimization model is evaluated within the simulation for an optimization period of 28 days ($T = 28$ days), which was repeated three times ($Q = 3$) and resulted in a planning cycle of 84 days. This planning cycle is chosen because the capacity allocation and surgeon availability is known three months in advance and the urgency term of elective patients of the CTC department is assumed to be 12 weeks. Four planning cycles are used to include seasonal demand throughout the year, so the number of planning cycles H was set to four. The daily arrival rates are displayed in Appendix B for both urgent and elective patients. We use the total arrival rate for the determination of the queue length distribution in the Markov model. Based on historical data the target rate is set at 85% since 15% of the patients in the data are emergency patients.

We test numerous scenarios to show the practicability of the model for hospitals. The model as presented in section 2.1 is compared to the model of Adan et al. (2009). In the remaining part of this paper, "new model" refers to the model as presented in this paper and "previous model" relates to the model of Adan et al. (2009), and "steady-state model" refers to the MSS resulting from the methodology presented in Section 2.2. The variable E_c is not used in the previous model as it does not take extra patients into account. The required patients R_c in the previous model are similar to the new model.

Table 3: Parameters per patient category

Category index c	Category name	O	IC	PO	MC	PC	BF	Start waiting list
1	CABG	4	1	1	4	120	12	21
2	AVR	4	2	1	5	120	12	14
3	CABG + AVR	4	2	1	6	120	12	5
4	TAVI	1.5	0	0	3	45	4.5	10
5	Mitral valve	4	2	1	6	150	15	0
6	Mitral valve complex	5	3	1	6	150	15	10
7	Minimally invasive surgical ablation	5	1	1	5	150	15	9
8	Aortic / other surgery	5	2	1	8	150	15	3
9	Aortic/ other surgery complex	8	3	1	8	240	24	1
10	MIDCAB	3	1	1	3	90	9	15
11	Minimally invasive mitral valve	5	2	1	6	150	15	11
12	Other small cardiac surgery	2	0	0	3	80	8	4
13	Lung surgery	2	1	1	9	80	8	2
14	Lung surgery complex	3	0	1	7	90	9	3
15	Thymus / oncological	3	0	1	3	90	9	21

Table 4: Maximum resource capacity and resource weights

	OT	IC	MC
Monday	16	6	20
Tuesday	16	6	20
Wednesday	16	6	20
Thursday	16	6	20
Friday	16	6	20
Saturday	0	6	20
Sunday	0	6	20
W_r	10	10	7

Scenario 1: Base case

In the first scenario, the new model is compared with the previous model and the steady state model in the optimization-simulation approach. The new and previous model are compared in the optimization-simulation approach for a year. A new MSS is optimized every planning cycle by both models and the outcomes were compared.

For the comparison with the steady-state model, a constant MSS is designed first based on the algorithm as described in Section 2.2. Then the simulation is used to analyze the difference between the constant MSS and the dynamic MSS. The dynamic MSS is optimized for every planning cycle of 12 weeks and the simulation length for this comparison is 20 years.

Scenario 2: Including planning restrictions
The second scenario aims to demonstrate the impact of the current tactical plan and corresponding surgical staff availability of the hospital on resource utilization and waiting list development. Two versions of the current planning practice are tested. Scenario 2a includes the tactical schedule of the hospital, which is shown in Table 5 and scenario 2b only contains restrictions that resulted from the tactical schedule. Table 6 shows the categories that can be planned on each day following from Table 5.

Table 5: Current tactical schedule scenario 2a

Monday	Tuesday	Wednesday	Thursday	Friday
$\geq$ 2 of category 13,14,15	$\geq$ 2 of category 1,2,3,5,6,8	$\geq$ 2 of category 1,2,3,5,6,8	$\geq$ 5 of category 4 / 1 of category 5,6	$\geq$ 2 of category 10
$\geq$ 1 of category 7	$\geq$ 0 of category 13,14	$\geq$ 1 of category 11	$\geq$ 1 of category 11	$\geq$ 1 of category 7,8,9
$\geq$ 0 of category 1,2, 12,13	$\geq$ 1 of category 7,8,9	$\geq$ 1 of category 1,2,3,5,6,8,12,13	$\geq$ 0 of category 1,2,3,8,12	$\geq$ 0 of category 1,2,3,8,12
	$\geq$ 0 of category 1,2,3,8,12			

Table 6: Plan options scenario 2b

	Monday	Tuesday	Wednesday	Thursday	Friday
1	x	x	x	x	x
2	x	x	x	x	x
3		x	x	x	x
4				x	
5		x	x	x	
6		x	x	x	
7	x	x			x
8		x	x	x	x
9		x			x
10					x
11			x	x	
12	x	x	x	x	x
13	x	x	x		
14	x	x			
15	x				

Scenario 3: The beginning of the pandemic
The third scenario is based on the start of the pandemic. In this scenario, fewer resources are available from the second up to and including the fourth period of the year because of the allocation of hospital beds and anaesthesia personnel to COVID-19 patients. The maximum resource capacity for the second up to and including the fourth period is displayed in Table 7. The start waiting list is estimated as the arrival rate multiplied by a waiting time of six weeks and is displayed in Table 8.

Table 7: Maximum resource capacity scenario 3

	OT	IC	MC
Monday	8	3	10
Tuesday	8	3	10
Wednesday	8	3	10
Thursday	8	3	10
Friday	8	3	10
Saturday	0	3	10
Sunday	0	3	10

Table 8: Start waiting list scenario 3

Category	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Start waiting list	48	10	2	20	1	4	2	4	2	9	4	3	7	8	7

Scenario 4: During the pandemic
The fourth scenario is based on 2021 which was during the COVID-19 pandemic. At the beginning of that year, the waiting list length was higher than usual (Table 9) and more capacity (Table 10) was available because the hospital had to catch up with the backlog of surgeries.

Table 9: Start waiting list scenario 4

Category	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Start waiting list	56	26	8	45	4	8	10	14	4	29	18	3	2	4	10

Table 10: Maximum resource capacity scenario 4

	OT	IC	MC
Monday	20	9	20
Tuesday	20	9	20
Wednesday	20	9	20
Thursday	20	9	20
Friday	20	9	20
Saturday	0	9	20
Sunday	0	9	20

Scenario 5: Misjudged weights
The fifth scenario is almost similar to the base case scenario. However, the weights are misjudged and not adjusted based on trial and error. The settings of these weights are displayed in Table 11. Medium implies that the weights are chosen similarly to the first scenario. The low patient weights are set equal to the surgery duration and low over-utilization weights are all equal to one.

Table 11: Weights in scenario 5

	Over-utilization	Capacity	Patient weights
5a	Medium	Medium	Low
5b	Low	Medium	Medium
5c	Medium	Zero	Medium
5d	Medium	Medium	High variation

3 Computational results

Many results were generated from each of the scenarios. In the first scenario, we compared the MSS from the steady-state model with the new optimization-simulation approach, which showed that frequent optimization provides better results and that the assumption of stationary demand is not valid. Therefore, the optimization-simulation approach was applied to the other scenarios.

Five simulation runs were generated for each scenario. For each of these runs, a new arrival sample was drawn from the Poisson distribution. These distributions were similar for both models. Within these simulations, four optimizations took place, one for each planning cycle. One simulation is similar to the approach as described in Figure 2, the new model is described in Section 2.1, the previous model is adopted from Adan et al. (2009), and the scenarios are described in Section 2.4.

Gurobi was used as an optimization tool, which transformed the new model into a Mixed Integer Linear Programming (MILP) model. Each optimization was given a maximal computational time of ten minutes because of the large computational time for the whole simulation. A computational time of ten minutes for one optimization model results in a run time of over 3 hours per scenario and model. Both models were not always able to solve the problem to optimality within 10 minutes. The optimality gaps ranged from 0-4.8%. Running the optimization models with more computational time would probably only lead to a small improvement in the objective, a shift of only a few patients in the schedule, and minimal implications for resource utilization and waiting list outcomes.

The results of the optimization-simulation approach are summarized in Appendix E and Appendix F. The results in the tables show the average values of five simulation runs per model and scenario.

Appendix E shows the results related to the resource utilizations, which are the average utilization percentage and the required capacity. The average utilization percentage is defined as the expected utilization, which is the planned utilization adjusted downwards to the cancelled slots, divided by the target utilization over the planning cycle. The required capacity is also shown because the new model is able to adjust the target utilization downwards and the previous model is not. The required capacity is defined as the maximum utilization of OT hours, IC beds, and MC beds. A deviation is made between week and weekend days since no surgeries are performed during the weekends and this affects the utilization of the other resources.

Appendix F displays the results related to the waiting lists, which are the cancellations of surgery slots, the number of tardy patients and average waiting list lengths. These were calculated per patient category but are conveniently displayed as the average, maximum, and sum over the fifteen patient categories.

The remaining part of this chapter highlights the main findings of each scenario and discusses them in more detail. The graphs shown were made for each planning cycle, scenario and model but only the most meaningful ones are presented in this chapter.

3.1 Scenario 1: Base case

In this first scenario, two comparisons were made. Firstly, we present the comparison between the previous model and the new model by using the optimization-simulation approach. Secondly, we provide the results of the second comparison, which compares a dynamic and constant MSS. The MSS was designed based on sufficient steady-state probabilities of the waiting list length.

3.1.1 Comparison between the previous and new optimization model

The results first comparison, between the previous model of Adan et al. (2009) and the new optimization model, are shown in Table 12. These numbers are the average values over five simulation runs and four planning cycles. The new model resulted in fewer tardy patients, fewer cancelled slots, less required resource capacity, and a higher utilization compared to the target. The required resource capacity is the maximum expected utilization during the planning cycle. The results in Appendix E show that the required resource capacity was similar for both models in the first planning cycle. The demand and supply matched better in the first cycle compared to the other cycles where the booked capacity in the new model was adjusted downwards.

Table 12: Comparison between the new and previous optimization model in scenario 1

	Previous model	New model
Total # of tardy patients	33	23
Total # of cancelled slots	62	60
Required OT hours	14.5	11.75
Required IC beds weekdays	5	3.75
Required MC beds weekdays	16.5	13.75
% of target OT utilization	0.71	0.88
% of target IC utilization weekdays	0.60	0.67
% of target MC utilization weekdays	0.67	0.87

We will explain these numbers in more detail. The number of tardy patients was counted at the end of every planning cycle, which is the number of patients who are still on the must-do waiting list at the end of the cycle. There are often some tardy patients since urgent patients can still arrive at the end of the cycle on the must-do waiting list, leaving limited time to plan them. This affected the outcomes of both models equally since demand arrivals were similar for both optimization models. The results show an average of 33 tardy patients for the previous model and only 23 tardy patients for the new model.

Figure 3 provides an example of the results of one simulation run for patient category 14. We observe four tardy patients in the outcomes of the previous model since at the end of the second and third planning cycle two patients remain on the must-do waiting list, whereas only two tardy patients resulted from the new model.

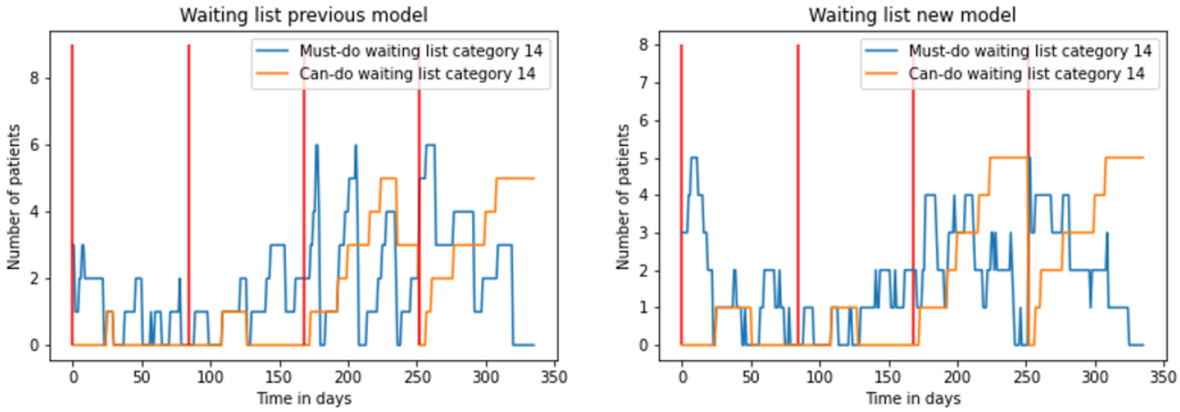


Figure 3: Waiting list results scenario 1 of patient category 14

A smaller difference is observed in the number of cancelled slots. Slots are cancelled when patient categories are planned, but the waiting list is empty. These were tracked in the simulation each day and the planned utilization is then adjusted downwards to the expected utilization. On average 62 cancelled slots resulted from the previous model, whereas only 60 cancelled slots resulted from the new model.

Figure 4 explains the differences between both models in required capacity and percentage of target utilization. This figure displays the results of both optimization models for the first scenario in the fourth planning cycle. The new model is able to adjust the capacity downwards by reserving only the booked capacity and adjusting the target utilization accordingly. Therefore, the utilization is levelled over the planning cycle and fewer OT hours are required. The utilization in the new model did not exceed 10 OT hours, whereas the previous model required 14 OT hours on some days. Furthermore, the expected utilization, which is the planned utilization adjusted downwards when surgeries are cancelled, was closer to the target utilization. Similar outcomes were observed for the other resources and planning cycles.

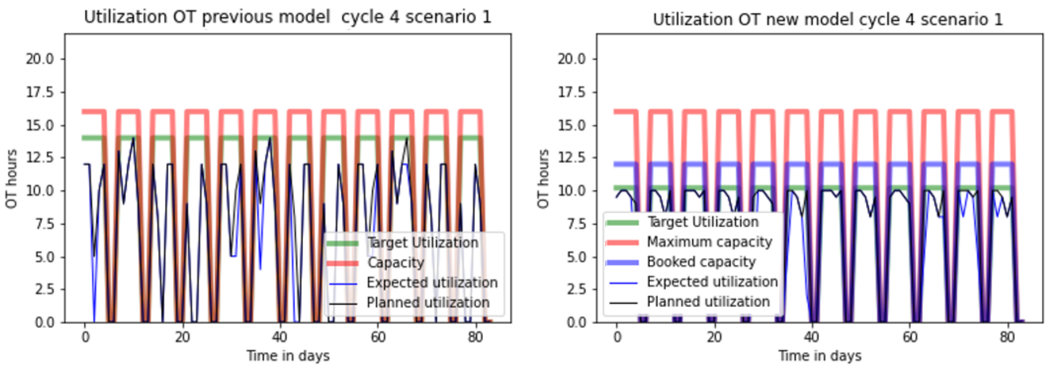


Figure 4: OT utilization scenario 1 cycle 4

3.1.2 Comparison between dynamic and constant MSS

The second comparison in this scenario is between the constant MSS as designed with the steady-state algorithm and a dynamic MSS. Firstly, the algorithm was applied with a maximum capacity of 16 OT hours, 6 IC beds, and 20 MC beds to design an MSS. However, the results showed that reaching sufficient waiting time was impossible with this maximum capacity. Therefore, the maximum capacity was increased to 20 OT hours, 9 IC beds, and 20 MC beds, as shown in scenario 4. Since the optimization model is able to adjust the booked capacity downwards, the algorithm determined how much capacity was required.

The algorithm was stopped after the fourth iteration because sufficient waiting time was reached for all categories. The fourth iteration reached an optimality gap of 2.4% after 600 seconds. The reason to stop the algorithm implies that the input capacity was enough to fulfil the average demand. The results indicate that 17 OT hours, 6 IC and 20 MC beds would be sufficient to plan patients within their urgency term of 12 weeks and still reserve 15% of the capacity for emergency patients.

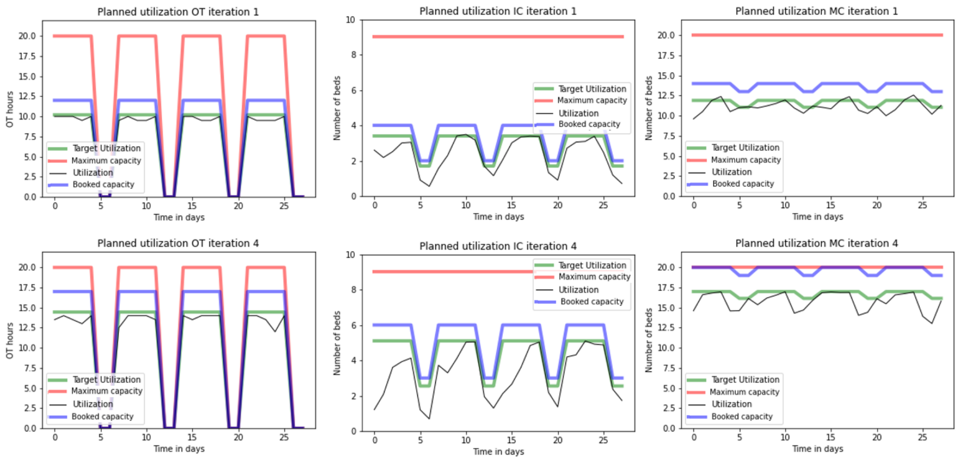


Figure 5: Steady-state utilization

The resource utilization of the first and final iteration are shown in Figure 5. The booked capacity increased because more slots are required to ensure sufficient waiting time.

In each iteration, the steady-state probabilities for the waiting list length were calculated. Figure 6 shows the average waiting list length for patient category 2 for the first and fourth iterations. The target waiting time of 84 days and an average arrival rate of 0.17 patients per day indicate a target waiting list length of around 14 patients.

In iteration 1 the steady-state waiting list length as a result of the optimized schedule was almost 100 patients for category 2, which is much higher than the target. Therefore, in the next iteration, an extra patient was added to the patient throughput target.

In the final iteration, the average waiting list length became steady and was below the target, which led to a sufficiently low waiting time. The line is not a small straight line because the average waiting list length fluctuates throughout the optimization period based on the schedule. This analysis was conducted for each patient category.

Results from the final iteration are displayed in Table 13. The table shows the average daily arrival rate of a combination of urgent and elective patients, the average waiting list length that results from the optimization model and steady-state calculations, the average waiting time according to Equation 20, and the number of required slots.

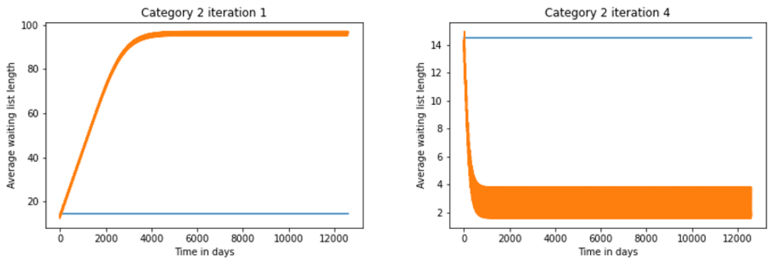


Figure 6: Steady-state waiting list length of category 2

The second step is the comparison between the constant MSS that resulted from the steady-state (SS) model with the new optimization-simulation approach. The maximum available capacity for the new approach was set to 17 OT hours, 6 IC beds, and 20 MC beds since that was the booked capacity of the SS model. Testing the approach with more capacity leads to incomparable results.

The first performance indicators are the waiting list length and the number of tardy patients. Figure 7 displays the total waiting list and the number of tardy patients of both models for over 20 years. A tardy patient is a patient who remains on the must-do waiting list at the end of the cycle. Therefore, a higher number of tardy patients implies a lower number of patients planned within their urgency term. The waiting list that resulted from the constant MSS fluctuates less but has higher peaks in waiting list length compared to dynamic MSS. Furthermore, fewer tardy patients resulted from the dynamic MSS.

Table 13: Results of steady-state waiting list length

Category	Average arrival rate	Average waiting list length	Average waiting time in days	Number of slots required per 28 days
1	0.85	39.05	46	24
2	0.17	2.44	14	6
3	0.03	0.42	14	2
4	0.35	19.35	55	10
5	0.01	0.36	36	1
6	0.07	1.5	21	3
7	0.03	0.44	15	2
8	0.07	0.97	14	3
9	0.04	0.58	15	2
10	0.15	3.59	24	5
11	0.07	1.29	18	3
12	0.05	1.65	33	2
13	0.12	3.0	25	4
14	0.15	2.66	18	5
15	0.12	3.0	25	4

The next performance indicators are the booked capacity and expected resource utilization. The expected resource utilization was calculated by adjusting the planned utilization downwards based on the number of cancelled surgeries due to insufficient patients on the waiting list. Since the SS model had a constant schedule, the booked capacity remained fixed at 17 OT hours, 6 IC beds and 20 MC beds. However, the new modelling approach can adjust the booked capacity downwards. Figure 8 illustrates the booked capacity and expected utilization for each cycle over a 20-year period.

The results from Figures 7 and 8 are interrelated to each other as they represent the same time period.

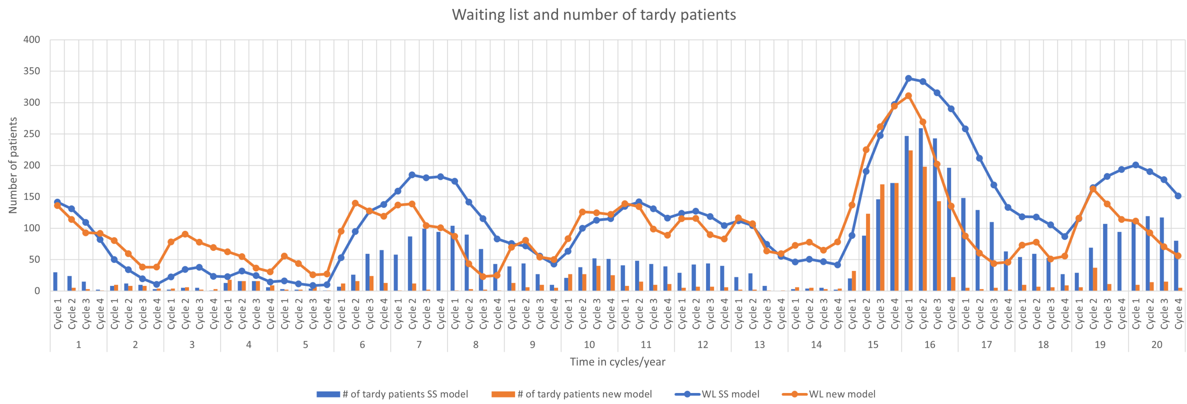


Figure 7: Comparison based on the waiting list and number of tardy patients

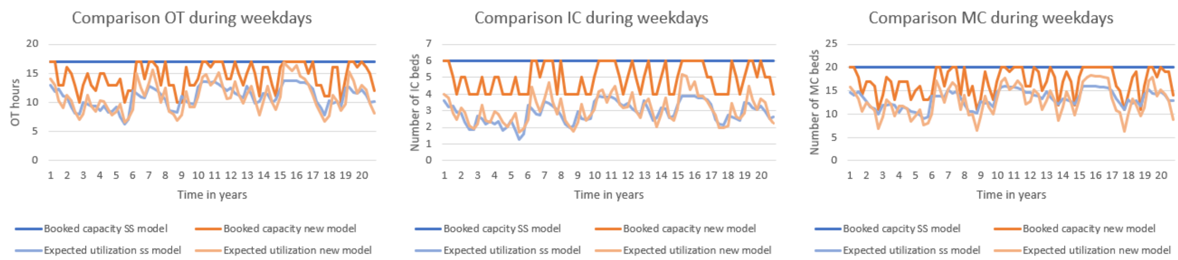


Figure 8: Comparison based on the booked capacity and expected resource utilization

3.2 Scenario 2: The current situation

The second scenario was designed to evaluate the current planning practice and corresponding surgical staff availability of the hospital. Scenario 2a demonstrates that planning with the current tactical plan is not possible. The previous model was infeasible which implies that the number of patients who should be planned according to the tactical plan did not correspond with the number of target patients from the waiting list and demand rate. The new model worked for the first cycle because additional patients could be planned to fulfil the tactical plan. However, the waiting lists at the beginning of the second planning cycle were not long enough to fill the tactical plan for the second cycle.

The restrictions related to the number of patients for each category were removed in scenario 2b. This scenario only contained restrictions on the category of patients. This scenario was compared to the first scenario, where no restrictions were included.

The first comparison is based on resource utilization. More IC beds and MC beds were required by the new model when restrictions were added, as shown in Resource results. Figure 9 displays the utilization of the IC and MC in the first and second scenarios. This figure demonstrates that the planning rules impact the utilization of the resources, especially the IC beds. Six IC beds were required in scenario 2b, whereas in the base case scenario, only five IC beds were required. Moreover, the expected utilization of the OT passed the target utilization in scenario 2b, which implies that insufficient capacity was available for emergency patients.

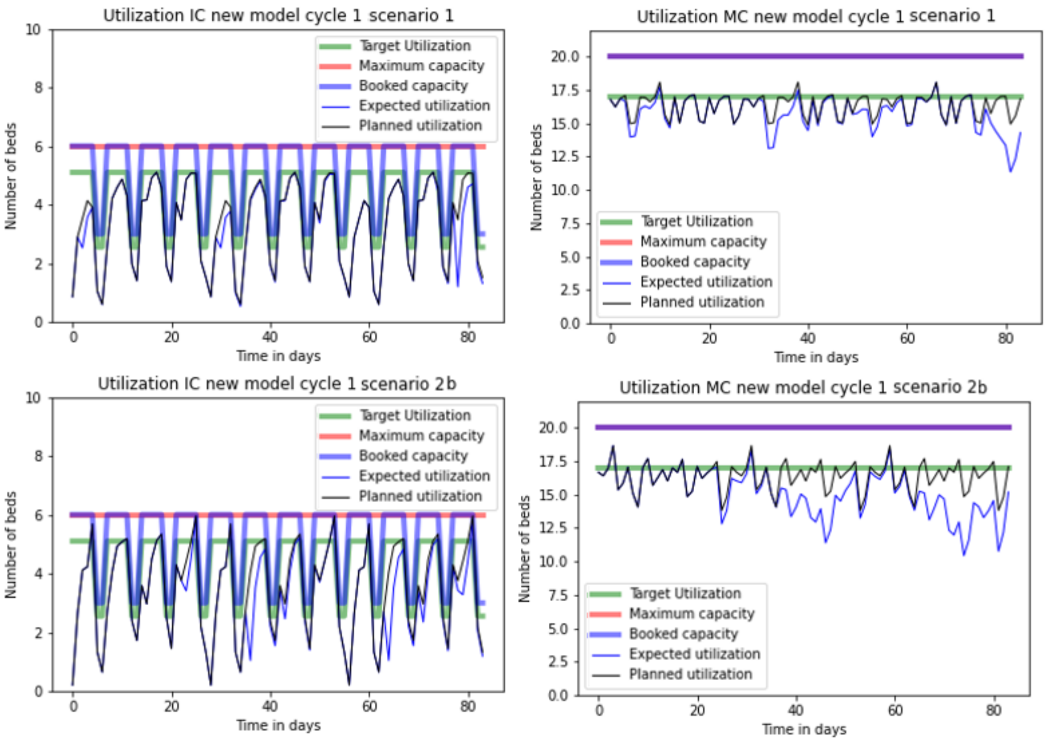


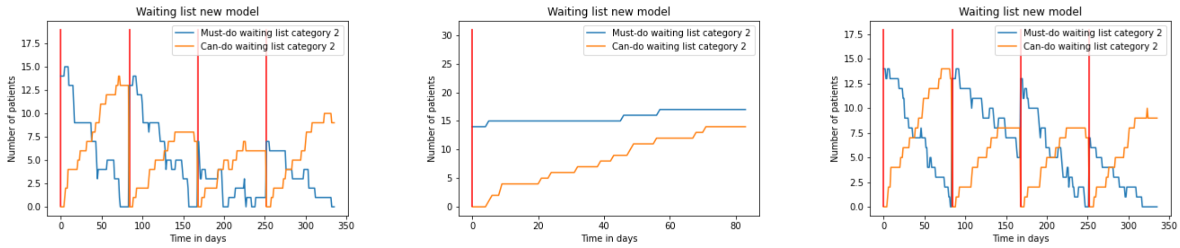
Figure 9: Bed utilization with (scenario 2b) and without (scenario 1) restrictions

The second comparison between the first and second scenarios is based on the waiting list characteristics. The total numbers of tardy patients for scenarios 1, 2a, and 2b for the new model are 33, 31, and 23 respectively. Scenario 2a was only simulated for one cycle and already reached this number of tardy patients. The absence of restrictions leads to a lower number of tardy patients. An example of the waiting list of category 2 is presented in Figure 10. The must-do waiting list length was higher than zero at the end of the first planning cycle for scenario 2a and therefore many tardy patients resulted from this scenario. This figure illustrates that the first scenario, without planning restrictions, resulted in fewer tardy patients than the second scenario for patient category 2.

The total number of cancelled slots for both scenarios and optimization models in the first and second scenarios ranged between 60 and 64, indicating minimal differences in cancellations. Small contrasts were also present in the average waiting list lengths.

3.3 Scenario 3: The beginning of the pandemic

Scenario 3 is based on the beginning of the pandemic with limited resource availability from the second up to and including the fourth planning cycle. The previous model was only able to design an MSS for the first cycle. In the second cycle, the capacity could not meet the target patient throughput and therefore the model became infeasible.



(a) Scenario 1 **(b)** Scenario 2a **(c)** Scenario 2b

Figure 10: Waiting list results of category 2

The new model was able to design an MSS for all planning cycles. The mismatch between demand and supply caused high resource utilization and many tardy patients. The utilization was high, resulting in minimal capacity for emergency patients.

Figure 11 displays the waiting list development of category 4, which is similar to other categories, and the utilization of the OT of cycle 2, where no capacity was available for emergency patients.

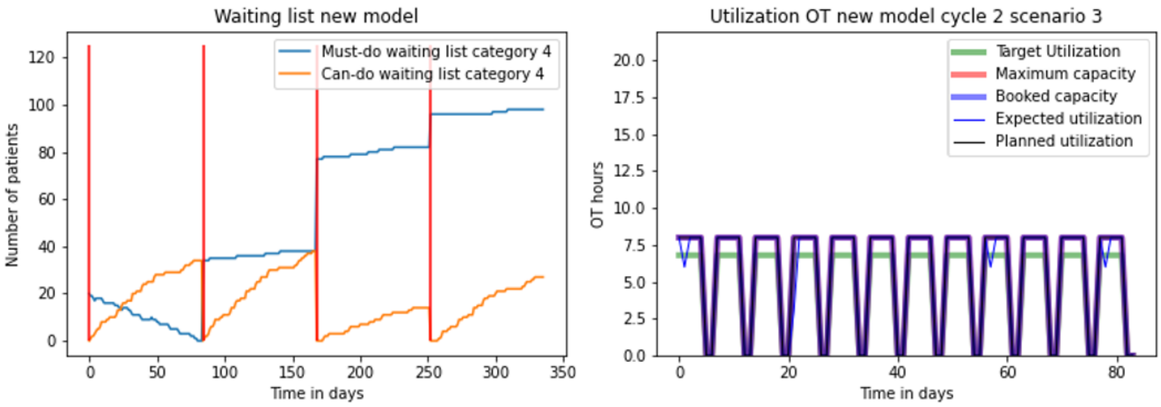


Figure 11: Waiting list results and OT utilization scenario 3

3.4 Scenario 4: During the pandemic

The next scenario is based on the year 2021, which was during the COVID-19 pandemic. Due to the large waiting lists, hospitals needed to increase their capacity in order to catch up with the backlog of elective surgeries. Even though the capacity was increased, the previous model was still not able to solve this scenario. The target patients did not fit in the capacity and therefore the model became infeasible. On the other hand, the new model was able to generate a schedule and results. The number of tardy patients for this scenario is high compared to other scenarios because not all target patients could be planned.

The number of tardy patients differs between patient categories. Figure 12 illustrates this difference by showing that the must-do waiting list of category 8 was empty at the end of all planning cycles, resulting in zero tardy patients, whereas the must-do waiting list of category 14 was not empty at the end of the first and third cycle, resulting in a total of 16 tardy patients. The resource utilization during the first cycle was significantly higher compared to the other planning cycles. This is likely due to the initial waiting list being longer, indicating a higher demand at the beginning of the planning cycle. Furthermore, more capacity was required in the first cycle than in the other cycles. The OT was the bottleneck in the first cycle and not enough capacity could be reserved for the emergency patients. For the remaining cycles, the extra capacity was too much, and the capacity was adjusted downwards by the new model.

Figure 13 shows the utilization of this scenario for the OT. These results show that 20 OT hours were not sufficient in the first planning cycle to plan the elective patients within 12 weeks, whereas 14 OT hours were enough in the third cycle to plan the elective patients and reserve space for emergency patients.

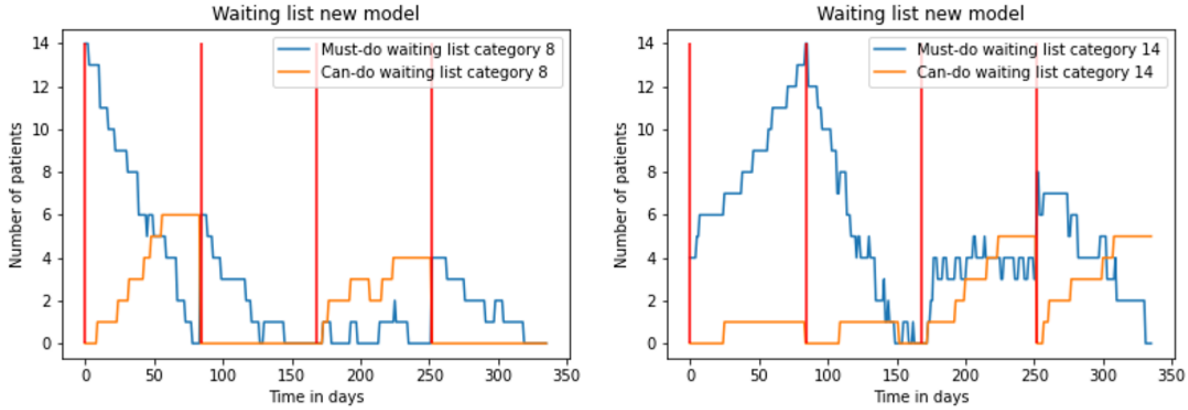


Figure 12: Waiting list results scenario 4

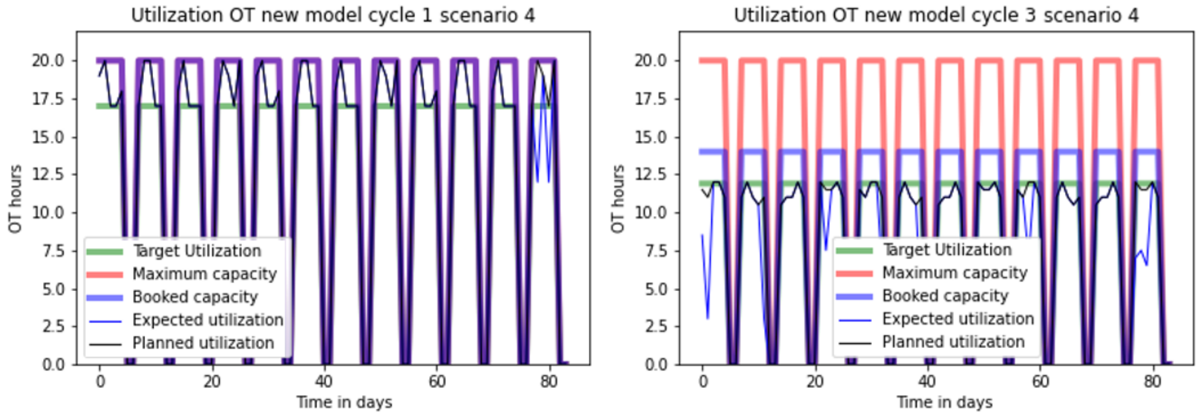


Figure 13: OT utilization scenario 4

3.5 Scenario 5: Misjudged weights

Various configurations of the weights were chosen in this scenario. The previous model demonstrates similar outcomes compared to the base case scenario since the unfortunate choice of weights only affected the resource utilization of the previous model and therefore only scenario 5b. The differences were minimal. This scenario shows much more impact on the new model.

Setting the patient weights low (scenario 5a) resulted in an empty schedule for the new model. The under-utilization was not penalized and therefore the model decided not to plan patients. In this scenario, where no patients were planned, the waiting lists kept increasing resulting in an average number of tardy patients of 1790, which is considered extremely high for the new model. Consequently, the resource utilization was zero.

Scenario 5b, where the penalty for over-utilization is lower ($w_r = 1 \quad \forall r \in RS$), mainly affected the new model. The new model unnecessarily adjusted the booked capacity downwards, which resulted in less capacity being available for emergency patients. This is shown in Figure 14, which displays the OT utilization for both optimization models in scenario 5b in comparison to the base case.

Scenario 5c only influenced the new model. For this scenario, the weight of the required capacity was set to zero and was therefore removed from the objective function. Accordingly, the model was not forced to adjust the required capacity downwards. As many surgery slots as possible were planned in this scenario because that is rewarded by the objective function as long as the utilization remains under the target utilization. However, not all slots could be filled during the simulation because the waiting list length was too short. This resulted in 184 cancelled slots and an average must-do waiting list level of 25 patients, which are the highest number of cancelled slots and lowest waiting list level over all scenarios.

The final scenario is scenario 5d, in which the patient weights were chosen with high variation. This resulted in some patient categories that were not planned and their waiting lists kept growing resulting in many tardy patients. As shown in Appendix F, the difference between the mean and maximum number of tardy patients is large in this scenario for the new model. In scenario 1, where the weights were chosen appropriately, the new model resulted in an average of two tardy patients and a maximum of nine, whereas in scenario 5d the average is five tardy patients and the maximum is 36 tardy patients.

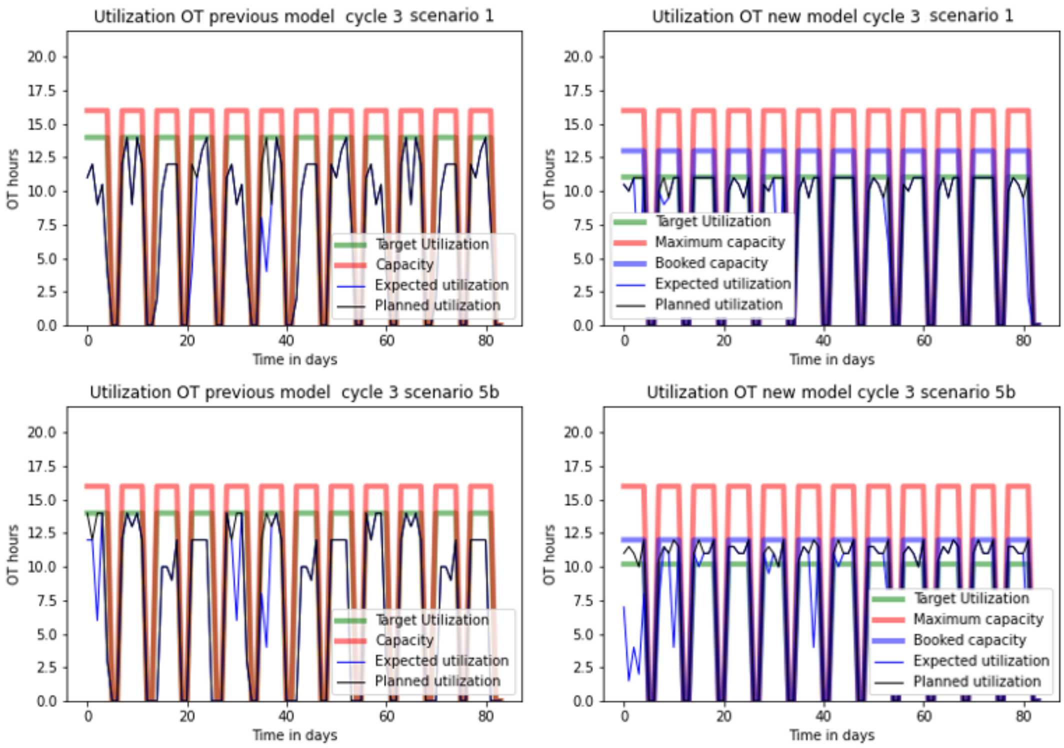


Figure 14: OT utilization scenario 5b

4 Discussion

Much research has been conducted on the tactical planning of elective surgeries, which involves the optimization of the MSS, also referred to as the MSSP. Whereas most papers included the optimization of resource utilization, only a limited amount of papers could be identified that considered the waiting list when solving or analysing the MSSP. This paper aimed to fulfil that gap by considering the waiting list in the optimization-simulation approach. Furthermore, we conducted a demand and supply analysis and tested the effects of surgical staff availability, as suggested for future research by previous papers.

The aim of this paper was to enhance previous models for better practicability. The hospital of the numerical study was concerned with improving waiting list management in order to treat the right patients within their urgency term while ensuring high utilization of resources and reserving capacity for emergency patients by designing an MSS for the CTC department. Therefore, a previous model, the model of Adan et al. (2009), was adjusted to reach this objective. The uncertainty in the length of stay was adopted from the previous model because their research highlighted the importance of uncertainty in these variables. Also, the optimization-simulation approach was acquired to test the effects of the models on the waiting list.

In this paper, we have presented an optimization-simulation approach to compare the previous model with our new model for the design of an MSS. Furthermore, the optimization-simulation approach was compared to a constant MSS, which was based on a sufficient steady-state waiting list length. Multiple scenarios were simulated to test the practicability of the models. The performance was assessed on waiting list development, resource utilization, the number of tardy patients, cancellation of slots, and booked capacity.

Firstly, results indicated that quarterly optimization of the MSS improved the performance in terms of waiting list length, the number of tardy patients, booked capacity and resource utilization compared to a constant MSS. This highlights the importance of a dynamic MSS that considers the waiting list when allocating resource capacity.

Furthermore, the comparison between the previous and new model demonstrated that outcomes in terms of resource utilization and waiting list characteristics were comparable in scenarios where demand and supply matched well. The demand is characterized by the resource needs of patients who should be treated within their urgency term and the supply by the available capacity of the OT, IC, and MC.

On the other hand, the new model achieved better results in scenarios where demand and supply did not match well. The previous model became infeasible when the capacity needs of the patients on the waiting list exceeded the available capacity. Additionally, the previous model performed worse on resource utilization when the demand was less than the supply because the new model was able to adjust the target downwards and therefore spread the utilization more equally over the planning cycle.

Fourthly, the results demonstrated that the previous model has an advantage when weights were changed. The adjustment of weight had a limited impact on the achievements of the previous model, whereas changing the weights had a major impact on the outcomes of the new model. Therefore, the determination of weights for the new model should be done by skilled people who understand the implications of their choices on model outcomes.

Finally, the results showed that the current tactical model of the hospital is unsuitable for their waiting list and demand rate. Removing the restrictions based on current surgeon availability would lead to fewer resources required and more patients being treated within their urgency term. Therefore, the implementation of the new model is advised for the design of a new MSS and the consideration of a change in surgical staff availability.

Contribution and practical implication

Our model contributes to improving all aspects of the quadruple aim. Firstly, the number of patients who are planned after their due date can be reduced by considering the waiting list when designing an MSS, which probably improves the health of the population. Secondly, the model reserves capacity for emergency patients, which leads to fewer interruptions in the schedule of elective patients and therefore higher patient satisfaction. Thirdly, results demonstrate that fewer resources are required when planning according to our optimization-simulation approach, which can reduce costs. Finally, the approach designs a cyclical schedule, provides the possibility to restrict surgery days, and smoothens bed occupancy, which aims to improve employee satisfaction.

Furthermore, our model is implemented in a user-friendly interface for the CTC surgery planning of the MUMC+, which indicates a significant practical application of this study. Screenshots of this tool are attached in Appendix G. Their planners should be trained properly to choose the weights and interpret the results because our study showed a major impact of the choice of weights on the schedule. The simulation tool can help to assess the impacts of the tactical plan of the MUMC+ on resource utilization and waiting list development. The optimization model could suggest another schedule. Redesigning the tactical schedule immediately is hard to implement because surgeons have their routine working days and other hospital processes are affected by the changes. However, gradual implementation is still possible because patient categories can be restricted. Subsequent research should examine the effects of the new schedules on the actual resource utilization, the number of cancelled surgeries due to insufficient capacity reserved for emergency patients, and patient waiting times.

Finally, a number of practical implications can be drawn from the results. Firstly, this paper shows that a dynamic MSS provides better results in comparison with a constant MSS. The difference between available and booked capacity can be allocated to other surgical specialisms. Secondly, this research highlights the importance of considering the waiting list when determining the MSS to allocate resources to the patient categories with the highest need. Finally, we provide insights into the influence of the planning of surgeries on bed occupancy.

Limitations and future research

Our research has some limitations that should be considered while reading this paper.

The first limitation relates to the use of weights. As shown in one of the scenarios, these weights have a huge impact on the model outcomes. However, the weights were set using trial-and-error and all other scenarios had similar weights. Moreover, the weights were only used for the design of an MSS and did not further impact the numerical results. These weights are not supposed to provide the best objective, but as a method to indicate a preference for the model. Therefore, no optimal determination of the weights is possible. Accordingly, the tool provides the possibility to adjust the weights easily to situational preferences.

The second limitation of this study is the aggregate level of the simulation, which leads to a limited ability to predict the operational outcomes of the MSS. For instance, the operational level can compensate for the cancellations of one patient category by filling them with patients from another category, but the tactical level does not consider this possibility. Future research could incorporate the operational level into the simulation model to have a better prediction of operational outcomes.

Additionally, the patient category data in this paper was only calculated based on one year of surgery data. Multiple years could be used to gather more reliable distributions in patient demand and resource needs. Nevertheless, the sample of 930 patients for the probability of length of stay can still be considered significant. Therefore, we recommend providing the tool with better predictions of patient demand and resource needs in the future.

The final limitation relates to the patient categories, which were composed in accordance with surgeons. The assumption of Poisson arrivals could change for a different configuration of patient categories. A goodness-of-fit test was performed to test the assumption for the current input data but was not valid for all patient categories. Still, a Poisson distribution was assumed to generate multiple demand simulations. Gathering data for multiple years could be useful for the prediction to validate the model. Future research could investigate the impact of these categories on the planning problem.

5 Conclusion

This paper aimed to improve waiting list management by solving the MSSP. The main contribution to the literature was the inclusion of the waiting list in this problem. Therefore, a MIP model was formulated by extending the optimization model of Adan et al. (2009). The aim of this optimization model was to develop an MSS which created sufficient surgery slots while reserving capacity for emergency patients and ensuring high utilization of the resources without wasting capacity. The new model incorporated the waiting list-based throughput as part of the objective function instead of being treated as a constraint and introduced the booked capacity as an additional variable to the maximum capacity.

The analysis of the MSS involved two approaches: modelling the waiting list as a Markov process and developing a simulation model.

The Markov model, which assumes stationary demand and supply, was used to design an MSS that ensured a sufficient steady-state waiting list length. This constant MSS was then compared with a dynamic MSS in the optimization-simulation approach.

The optimization-simulation approach combined the optimization model with a simulation model. This approach was introduced as a research method to model non-stationary demand and supply. A numerical study was conducted to compare the new optimization model with the previous model and the steady-state model.

The results confirmed that enhancing the previous model improved the outcomes in terms of the number of tardy patients, cancelled slots, utilization, and resource requirements.

In scenarios where a mismatch between demand and supply existed, the new optimization model showed significant improvements compared to the previous model. The previous model was not able to solve the optimization problem when the capacity was insufficient to plan the target patient throughput. Furthermore, the new model required less resource capacity when the supply exceeded the demand.

The comparison between the constant and dynamic MSS showed that quarterly optimization results in more patients being planned within their urgency term and a decrease in the waiting list length.

These results indicate that the new optimization model provides better results than the previous model. However, choosing the weights carefully is important. Future research should focus on elaborating the simulation model on the operational level and investigating the impacts of the patient category composition on the planning problem. The model can be used in practice with the planning tool. As such, we recommend the adoption of the optimization-simulation approach to improve waiting list management.

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Appendices

A Length of stay distribution

Table A1: Probability of length of stay in days at the ICU (sample of 930 patients)

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	> 15
1	0.00	0.81	0.11	0.04	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.72	0.15	0.03	0.03	0.03	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.53	0.29	0.06	0.06	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.78	0.16	0.03	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
5	0.00	0.43	0.57	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.04	0.46	0.14	0.04	0.11	0.04	0.07	0.00	0.00	0.04	0.00	0.00	0.04	0.04	0.00	0.00	0.00
7	0.00	0.89	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05
8	0.00	0.66	0.23	0.00	0.06	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
9	0.00	0.31	0.15	0.08	0.15	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.15
10	0.00	0.90	0.07	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.00	0.73	0.15	0.06	0.00	0.03	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.91	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.87	0.07	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.00	0.00
14	0.89	0.04	0.04	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.94	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A2: Probability of length of stay in days at the MC/ward (sample of 930 patients)

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	> 15
1	0.03	0.03	0.24	0.35	0.16	0.11	0.04	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01
2	0.01	0.03	0.25	0.24	0.15	0.01	0.09	0.07	0.01	0.00	0.04	0.00	0.00	0.01	0.00	0.00	0.06
3	0.06	0.00	0.12	0.12	0.18	0.24	0.00	0.00	0.06	0.06	0.06	0.00	0.00	0.00	0.06	0.00	0.06
4	0.03	0.05	0.06	0.57	0.12	0.06	0.06	0.02	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.29	0.14	0.14	0.00	0.14	0.00	0.14	0.14	0.00	0.00	0.00	0.00	0.00	0.00
6	0.18	0.00	0.04	0.04	0.32	0.14	0.07	0.04	0.00	0.00	0.00	0.00	0.04	0.04	0.00	0.00	0.11
7	0.00	0.00	0.21	0.32	0.16	0.05	0.00	0.11	0.05	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.05
8	0.14	0.03	0.11	0.17	0.23	0.06	0.06	0.03	0.03	0.03	0.00	0.03	0.00	0.00	0.00	0.00	0.09
9	0.15	0.15	0.00	0.15	0.08	0.00	0.23	0.00	0.00	0.08	0.00	0.08	0.00	0.00	0.00	0.00	0.08
10	0.06	0.03	0.52	0.28	0.04	0.00	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.01
11	0.06	0.00	0.03	0.18	0.21	0.21	0.06	0.03	0.03	0.00	0.03	0.06	0.03	0.03	0.00	0.00	0.03
12	0.41	0.00	0.36	0.09	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05
13	0.02	0.04	0.09	0.15	0.22	0.24	0.04	0.02	0.02	0.00	0.02	0.04	0.00	0.02	0.00	0.02	0.04
14	0.00	0.02	0.02	0.04	0.15	0.25	0.15	0.11	0.04	0.11	0.04	0.00	0.04	0.04	0.00	0.00	0.02
15	0.02	0.02	0.23	0.46	0.17	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

B Arrival rates

	Urgent	patients				Elective	patients			
	h_1	h_2	h_3	h_4	yearly	h_1	h_2	h_3	h_4	yearly
1	0.48	0.58	0.48	0.49	0.51	0.38	0.31	0.32	0.37	0.35
2	0.04	0.05	0.08	0.01	0.04	0.18	0.10	0.10	0.14	0.13
3	0.02	0.02	0.01	0.00	0.01	0.02	0.00	0.01	0.02	0.01
4	0.05	0.05	0.06	0.02	0.04	0.36	0.38	0.15	0.32	0.30
5	0.01	0.02	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.01
6	0.04	0.02	0.02	0.02	0.03	0.08	0.05	0.02	0.04	0.05
7	0.01	0.00	0.00	0.00	0.00	0.04	0.06	0.01	0.01	0.03
8	0.01	0.01	0.05	0.01	0.02	0.11	0.02	0.04	0.02	0.05
9	0.01	0.01	0.02	0.04	0.02	0.04	0.00	0.01	0.01	0.01
10	0.08	0.08	0.00	0.01	0.04	0.12	0.10	0.06	0.17	0.11
11	0.01	0.01	0.01	0.04	0.02	0.11	0.05	0.00	0.07	0.06
12	0.01	0.00	0.02	0.04	0.02	0.07	0.00	0.05	0.02	0.04
13	0.06	0.12	0.11	0.06	0.09	0.00	0.06	0.06	0.01	0.03
14	0.13	0.11	0.18	0.05	0.12	0.02	0.01	0.05	0.04	0.03
15	0.01	0.02	0.02	0.02	0.02	0.08	0.11	0.13	0.07	0.10

C Patient perspective on the MSSP

Many research papers on the MSSP that include waiting list characteristics assume that patients primarily prefer short waiting times. Anjomshoa, Dumitrescu, Lustig, and Smith (2018) optimized an MSS that minimizes the number of overdue patients, the number of patients on the waiting list, and the number of tardy days and maximizes the revenue. Dellaert et al. (2016) tested strategies to decrease the waiting times. The research of Makboul et al. (2022) focused on designing an MSS to maximise the surgery score which was defined as the maximal waiting time minus the number of days prior to the due date. However, none of these papers actually tested this assumption with real patients. Therefore, we conducted a focus group session with 8 cardiac patients. The main hypothesis that was tested is the assumption that waiting time is the most important factor in patient preferences.

Research method

We conducted a focus group within the MUMC+ with 8 cardiac patients. Four aspects related to waiting list management were investigated, which are presented below.

- Waiting time: time between the date that the need for surgery is indicated and the actual surgery.
- Notification time: how long before the surgery, the moment of surgery is announced. The surgery date is related to the admission date, which is for some patients one day before the actual surgery.
- Certainty: how certain the surgery moment is when it is announced.
- Specification: how specific the surgery date is announced. This could be the exact hour, day, or week of surgery.

Five statements were compiled based on these aspects. These statements were based on a conjoint analysis where the participants could choose between two aspects. An example statement of the trade-off between notification time and certainty was formulated as “would you rather know the surgery date 4 weeks in advance with a high cancellation probability or would you rather know the date 2 days in advance with a low cancellation probability?”. An open discussion took place regarding each statement to gather an understanding of patient preferences and motives. The second part of the focus group was a ranking of the four aspects. Participants had to indicate which aspects were most important to them and why.

Results and implications

The open discussion related to the statements showed that a preference in most trade-offs was highly dependent on personal characteristics and circumstances. The patients with a job were more concerned with the timely notification of their surgery date compared to retired patients. The patients also indicated that their preferences were highly dependent on the surgery type and the urgency as indicated by their doctor. For example, patients indicated that the waiting time for a cardiac device replacement which already occurred multiple times could be longer than for open heart surgery. Also, the fear related to their own condition played a part in this consideration. Some would therefore prefer a short waiting time over all other aspects. Past experiences affected the choice in favour of certainty. Certainty was tremendously desired by patients whose surgery had been cancelled multiple times in the past. The specification of the surgery moment was by all patients chosen to be in days instead of hours or weeks. Finally, patients were asked which aspect was most important to them. Almost all patients indicated that they preferred certainty over the other aspects. The second aspect in favour was the waiting time for most patients. Notification time and specification were considered the least important. In this ranking, patients were told to assume that based on their condition they could wait for surgery for 12 weeks.

From these results, we can conclude that the hypothesis of patient preferences in favour of short waiting time does not always hold. Based on this focus group, it does hold for urgent surgeries and anxious patients, but not for elective patients who can wait 12 weeks. For those patients, certainty in the surgery date is much more important. This could be incorporated into the MSSP by reserving capacity for emergency patients so that the emergency arrivals would have less impact on the elective program.

D Algorithm

Algorithm 1

```
Require: E[WT_c] <= TWT_c        ▷ Expected waiting time should be less than target waiting time
Ensure: BC_r <= C_r
  R_c ← int(λ_c * T)   ∀c ∈ N
  stop ← False
  while stop = False do
      within target ← True
      within capacity ← True
      Optimize MSS                                                   ▷ Use optimization model
      Evaluate the waiting time and planned resource utilization   ▷ Use Markov model and Little's law
      for r ∈ RS do
          if CN_r = C_r then
              within capacity ← False
          end if
      end for
      if within capacity = True then
          for c ∈ N do
              if E[L_c] > TL_c then
                  R_c ← R_c + 1               ▷ Add an additional patient slot in the next iteration
                  within target ← False
              end if
          end for
          if within target = True then
              stop ← True                     ▷ Stop: sufficient waiting time and capacity
          end if
      else if within capacity = False then
          stop ← True                                      ▷ Stop: capacity reached
      end if
  end while
```

E Resource results

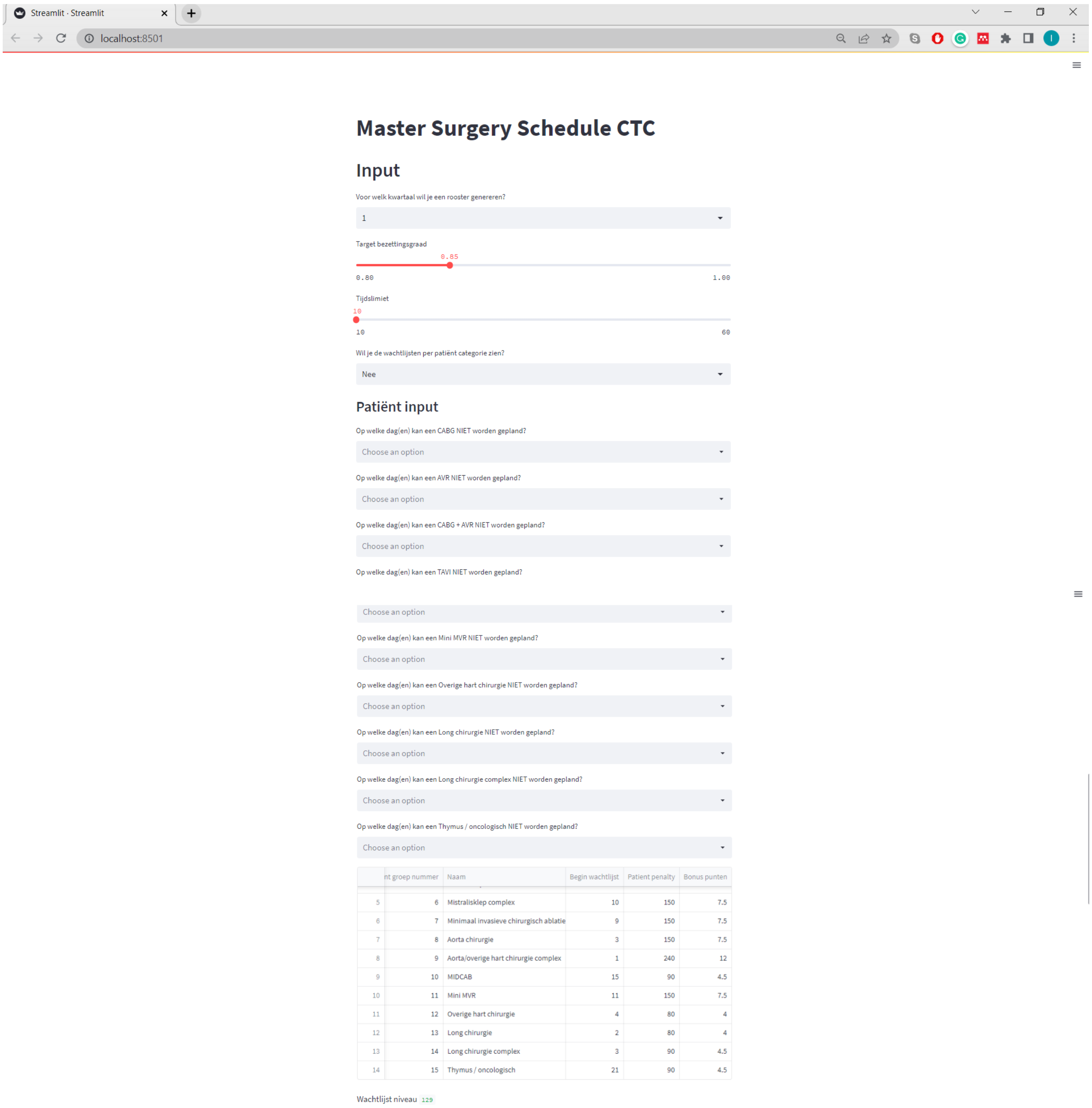
			OT utilization				IC utilization week				IC utilization weekend				MC utilization week				MC utilization weekend			
			Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 1	Cycle 2	Cycle 3	Cycle 4
Scenario 1	Utilization	Previous	0.97	0.75	0.62	0.50	0.85	0.65	0.49	0.41	0.31	0.21	0.17	0.12	0.90	0.69	0.64	0.46	0.88	0.68	0.64	0.47
		New	1.00	0.88	0.83	0.79	0.75	0.69	0.64	0.65	0.55	0.55	0.42	0.51	0.91	0.87	0.84	0.84	0.87	0.87	0.80	0.84
	Required capacity	Previous	16	14	14	14	5	5	5	5	2	2	2	2	18	17	16	15	17	15	15	13
		New	16	12	10	9	5	4	3	3	2	2	2	1	18	14	13	10	17	13	13	9
Scenario 2a	Utilization	Previous																				
		New	0.95				0.69				0.50				0.89				0.88			
	Required capacity	Previous																				
		New	16				6				2				20				18			
Scenario 2b	Utilization	Previous	0.97	0.74	0.62	0.51	0.84	0.64	0.49	0.42	0.34	0.21	0.18	0.14	0.90	0.69	0.64	0.46	0.90	0.70	0.63	0.48
		New	1.00	0.88	0.81	0.77	0.76	0.70	0.62	0.61	0.62	0.53	0.50	0.44	0.87	0.82	0.79	0.82	0.88	0.90	0.86	0.84
	Required capacity	Previous	16	14	14	13	6	5	5	4	3	2	2	2	18	17	17	13	17	15	14	12
		New	16	12	12	9	6	5	4	3	3	2	2	1	19	15	15	10	17	14	13	10
Scenario 3	Utilization	Previous	0.94				0.82				0.28				0.87				0.88			
		New	0.97	1.13	1.09	1.05	0.76	0.89	0.85	0.79	0.77	0.71	0.59	0.50	0.93	0.87	0.93	0.89	0.92	0.90	0.91	0.87
	Required capacity	Previous	14				5				2				17				17			
		New	14	8	8	8	5	3	3	3	2	1	1	1	18	9	10	9	16	8	9	9
Scenario 4	Utilization	Previous																				
		New	1.05	0.88	0.77	0.79	0.82	0.69	0.64	0.66	0.74	0.62	0.47	0.51	1.07	0.97	0.82	0.84	1.08	0.94	0.79	0.85
	Required capacity	Previous																				
		New	20	15	11	9	7	5	4	3	3	2	2	1	20	19	13	10	20	18	13	9
Scenario 5a	Utilization	Previous	0.97	0.75	0.62	0.50	0.84	0.66	0.49	0.41	0.32	0.21	0.17	0.12	0.91	0.69	0.64	0.46	0.88	0.69	0.64	0.47
		New	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Required capacity	Previous	16	14	14	14	5	5	5	5	2	2	2	2	17	17	16	15	17	15	15	13
		New	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Scenario 5b	Utilization	Previous	0.97	0.75	0.60	0.53	0.85	0.65	0.47	0.43	0.32	0.20	0.15	0.14	0.92	0.70	0.62	0.48	0.87	0.67	0.61	0.49
		New	1.03	0.93	0.87	0.94	0.96	0.74	0.68	0.79	0.89	0.59	0.48	0.63	0.98	0.92	0.89	0.90	0.99	0.90	0.88	0.92
	Required capacity	Previous	16	14	14	14	6	5	5	5	2	2	2	2	18	17	17	16	17	15	15	14
		New	16	14	11	9	5	5	3	3	2	2	2	1	19	16	15	11	19	16	14	11
Scenario 5c	Utilization	Previous	0.97	0.75	0.62	0.50	0.85	0.65	0.49	0.41	0.31	0.21	0.17	0.12	0.90	0.69	0.64	0.46	0.88	0.68	0.64	0.47
		New	1.00	0.85	0.67	0.64	0.77	0.64	0.42	0.46	0.31	0.21	0.13	0.14	0.90	0.81	0.69	0.62	0.87	0.80	0.65	0.59
	Required capacity	Previous	16	14	14	14	5	5	5	5	2	2	2	2	18	17	16	15	17	15	15	13
		New	16	14	14	14	6	5	5	5	2	2	2	2	17	17	17	17	17	17	17	16
Scenario 5d	Utilization	Previous	0.97	0.75	0.62	0.50	0.85	0.65	0.49	0.41	0.31	0.21	0.17	0.12	0.90	0.69	0.64	0.46	0.88	0.68	0.64	0.47
		New	0.91	0.86	0.86	0.83	0.79	0.76	0.75	0.73	0.80	0.56	0.53	0.58	0.87	0.85	0.84	0.86	0.88	0.85	0.82	0.86
	Required capacity	Previous	16	14	14	14	5	5	5	5	2	2	2	2	18	17	16	15	17	15	15	13
		New	14	12	11	9	4	4	4	3	2	2	1	1	17	14	14	10	15	13	13	9

F Waiting list results

			Scenario 1	Scenario 2a	Scenario 2b	Scenario 3	Scenario 4	Scenario 5a	Scenario 5b	Scenario 5c	Scenario 5d
Number of cancelled slots	Mean	Previous	4		4	1*		4	4	4	4
		New	4	2*	4	2	3	0	8	12	4
	Max	Previous	14		14	4*		14	13	14	14
		New	13	10*	14	8	10	0	22	27	14
	Total	Previous	62		64	9*		61	64	62	62
		New	60	28*	62	33	52	0	113	184	57
Number of tardy patients	Mean	Previous	2		2	0*		2	2	2	2
		New	2	2*	2	21	6	119	1	1	5
	Max	Previous	12		11	2*		12	13	12	12
		New	9	15*	10	168	50	638	7	8	36
	Total	Previous	33		33	4*		33	36	33	33
		New	23	33*	31	308	86	1790	22	20	76
Average must-do WL	Mean	Previous	2		2	3*		2	2	2	2
		New	2	4*	2	6	4	27	2	2	3
	Max	Previous	9		9	19*		9	9	9	9
		New	9	15*	9	43	25	140	8	6	13
	Total	Previous	35		36	50*		35	35	35	35
		New	34	64*	37	95	65	412	28	25	48
Average can-do WL	Mean	Previous	3		3	4*		3	3	3	3
		New	3	3*	3	3	3	3	2	2	3
	Max	Previous	13		13	16*		13	13	13	13
		New	13	16*	13	13	13	15	12	8	13
	Total	Previous	41		41	55*		41	41	41	41
		New	41	45*	42	44	43	48	34	27	42

* Results apply to the first cycle only

G Planning tool



Capaciteits input

Beschikbare capaciteit

Aantal OK uren (op een doordeweeksedag):

16 − +

Aantal IC bedden

6 − +

Aantal verpleegbedden

20 − +

Weights resources

Weight OK

10 − +

Weight IC

10 − +

Weight MC

7 − +

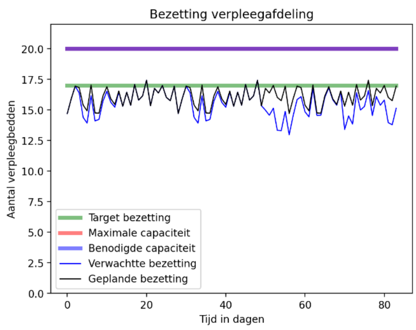
Hoe graag wil je de capaciteit naar beneden bijstellen?

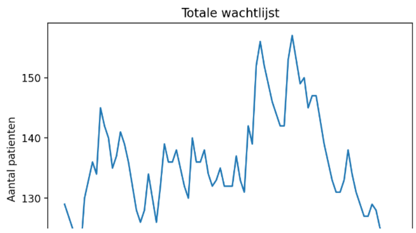
0 = niet; 1 = wel

Weight capaciteit

1,00 − +

Run model





	Week	Dagen	CABG	AVR	CABG + AVR	TAVI	Mitralisklep	Mistralisklep complex	Minimaa
0	Week 1	Maandag	0	0	0	0	0	0	
1		Dinsdag	1	0	0	0	0	0	
2		Woensdag	0	0	0	0	1	0	
3		Donderdag	0	0	0	0	0	3	
4		Vrijdag	0	2	0	2	0	0	
5		Zaterdag	0	0	0	0	0	0	
6		Zondag	0	0	0	0	0	0	
7	Week 2	Maandag	1	0	1	0	0	0	
8		Dinsdag	3	0	0	0	0	0	
9		Woensdag	1	0	0	0	0	0	

Resultaat

	ep	Verwacht aantal geannuleerde slots	Verwachte aantal patiënten te laat	M
0	G	0	0	
1		0	0	
2	G + AVR	2	0	
3	I	0	0	
4	alisklep	2	0	
5	ralisklep complex	0	0	
6	maal invasieve chirurgisch ablatie	0	0	
7	a chirurgie	0	0	
8	a/overige hart chirurgie complex	0	0	
9	CAB	0	0	