Final project report

A Heuristic Approach to Efficient Appointment Scheduling at Short-Stay Units

Author:

A. Stallmeyer, *University of Twente*

Assessment Committee

Prof. dr. R.J. Boucherie, *University of Twente*
Prof. dr. J.L. Hurink, *University of Twente*
Dr. J.B. Timmer, *University of Twente*

A. Braaksma, MSc., *Academic Medical Center*
H.F. Smeenk, MSc.,*Academic Medical Center*

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Author:

A. Stallmeyer

Applied Mathematics, University of Twente
Student number: s0194190
Specialization: Industrial Engineering and Operations Research
Chair: Stochastic Operations Research

Assessment Committee:

University of Twente, Enschede

Prof. dr. R.J. Boucherie,
Stochastic Operations Research

Dr. J.B. Timmer,
Stochastic Operations Research

Prof. dr. J.L. Hurink,
Discrete Mathematics and Mathematical Programming

Academic Medical Center, Amsterdam

A. Braaksma, MSc.,
Department for Quality and Process Improvement

H.F. Smeenk, MSc.,
Department for Quality and Process Improvement

UNIVERSITY OF TWENTE.

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Preface

This report is the result of my graduation project for the Master of Science program in Applied Mathematics at the University of Twente, Netherlands. The research for this project about appointment scheduling at Short-Stay Units took place at the Academic Medical Center in Amsterdam, at the department for Quality and Process Innovation. I enjoyed the challenge of this project during which I have learned a lot about doing research as well as operational processes in a hospital. After five years of more or less theoretical courses, through this project I really understand what the "applied" in applied mathematics stands for and hopefully my project contributes to improving appointment scheduling at Short-Stay Units.

I would like to thank Richard Boucherie for getting me interested in Operations Research in health care and for the constructive, to-the-point feedback during every step of my thesis. Aleida Braaksma and Ferry Smeenk, I would like to thank both of you for time you invested in supervising me at the Academic Medical Center. Aleida, you really showed me how exciting and challenging doing research can be. Our discussions and your detailed comments on my writing were extremely valuable to me. Ferry, you helped me a lot in analyzing the processes at the Short-Stay Unit. You made it easy for me to get into contact with the staff of the Short-Stay Unit and constantly reminded me to think of the application of my research. The atmosphere at the KPI department was always enjoyable and stimulating which I would like to thank my colleagues and especially my fellow graduation students for.
The insights into the processes at the Short-Stay Unit that the staff shared with me were extremely valuable and I hope that my results will be useful for them. A special thank you to Gonny Olivier and Fatiha Stitou Laaroussi who always made time to answer my questions.
Though exciting and challenging, it has also been a busy and at times stressful period, and I would like to express my gratitude to my family and Tony for their patience and support. Finally, a big thank you to my friends who made the last five years such an exciting time.

Astrid Stallmeyer,

Amsterdam, March 6, 2014

Summary

Short-Stay Units have become increasingly popular as an alternative for ordinary inpatient wards at large hospitals, providing care for a certain case mix of patients for a relatively short time. The Academic Medical Center (AMC) in Amsterdam accommodates a Short-Stay Unit as part of the Internal Medicine Division. At the Unit, only those patients are admitted, whose entire stay can be planned in advance, that is the arrival of the patient is scheduled before hand and only treatments are performed of which the duration is known. The challenge lies in scheduling these appointments online, that is one by one, without knowing what appointment requests will arrive in the future. Ideally, the scheduling should be done in such a way that the capacity of the unit is used efficiently and that patients can receive treatment within a certain time, determined by their physician. This time is called the required access times. The goal of this research is hence to develop a scheduling method that aims at scheduling patients within their required access times whilst maximizing the resource utilization of the unit. Such a method has to take into account efficiency, i.e. resource utilization, as well as patient-centered service, i.e. patient preferences and access times. To develop such a method, the Short-Stay Unit of the AMC is used as a case study.

A detailed process and data analysis of the scheduling procedure at the AMC Short-Stay Unit revealed that the current scheduling procedure is done manually in a very straight forward manner that does not take into account future appointment requests. The average bed utilization of the unit was found to be 52.9%, which indicates that the unit operates with over-capacity in terms of beds. Looking at the admission and discharge times of patients together with the average number of patients present at the unit also suggested that fewer nurses are required to handle the patient load than currently staffed. Because the number of required nurses depends largely on the times at which patients are admitted and discharged, it seems that with a more efficient scheduling method, even fewer nurses would be required. These results give an indication that with a more efficient scheduling method, fewer resources could be used while the same amount of patients can be treated.

To make the scheduling of appointments at Short-Stay Units more efficient with respect to bed capacity and the required nurses, a heuristic is developed that combines a rolling horizon approach with advance planning. At the core of the heuristic is a Linear Program (LP) that is used to obtain a blueprint schedule, which reserves blocks for appointments of given types. Assignment rules then specify to which of the reserved blocks an appointment request should be assigned. The optimization problem is hence broken down into two parts: first, of all possible blueprints, the best blueprint has to be found, which is achieved by choosing an appropriate objective function for the LP. Second, assignment rules have to be formulated that assign appointments to one of the reserved blocks in the blueprint. These assignment rules have to ensure efficiency of the schedule, i.e. they have to find the best place for an appointment in

the blueprint schedule.

In order to test the developed heuristic, a simulation study with data of the AMC Short-Stay Unit is conducted. Historical data of the unit is used to define the input for the heuristic. The simulation then imitates the scheduling process, i.e. appointment request arrivals are simulated and the heuristic assigns the request to a time period and a bed. Several experiments are conducted to test the effect of changes in the input parameters. With these experiments the effects of reducing the bed capacity of the Short-Stay Unit and limiting the opening hours are investigated.

The simulation model has been verified and validated using a model of the scheduling method that is currently applied. Experiments with the scheduling heuristic investigate decreasing the bed capacity of the unit, increasing the demand by increasing the amount of appointment requests, and the way patient preferences are taken into account. Outcomes of these experiments clearly show that it is possible to reduce capacity at the AMC Short-Stay Unit. However, with the heuristic, a small amount of appointments, mainly appointments with short access times, could not be scheduled within these access times. This percentage lies however under 1% for most experiments. To have a direct comparison between the scheduling heuristic and the currently applied scheduling method, with models of both methods the experiment in which the capacity of the unit is reduced to 16 beds is conducted. The results show that the scheduling heuristic outperforms the current method with respect to the required number of nurses and the fraction of not scheduled appointments. Hence it can be concluded that in order to reduce the unit's capacity, indeed a more efficient scheduling method is required. When reducing the bed capacity to 14 beds, the bed utilization during most day shifts reaches 90%, which indicates that the limit of the capacity reduction is reached. Although in this scenario a strong increase in the fraction of not scheduled appointments occurs, this fraction still lies under 1% of all appointment requests, which leads to the conclusion that the developed heuristic performs well even when the capacity is strongly reduced.

In conclusion, with the developed scheduling heuristic the goal of this research, to find a scheduling method that aims at maximizing the bed utilization while scheduling patients within their access times is reached. The experiments show that in order to reach a higher resource utilization, indeed a more efficient scheduling method is needed. Although further research on the effects of the parameters of the heuristic is required, the results of the experiments show that with the chosen setting the heuristic performs well. With the heuristic it is possible for the AMC Short-Stay Unit to reduce capacity while keeping the fraction of patients that cannot be seen within their required access times at the same, very low, level as with the current capacity and reaching lower staffing levels than currently applied.

Contents

Chapter 1

Introduction

In this chapter, the setting of this research is introduced. After brief introductions into applications of Operations Research (OR) in healthcare, Short-Stay Units and the Academic Medical Center in Amsterdam are given, the objective of this research and the central research question are defined. Finally, the methodology of this research is described and an overview of the structure of this report is outlined.

1.1 Operations Research in Health Care

Rising costs for health care due to factors such as an aging population in most Western countries and expensive new technologies and treatments, force decision makers in hospitals and other health care institutions to find a balance between high quality patient centered services and efficient use of resources. Since health care policies have an effect on the whole society and many stakeholders are involved, these decisions have to be made carefully. Operations Research is a branch of mathematics that deals with various applications of analytical methods as decision support. It is widely recognized in fields such as production logistics but in recent years also healthcare applications have been in the focus of OR researchers [4]. Mathematical methods and models are used to analyze health care processes in order to provide decision makers with tools to make a decision that takes into account efficiency and quality of care. This in turn can help managers to improve the health care services and make them more cost-efficient. Common applications of OR techniques in health care involve designing the master surgical schedule or an operating room complex, appointment scheduling for outpatient facilities, nurse staffing models and many more [19].

1.2 Research Background and Setting

In recent years, Short-Stay Units have become increasingly popular at large hospitals because they provide an alternative to normal inpatient wards [12]. Usually Short-Stay Units specialize in a certain case mix of patients and provide inpatient care for these patient profiles. Although the design and organizational structure may vary, common to all Short-Stay Units is that they admit patients for a limited amount of time, varying from 48 hours to seven days. By providing an alternative pathway for a certain case mix, Short-Stay Units can help to relieve the pressure on inpatient wards, since those patients that only need care for a short period omit admission at the ordinary inpatient wards and are admitted to the Short-Stay Unit instead.

1.2.1 Academic Medical Center Amsterdam

The Academic Medical Center (AMC) in Amsterdam is one of eight university hospitals in the Netherlands. It is the result of the merger of two hospitals in Amsterdam and the medical faculty of the University of Amsterdam in 1983 [3]. As a university medical center, the AMC focuses on three main tracks, being patient care, scientific medical research and education.
In December 2011, the AMC had 7041 employees [3], and in the same year 387,549 visits at outpatient clinics and 61,215 inpatients [1].
Focusing on patient centered high quality care, the AMC has had a lot of teams and working groups trying to improve the processes at the AMC. In 2007 these teams merged into one department, the department for quality and process innovation (KPI), where this research is conducted. At KPI a multi-disciplinary team works on continuously improving the quality of care at the AMC and at the same time maintaining efficiency.

1.2.2 The Short-Stay Unit of the Internal Medicine Division

Alongside a reorganization of the internal medicine division of the AMC, in December 2012 the Short-Stay Unit for internal medicine was newly organized and its capacity was increased. At the Short-Stay Unit, patients who are referred by a specialist within the AMC are admitted up to a maximum of five days. Only those patients are admitted for which the arrival and the entire treatment process can be planned in advance. Typical treatments provided by the unit therefore are intravenous therapy, blood transfusions or chemotherapy, since the duration for these treatments is known in advance.
Until now, the scheduling of the patient appointments is done manually with the help of scheduling software by two planners who receive admission requests from physicians in the AMC.
The admitting physician specifies a time or time period, within which the patient should be admitted to the Unit, the so called required access time. Ideally, the scheduling should be done in such a way that the capacity of the unit and human resources are used efficiently and patients receive their treatment within their required access times. The planners are presented with the challenge to schedule the admission requests online one by one, that is every appointment has to be scheduled directly after receiving the request, without knowing the future requests. It is the uncertainty that is implied by planning appointments online that makes creating an efficient schedule such a demanding task.

1.3 Research Goal

The goal of this research is to develop a scheduling method for Short-Stay Units that aims at seeing patients within their access time targets and at the same time maximizing resource utilization.

1.3.1 Research Question

This goal leads to the following research question:
How can the online appointment scheduling process for patients of a Short-Stay Unit be designed in order to create a schedule that implies efficient use of resources and high patient throughput with respect to the required access times?

Further Questions

- What is an optimal schedule? What performance measures have to be considered?
- What is the relation between a scheduling method and the performance of the unit?
- Regarding the specific case of the Short-Stay Unit at the AMC
  - What is the current performance of the Short-Stay Unit?
  - What is the current planning process of the unit?
  - What scheduling rules are currently applied by the planners?

1.3.2 Approach

Using the AMC Short-Stay Unit as a case study, first the important processes and steps that are involved in scheduling patient appointments for a Short-Stay Unit will be identified through a process and data analysis. This step will provide insight into the process, reveal relevant performance indicators with respect to the scheduling process and help to point out difficulties and possible improvements for the planning.
On the basis of the process and data analysis, a mathematical model will be developed to optimize the patient scheduling with respect to resource utilization and realizing patients' access times in an online fashion.
Finally a simulation model will be developed with which the obtained model can be tested and evaluated. The current planning process of the AMC Short-Stay Unit can be compared to the obtained model through the simulation model.

1.3.3 Scope

The aim of this research is to develop a scheduling model for Short-Stay Units that provides the basis for a decision support tool. The Short-Stay Unit at the AMC will serve as a case study for this research, that is historical data and information of the unit will be used as a baseline scenario for the developed model. However the model should be generic and flexible in terms of input so that the performance of different scenarios can be calculated and different settings for a Short-Stay Unit can be implemented.
The focus of this research is on the scheduling method. Medical procedures and other processes that do not directly have impact on the planning are not considered.
The final implementation step to a fully functional ready-to use scheduling tool is beyond the scope of this research, but the aim is to provide the theoretical basis for such a decision support tool.

1.4 Outline

This report is structured as follows: Chapter 2 provides a process and data analysis of the Short-Stay Unit at the AMC with focus on the appointment planning. An overview of the relevant literature for this research is given in Chapter 3. Chapter 4 introduces a scheduling heuristic which will be simulated with the simulation model developed in Chapter 5. A brief description of the applied statistical analysis of the output of the simulation is given in Chapter 6. The results of the simulation experiments are provided in Chapter 7 and finally, in Chapter 8, conclusions and recommendations are given. For an overview of used symbols, the reader is referred to the list of used symbols at the end of this report.

Chapter 2

The Short-Stay Unit

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Chapter 3

Literature Review

The aim of this chapter is to provide an overview of the literature relevant for this research. First, descriptive literature on Short-Stay Units as an alternative to ordinary hospital wards is investigated in Section 3.1 after which in Section 3.2 the problem of appointment scheduling is placed in the context of other OR applications in health care. The various appointment scheduling approaches are reviewed in Section 3.3 and in Section 3.4 briefly the topic of evaluation functions is covered. Finally in Section 3.5 conclusions about the implications for this research are drawn.

3.1 The Short-Stay Unit

Short-Stay Units are a relatively new alternative to ordinary hospital wards. In their review [12], Damiani et al. compared Short-Stay Units to ordinary wards in terms of length of stay (LOS), mortality and readmission rate. They found that Short-Stay Units provide a good alternative since the shorter hospitalization period yields an increase in patient satisfaction, in resource utilization and also results in a decreased risk for hospital acquired infections.
Lucas et al. [24] and Yong et al. [39], instead of comparing Short-Stay Units to traditional wards, both focus on the characteristics of short-stay patients that could predict the LOS or could predict a successful admission. While Lucas et al. find the inaccessibility of diagnostic tests and the need for specialty consultations to be the most important predictors of long LOS, Yong et al. point out that the day of admission and the age of the patient are the most contributing factors.
The type of Short-Stay Unit considered in this research is not comparable to Acute Medical Units (AMU), Medical Assessment Units (MAU) or Emergency Short-Stay Units because the considered type is a unit that provides care for patients who can be planned in advance. So patients in Short-Stay Units have to be stable and, unlike in AMU's, MAU's and Emergency Short-Stay Units, patients have scheduled appointments. For the remainder of this report, the term Short-Stay Unit will refer to a type of inpatient ward that admits patients for a short period of time, providing care that can be planned in advance and where appointments for patients are scheduled beforehand.
Literature on these Short-Stay Units consists mostly of studies that compare Short-Stay Units to other hospital wards and studies that analyze the performance and quality of care of Short-Stay Units. The literature about OR approaches concerning Short-Stay Units is limited, but appointment scheduling problems are broadly covered. The following sections describe the relevant OR literature, focusing on appointment scheduling problems.

3.2 Taxonomy and Review of Literature

The applications of OR in health care are almost countless and cover a variety of different areas. For a general overview of the amount of papers published, the review of Brailsford et al. [4], although limited to Europe, provides a quantitative analysis of papers published during meetings of the European Working Group Operational Research Applied to Health Services (ORAHS) conferences since 1975.
In their study, [19], Hulshof et al. provide a taxonomic classification of operational research decisions in health care. Their taxonomy contains two axes: the vertical axis corresponds to the hierarchy of the decision, whereas the horizontal axis corresponds to the health service. On the horizontal axis, Short-Stay facilities can be placed at inpatient services (although they differ from ordinary hospital inpatient wards). The research question of this report, that is how to schedule patients' appointments at a Short-Stay Unit in an efficient manner, can be placed on the vertical axis under operational planning decision. Therefore, using the taxonomy of Hulshof et al., the problem addressed with this research can be classified as an operational planning decision for an inpatient service. This classification is helpful for the search of further literature related to the Short-Stay Scheduling problem.
Cayirli et al. [6] provide a comprehensive literature survey on appointment scheduling of outpatient facilities. Although Short-Stay Units are inpatient units, the problem of appointment scheduling for these units shows similarities to the problem of scheduling an outpatient or ambulatory facility, because patients' appointments are planned in advance and patients leave the Short-Stay Unit after a short period of time. The review first lists structural aspects of the scheduling problem such as the arrival process or the queuing discipline. Then the authors go on reviewing the different performance measures that are used to evaluate the appointment systems, which can be grouped into cost-based, time-based, congestion and fairness measures. After listing the structure of different appointment systems they finally review the different methodological approaches that are used to solve the scheduling problem. As analytical methods they list queuing theory and mathematical programming (dynamic, nonlinear and stochastic linear). They also note that simulation is often a tool to compare the performance of an alternative or previously used appointment system to the new designed system. Their review serves to give a broad overview of the approaches taken in scheduling problems and the relevant performance measures related to these approaches. These approaches from the literature are addressed in the following sections.

3.3 Appointment Scheduling Models

Appointment scheduling is a widely studied field of OR. A wide range of literature covers the scheduling of outpatient facilities, and in particular diagnostic imaging services. This topic shows similarities to the problem of scheduling appointments for the Short-Stay Unit: patients come from outside the Short-Stay Unit, they are planned in advance, receive a specific type of treatment and are discharged after a short period of time.
A variety of aspects is covered: the type of scheduling system considered (online, that is schedule appointments directly as their requests arrive or offline, where appointments are scheduled after all requests have arrived), the patient characteristics taken into account (a single or several patient types, patient preferences), the type of appointments (varying appointment lengths and types), the characteristics of the facility (single server or multiple servers), other factors included in the model (no-shows, staff capacity, overtime etc.) and finally the methodological approach used to obtain a schedule. In the following section, articles are grouped according to their approach.

3.3.1 Markov Decision Models

Markov decision theory is a widely used approach to tackle appointment scheduling problems because of the sequential decision structure: At any state of the system, that is the current schedule, an action of scheduling a patient will lead to another state. To which state an action leads depends on the transition probabilities. This structure provides a powerful framework to analyze a scheduling problem. The stochastic nature of the problems described in these articles, lies either in the arrival process of the patients or the appointment duration.
Patrick et. al look at two different scheduling problems. In [26] they demonstrate that the open access method, that aims at doing today's work today, is not always better than other methods (as they showed already in [27]): through simulation the authors show that a short booking window performs better for their specific setting. In their study, they assume that a fixed number of patients has to be seen per day and that requests arrive only at the beginning of the day, so the planning is done online and their setting differs from that of the Short-Stay Unit. In [28] the authors investigate how to schedule patients for a CT-scan with different priorities such that waiting time targets can be met efficiently. In their case, all patients have equal service times. Hence the authors only look at the day where the appointment has to be placed, not at the time slot. Because of the high dimensionality of the Markov model, they solve the equivalent linear program with approximate dynamic programming.
Green et al. [17] analyze two related tasks: designing outpatient appointment schedules and establishing dynamic priority rules for admitting patients. They consider outpatients, inpatients and emergency patients. Their model is a discrete time Markov chain and is solved with finite-horizon dynamic programming. Because of the high complexity, they identify heuristic policies which are easier to implement. The problem Green et al. consider, however, is different from the Short-Stay Unit, because they assume identical service time distributions for all patients and do not work online.
In their study [16], Gocgun et al. look at a similar problem as Green et al. They model the appointment scheduling problem for a CT-scan as a Markov Decision Problem and compare the solution with several other scheduling heuristics in a simulation study. However, their model is not online, as they work with a waiting list.

3.3.2 Integer Linear Programming

In their article, Conforti et al. [10] describe a scheduling system for a week hospital. The structure of the week hospital they are considering can be compared to that of a Short-Stay Unit but their planning is offline: The planning is done weekly and they use a waiting list of patients. To maximize the number of admitted patients to the week hospital while keeping the patient waiting time at a minimum they solve an integer linear program (ILP). Since the structure of the week hospital they consider shows similarities to the Short-Stay Unit, their formulation and structure of the ILP is of relevance for this research although the planning is offline.

3.3.3 Stochastic Programming

Pérez et al. [29] and Gerchak et. al [15] use a stochastic model to find an optimal appointment scheduling rule. Both apply stochastic programming by taking into account a series of expected future day scenarios.
Gerchak et al. look at the problem of scheduling surgeries and deciding on how many elective surgeries to perform on a given day, taking into account possible emergency surgeries and exceeding the capacity, which results in doctors' overtime. They define a profit function which

includes the expectation of future revenues. The authors found that the optimal policy they obtained was not, as expected, of a cut-off structure (that is a cut-off number on how many elective patients to admit). However, they also found that the best cut-off policy achieved performance results similar to the obtained optimal policy, and hence the simple structure can still be used.
Pérez et al. describe the problem of scheduling patients for a nuclear medicine facility and present three possible approaches: An offline approach which can be solved with an integer program, an online approach and a stochastic online approach. The difference in the last two is that while they both consider scheduling requests as soon as they arrive, the first approach only looks at minimizing the access time of the current request while not taking into account future request, the second approach takes the expected outcome of future scenarios into account in the objective function. For these two online approaches the authors describe algorithms which they compare to the offline approach by simulation. The stochastic online approach showed promising results in terms of patient waiting time, number of patients who are served and in terms of resource capacity. This approach is interesting for the Short-Stay Unit, because it addresses the scheduling problem in an online fashion and takes into account future requests. However Pérez et al. point out that in addition to the online approach, what makes their scheduling problem so complex is the fact that in nuclear medicine scheduling the procedures not only require multiple resources at different times, but are also planned in sequential steps with specific time constraints. So while their approach of taking future requests into account is highly relevant for the Short-Stay scheduling problem, the sequential nature with specific time constraints and multiple resources does not apply to the Short-Stay problem.
Van Hentenryck et al. [18] address the problem of dynamically allocating requests online to limited resources in order to maximize profit. They contrast their problem to other problems like stochastic routing because they address the problem of how to serve a request best, and not of selecting the best request to serve. This distinction is relevant for the scheduling of the Short-Stay Unit, because at any point the schedulers do not have to decide on which patient to treat next, but on where to schedule the appointment for the patient in the already existing schedule with the previous requests. First, the authors define the offline problem as a multi-knapsack problem, which they use as a basis for their online approach. For that approach, they define an objective function which involves the expected values of the outcomes of future scenarios. They solve this problem with a stochastic algorithm that uses either a Consensus or a Regret algorithm.
Chang et al. [7] consider the problem of scheduling tasks on a single server in an online fashion. Although they only look at a single server, their approach is interesting as they discuss several sampling techniques which are used for evaluating the outcomes of possible future scenarios. With these samples, they solve their problem which they model as a Partially Observable Markov Decision Process.

3.3.4 Heuristics

A popular approach is to define the problem as an optimization problem and solve it with heuristics if no analytical solution is available: The objective function is usually a weighted sum of patient and hospital oriented performance measures (waiting time, idle time and patient throughput for example). The models vary in their level of detail and in their optimization goal.
In [37], Vermeulen et al. look at a diagnostic facility that receives patients with different urgencies. The facility closes during the weekend, and patient preferences are taken into account. As performance measure, they look at the fraction of patients that is scheduled on time, that

is before the due-date of their appointment, depending on their urgency. As a first step of their heuristic they allocate capacity to patient groups (defined by urgencies). The second step selects available time slots from all time slots available for a given patient. This is done with a combination of First Come First Serve (FCFS: selection of the earliest available time slot) and balanced utilization (ordering time slots based on increasing utilization level). As a third step the authors include patient preferences by defining a weighted combination between the scheduling performance and patient preference fulfillment. They solve their model with an Estimation of Distribution Algorithm.
In [36] Vermeulen et al. describe a similar setting, a CT-scan facility. Here they define patient groups depending on more attributes than just urgency, namely request time, in- or outpatient, duration of treatment and more. The scheduling problem they define is similar to that of a Short-Stay Unit: patients have a target access time and the scheduling is done manually by planners, who receive requests from physicians and have to schedule the requests immediately. They first define a scheduling method that represents the current scheduling method at the facility and use simulation to compare the performance of this method to that of their adaptive allocation model. In this model they reserve time slots for urgent patients but allow to use these slots for other patients, if the patient cannot be planned on time otherwise. They define an algorithm to implement this rule into the scheduling and show in their simulation study that this algorithm outperforms the current scheduling practice.
Chew et al. [8] and Kaandorp et al. [20] both aim at optimizing a weighted sum of patient waiting time, staff idle time and overtime. The problem they consider is different from that of the Short-Stay Unit though:
Chew et al. look at an appointment system where the day is divided into blocks, and per block a certain number of patients has to be scheduled. They assume the number of patients per day and the number of blocks is known, and consider the question of how to distribute the patients over the blocks, and how to determine the inter-appointment times. They solve their model with a simulation-based heuristic algorithm.
Kaandorp et al. also look at a scheduling system where the number of patients on a given day is fixed and they look at how many patients have to be scheduled in a given interval and assume a common service time distribution of all patients. They take no-shows into account explicitly and solve their model with a local search method, comparing a given schedule to a neighbor schedule, starting at a feasible solution. The search method is made available on the web for the public but long computational times are noted for large instances.
Patrick et al. also look at a diagnostic facility, [27]. The schedule they consider has to be made weeks in advance and has to have capacity reserved for high priority cases. Their main question hence is how much capacity has to be reserved for these cases (they call this a cut-off policy). They formulate and solve two optimization problems as follows: The authors divide the priority cases into those that have to be seen the same day and those that can be delayed for one day. For both cases they reserve time slots. Additionally, they identify non-priority cases that can be on-call to fill up unused time-slots. Although their setting is different from that of the Short-Stay Unit, reserving time slots for urgent cases is also interesting for the Short-Stay case. They develop a simulation model to test the effects of different parameter values. Their results show that dividing the priority cases into two groups can reduce waiting times for non-priority cases.

3.3.5 Online Parallel Machine Scheduling

Naturally, when talking about online patient scheduling on several beds, the area of online parallel machine scheduling comes to mind. In parallel machine scheduling, jobs have to be

scheduled onto a number of parallel machines. These jobs have characteristics such as processing times, release and due dates and weights. In the online case, neither the number of jobs to be scheduled nor their characteristics are known to the decision maker beforehand, [30]. Algorithms for online scheduling problems are evaluated by their competitive ratio ρ, which indicates that in the worst case, the algorithm achieves a performance at most ρ times the value of the optimal offline solution.
In [11], Correa et al. present three algorithms for parallel machine scheduling, one of which is a randomized algorithm for the non-preemptive case in order to minimize the weighted completion times. They introduce a virtual machine which operates faster than the others and make an LP-based schedule for that virtual machine. They use this schedule as a basis for the schedule for the normal machines. Their algorithm is a list-scheduling algorithm which achieves a competitive ratio strictly smaller than 2.
Although the area of online parallel machine scheduling at a first glance seems to be a suitable approach for the Short-Stay scheduling problem, there are significant differences that make this approach less appropriate: First of all, most algorithms provide a solution to the decision which job to process next (either at the moment the job becomes available or at the moment a machine is idle for the first time after a new job becomes available). They do not allow for assigning time slots in the future established schedule for a certain job, which is what a model for the Short-Stay case should be capable of. At the Short-Stay a decision has to be made on arrival of a request on where to place the request in the existing schedule. What is more, scheduling problems know a certain amount of objectives, such as minimizing the make span. There is a lot of literature about online parallel machine scheduling for minimizing the make span or the (weighted) total completion time, the articles above being only a selection. But in the setting of a department with fixed operating hours, these measures are less significant. These objectives also do not relate to any characteristics of the patients (the jobs). For the Short-Stay scheduling problem the objective function should take the patients' access times as well as the bed utilization into account. Objectives that do take job characteristics such as release and due date into account are lateness and tardiness related measures. But for these measures the literature on online parallel machine scheduling is limited. This is due to the fact that for the offline single machine case, the problems concerning the total tardiness and the maximum lateness with release dates are NP-hard [13, 23]. Hence in the parallel machine setting they receive less attention [30] and for the online approach these objectives are not often considered.

3.3.6 Simulation

A substantial amount of articles on appointment scheduling use simulation as a method to experiment with different factors of scheduling processes that have effect on the schedule. While some articles focus on how such a simulation should be built, others test a wide range of scenarios and focus on finding important factors that affect the performance. While most of the articles described in the previous sections use simulation to evaluate a policy they obtained with an analytical model, the following articles use simulation alone to experiment with different rules.
In [32], Robinson et al. focus on simulation to analyze scheduling systems for elective patients. Their simulation works with three steps: The first step generates appointment requests, the second step schedules appointments and the third and final step evaluates the performance of the resulting appointment schedule. The authors simulate three different appointment rules: The first simply schedules the patient at the first available date, the second and third use the expected LOS and a probability distribution of the LOS respectively to schedule patients in

such a way that a certain census is not exceeded. Furthermore the authors vary the degree to which the LOS is estimated correctly which resulted in six scenarios. There is no clear result on which system yields the best performance.
While the former article focuses more generally on the structure of a simulation of an appointment system, in [14], Elkhuizen et al. show that with simulation the capacity needed for an appointment based facility can be analyzed. While a simple queuing model could also provide some insight into this question, the added value of the simulation is that more realistic schedules and varying demand can be implemented.
In [21], Klassen et al. experiment with factors such as client load, scheduling rules, variation of service times, density of the schedule (how filled up the schedule is) and how many time slots will be reserved for urgent patients. The performance measures they consider are client waiting time, access times for regular and urgent patients, server idle time, server utilization and the end of the day time. They also combine server idle time and waiting time of all patients into one patient and server oriented measure. They found that it is best to schedule patients with a low variation in service time at the beginning of the day, and that the placement of urgent slots had little effect on the performance in general.
Finally, Santibáñez et al. analyze the impact of resource allocation and appointment scheduling simultaneously through simulation, instead of analyzing one under the effect of the other, [33]. They found that the combination of both outperformed scenarios in which they are taken into account in isolation. As important factors they noted the on time start of the clinic. They conclude that possible improvement could be achieved by dynamic room allocation.
White et al. also investigated the effect of integrated scheduling and capacity policies through simulation. Their discrete event simulation is used to set up a wide range of experiments to examine the interactions between appointment policies and capacity policies, [38].

3.4 Evaluation Functions

While most of the above mentioned approaches model the scheduling problem by defining constraints and an objective function that is related to resource and patient centered performance measures, these approaches do not touch on the issue of defining what a ”good state” in a scheduling problem is. The difficulty of scheduling an appointment for the Short-Stay Unit can essentially be described as not knowing how good a certain appointment placement will turn out for the overall schedule, because the future requests are not known at the time of scheduling the appointment. Hence one would like a characterization of what a good placement of an appointment is. A similar problem is observed in Artificial Intelligence (AI) when programming a computer to play chess. In chess one would like to know how good a certain position is with the overall goal of winning the match in mind. Calculating all possible outcomes of any possible move through to the end of the game is computationally highly complex and not efficient for programming a computer. To this end, heuristic evaluation functions provide the basis for choosing strategies in chess by assigning a value to a given position [34]. Shannon’, [34], points out that the goal is not to find an exact evaluation function that will always identify the optimal move, but to find a good approximation. There is a vast literature and research body on evaluation functions for chess, which as Buro points out in [5], indicates how hard constructing a good evaluation function is. Usually, an evaluation function consists of a combination of several evaluation features. These features depend on the game. In [34], Shannon uses the difference between the sum of all game figures of the two players, the number of doubled, backward and isolated pawns and mobility as features. Often a trade-off has to be made between the complexity of the features and a simple structure. Christensen et al. consider evaluation functions for games in general. In [9], they claim that an ideal heuristic evaluation function has to fulfill two properties, namely being invariant along an optimal solution path and when being applied to an optimal goal state, the function should return the exact value of that state. on the issue of defining what a "good state" in a scheduling problem is. The difficulty of scheduling an appointment for the Short-Stay Unit can essentially be described as not knowing how good a certain appointment placement will turn out for the overall schedule, because the future requests are not known at the time of scheduling the appointment. Hence one would like a characterization of what a good placement of an appointment is. A similar problem is observed in Artificial Intelligence (AI) when programming a computer to play chess. In chess one would like to know how good a certain position is with the overall goal of winning the match in mind. Calculating all possible outcomes of any possible move through to the end of the game is computationally highly complex and not efficient for programming a computer. To this end, heuristic evaluation functions provide the basis for choosing strategies in chess by assigning a value to a given position [34]. Shannon', [34], points out that the goal is not to find an exact evaluation function that will always identify the optimal move, but to find a good approximation. There is a vast literature and research body on evaluation functions for chess, which as Buro points out in [5], indicates how hard constructing a good evaluation function is. Usually, an evaluation function consists of a combination of several evaluation features. These features depend on the game. In [34], Shannon uses the difference between the sum of all game figures of the two players, the number of doubled, backward and isolated pawns and mobility as features. Often a trade-off has to be made between the complexity of the features and a simple structure. Christensen et al. consider evaluation functions for games in general. In [9], they claim that an ideal heuristic evaluation function has to fulfill two properties, namely being invariant along an optimal solution path and when being applied to an optimal goal state, the function should return the exact value of that state.

3.5 Conclusions

Both Short-Stay Units and appointment scheduling have been studied extensively, but literature about OR applications on the specific type of Short-Stay Unit considered in this research is limited. OR applications on outpatient scheduling in general however are covered in numerous articles.

Markov Decision Theory provides a general framework for the sequential nature of the decision making for appointment scheduling. This approach is popular for mostly semi-online planning decisions, because then the number of requests that have to be scheduled for a certain period is known. For the Short-Stay Unit, the question however is when to schedule an appointment not knowing what other appointment requests have to be considered. Nonetheless, the structure provided by Markov Decision Theory, defining states, actions and transitions, is still useful for the Short-Stay case. For the online case Stochastic Programming is an interesting approach because it takes into account future scenarios. By taking into account samples of possible future scenarios, that is future patient requests, these kind of models are able to include more than just the present state in one decision.

Online parallel machine scheduling also considers the online case, but looking in detail at the problems these studies address, it can be seen that the structure of these models is not suitable for the Short-Stay scheduling problem as considered in this study. This is due to the fact that for the objectives that would be relevant for this study, these models are NP-hard in the offline approach and hence not often considered for the online approach.

When the scheduling is done offline, an ILP model is a suitable approach as Conforti et al. in

[10] show.
The heuristics used to solve optimization problems indicate important aspects that have to be taken into consideration when designing a scheduling method, such as grouping patients according to their characteristics and then allocating capacity to these groups and reserving time slots for urgent patients. Common to almost all relevant articles in appointment scheduling is that they make use of simulation, either to test an algorithm or scheduling rule they obtained analytically, or to compare heuristics.
Evaluation functions aim at assigning a value to a given state that indicates how good the state is for the overall goal. There is a vast body of literature on evaluation functions for chess playing computer programs. The central task, Buro points out in [5], is to construct the evaluation function of several evaluation features. Defining evaluation features for the Short-Stay scheduling problem and constructing an evaluation function that assigns a value to a certain appointment placement, is a promising approach since it provides the planner with a tool that indicates which placement option is the best for the overall schedule. For the purpose of this study however, the focus will lie on developing an online scheduling heuristic for Short-Stay Units.

Chapter 4

Scheduling Model

In Chapter 2 the current scheduling procedure of the Short-Stay Unit is described. The results of the data-analysis clearly show that there is room for improvement with respect to use of available capacity and nurse staffing. The literature review in Chapter 3 revealed possible approaches for a scheduling model. In this chapter, a scheduling model for Short-Stay Units is described that aims at scheduling as much patients as possible within their required access times while using minimum capacity. In Section 4.1 an outline of the chosen approach is given. Then a scheduling heuristic is developed in Section 4.2. The two main components of the heuristic are addressed in Sections 4.3 and 4.4. Finally conclusions of this chapter are drawn in Section 4.5.

4.1 Approach

The objective of this research is to improve the scheduling procedure of the Short-Stay Unit by providing the basis for a decision support tool for Short-Stay Units in order to schedule patients in such a way that resources are used efficiently and patients can be seen within their required access times.
While with offline scheduling problems, decisions can be made considering all appointment requests (over a given horizon), with online scheduling problems appointments have to be scheduled one by one, into an existing schedule of previously scheduled appointments. Not knowing exactly what other requests will come later on is what makes creating an efficient schedule so difficult for planners of Short-Stay Units.
In general, the dynamics of the scheduling procedure can be described with states, actions and transitions. This notation will be the framework for the further development of the model.

4.1.1 States, Actions and Transitions

This decision making problem can be placed in the framework of Markov Decision Theory, since it can be described with states, actions and transitions, [31].

State Within a fixed planning horizon τ, let $s = (n, r)$ denote the state. It is described by the pair n, which denotes the current schedule, and r the current appointment request. n provides complete information about the partly filled schedule. With r the type and length of the appointment, the release and due date of the appointment and, if necessary, any additional information is given.

Actions Given the current state s, a decision a has to be made about when and where to schedule the appointment that is requested. Depending on the state s, let A_s denote the set of all possible decisions.

Transitions Once the decision a is made, the system changes to a state $\bar{s} = (\bar{n}, \bar{r})$ with probability $p_{s,\bar{s}}$. Note that while the transition from n to $\bar{n}$ is deterministic, the transition from r to $\bar{r}$ is stochastic. This transition is determined by the probability distribution that describes the arrivals of new appointment requests.

To summarize, the system dynamics can be described by

$$(n, r) \xrightarrow{a,\ p} (\bar{n}, \bar{r}) \tag{4.1}$$

Since any transition leads to a new state, information on the new schedule has to be updated, that is all parameters and sets that define n have to be updated in order to provide information for $\bar{n}$. The arrival of a new appointment request will provide information on $\bar{r}$ and hence complete information on state $\bar{s}$ is given.

4.2 Scheduling Heuristic

The question is hence how to choose an action in order to obtain an efficient schedule. Since the scheduling is done online, it is desirable to take future requests into account. Making use of available historical data in order to estimate how many appointments of which type occur in a given period is a way to do so. In the following, a heuristic method based on a rolling horizon approach combined with advance planning will be developed, that uses historical information about the occurrences of appointments of different types. In that manner, the online problem is partly approached in an offline fashion: Given the statistics of the occurrences of the appointments, the answer to where and when to allocate appointments of a certain type in order for the resulting schedule to be efficient can be determined offline. The allocation of appointments of different types to time slots over a short scheduling horizon (compared to the overall scheduling horizon) can be seen as a blueprint that is used to schedule the real appointment requests.
The blueprint schedule can be obtained by solving a linear program (LP). Once the blueprint is determined, arriving appointments can be scheduled at one of the blocks that are reserved for that type of appointment in the blueprint according to specified assignment rules. The whole procedure can then be repeated, i.e. a new blueprint is generated taking the previously scheduled appointments into account and the next requests can be scheduled.
Note that the heuristic breaks the decision problem down into two core questions:

- What is the best blueprint schedule?
- What is the best way to assign an appointment to a block in the blueprint?

The first question will be answered in Section 4.3 and the second will be addressed in Section 4.4. Finally, simulating the scheduling method allows to compare the performance of this method to the currently used scheduling method and also allows to create several alternative scenarios. With different scenarios, the effect of the assignment rules and also the effect of less bed capacity and in general slightly different input data can be assessed. Figure 4.1 shows a graphical representation of the heuristic.

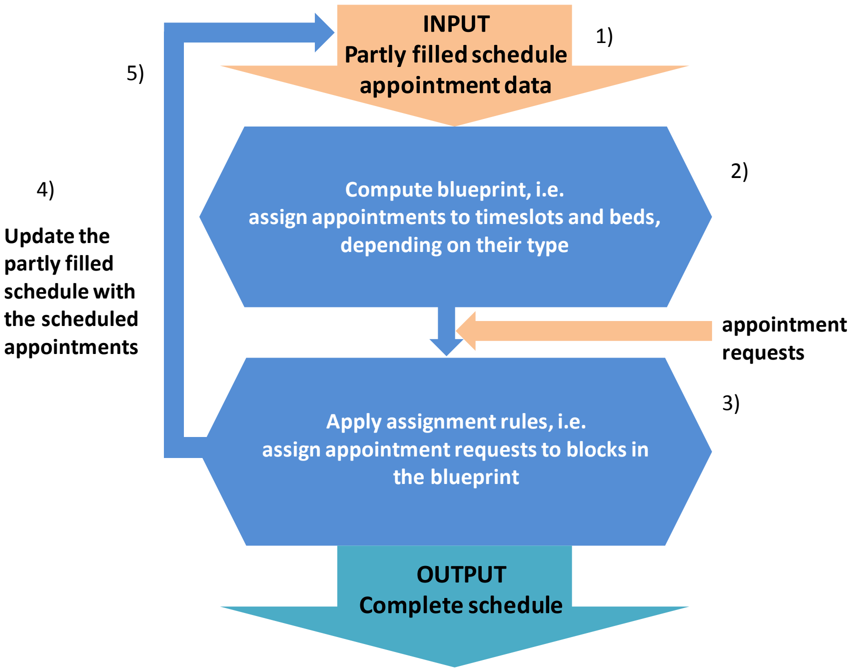

Figure 4.1: Schematic representation of heuristic

4.3 Constructing the Blueprint Schedule

Making use of the notation introduced in Section 4.1.1 the heuristic can be described as follows, the numbering of steps corresponding to the steps in Figure 4.1: Let D denote the time in days, starting at $D = 0$, running up to $D = \tau$, where τ denotes the scheduling horizon of the overall schedule. Let X be the obtained blueprint schedule and let R denote the assignment rule that assigns to each state depending on X an action, i.e. $R : s, X \mapsto a$ and let ρ denote the frequency with which a new blueprint will be generated.

1. **Initialization**
   $D = 0,\ s_0 = (n_0, r_0)$

2. **Blueprint**
   With frequency ρ, construct a blueprint with LP as in Section 4.3. Otherwise, move on to step 3.)
   Let X_i be the solution if the system is currently in state s_i.

3. **Choose action**
   Apply R_{s_i,X_i} to find a_i.

4. **Transition**
   $s_i \xrightarrow{a_i,\ p} s_{i+1}$
   $D := D + 1,\ s_1 = (n_1, r_1)$

5. **Repeat**
   while $D \leq \tau$, go to step 2).

So each time a new blueprint is calculated, the horizon shifts forward and that way, the heuristic will lead to a complete schedule for the defined scheduling horizon.

The optimization problem of finding the best blueprint schedule can be solved with a LP. LP's are mathematical optimization problems of the form as in Table 4.1, [25].

min	$c^T x$	
subject to	$a_i x = b_i$	$\forall i \in I$
	$a_i x \geq b_i$	$\forall i \in [n] \setminus I$and
	$x_j \geq 0$	$\forall j \in J$

Table 4.1: General form of a linear program

To define such a program, parameters, variables, constraints and the objective function need to be specified. In the following the linear program used to obtain the blueprint schedule is defined. The task of finding the best blueprint schedule will reduce to defining the objective function of the LP.

4.3.1 Notation

Parameters and sets

The subscript k refers to the type of the appointment, j to a bed, t to a time slot, c to a shift and f to a day as can be seen in Table 4.2.

Notation	Description
k	Subscript for an appointment type
j	Subscript for beds
t	Subscript for time slots
c	Subscript for shifts
f	Subscript for days

Table 4.2: Subscripts

The parameters listed in Table 4.3 form the input of the linear program. Note that in the definition of f_{jt} opening hours of the Short-Stay Unit and the current, partly filled schedule, that is which bed is occupied at which time, are already implied. The lengths of the blueprint scheduling horizon, δ, is a parameter that is not externally given, but has to be chosen. This means that choosing δ is part of finding the optimal blueprint.

By replacing S (south) with N (north) in the binary parameters a_t^S and d_t^S, the equivalent definition with respect to the north wing is given. More wings can be defined in that way if necessary. The relevant sets with respect to the parameters are given in Table 4.4.

Note that the release and due dates of appointments do not appear in the list of parameters. Since in the blueprint not actual appointments are scheduled, but only a potential allocation of capacity is made, characteristics of specific appointments do not have to be taken into account, but only general data on the occurrences of appointments.

Notation	Description
	General parameters
δ	Length of the blueprint schedule period in time slots
μ_k	Number of appointments of type k that have to be scheduled
l_k	Length of an appointment of type k in time slots
e	The minimum number of nurses that has to be present
s_c	The maximum number of patients that one nurse can be assigned to during shift c
w_t	The number of patients being admitted or discharged at time t
z_t	The number of patients present at time t
	Binary parameters
f_{jt}	1 if bed j is available at time t
a_t^S	1 if time slot t is a time slot where patients can be admitted at the south wing
d_t^S	1 if time slot t is a time slot where patients can be discharged at the south wing

Table 4.3: Parameters

Notation	Description
K	Set of all appointment types
J	Set of all beds
T	Set of all time slots in the scheduling horizon
C	Set of all shifts
F	Set of all days
T_c	Set of all time slots belonging to shift c
T_f	Set of all time slots belonging to day f
J_S, J_N	Set of all beds j located on the corresponding wing
A_S, A_N	Set of all time slots where patients can be admitted on the corresponding wing
D_S, D_N	Set of all time slots where patients can be discharged on the corresponding wing

Table 4.4: Sets

Variables

For simplicity of notation, variables will be denoted with capitals, parameters with small letters. The decision variable denotes whether an appointment of type k is assigned to bed j, starting at time slot t.

$$X_{kjt} = \begin{cases} 1 & \text{appointment of type } k \text{ is assigned to bed } j\text{, starting in time slot } t \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

Also relevant for the blueprint schedule is the number of nurses who have to be present at the unit at time t during shift c.

$$Y_{tc} : \text{number of nurses present at time } t \text{ in shift } c \tag{4.3}$$

Constraints

In the following, the constraints of the scheduling problem are described. Since in the blueprint schedule appointment types are assigned to available capacity, but not actual appointments are scheduled, patient characteristics such as release and due date are not taken into account.

- Department characteristics
  - Patients can only be admitted or discharged during certain specified hours every day that the department is open. That is, an appointment of type k can only start at time slot t if admission is allowed at time t and discharge is allowed at time $t + l_k - 1$.

$$\sum_{j \in J_S} X_{kjt} \leq a_t^S \cdot d_{t+l_k-1}^S \qquad \forall t, \forall k \tag{4.4}$$

$$\sum_{j \in J_N} X_{kjt} \leq a_t^N \cdot d_{t+l_k-1}^N \qquad \forall t, \forall k \tag{4.5}$$

- Patient - bed assignment
  - At a given time t at most one appointment of any type can be scheduled to use bed j. This is expressed in two constraints. Firstly, it implies that during an appointment of a given type, no appointments of another type can be scheduled on the same bed. Secondly, it implies that also any other appointment of the given type cannot be scheduled on the same bed during the time of that appointment.

$$X_{kjt} + \sum_{\hat{k} \neq k} \sum_{\hat{t}=t}^{t+l_k-1} X_{\hat{k}j\hat{t}} \leq 1 \qquad \forall k, \forall j, \forall t \tag{4.6}$$

$$X_{kjt} + \sum_{\hat{t}=t}^{t+l_k-1} X_{kj\hat{t}} \leq 2 \qquad \forall k, \forall j, \forall t \tag{4.7}$$

  - An appointment of any type k can only be assigned to an available bed j

$$l_k \cdot X_{kjt} \leq \sum_{\hat{t}=t}^{t+l_k-1} f_{jt} \qquad \forall k, \forall j, \forall t \tag{4.8}$$

- Required nurses
  - At a given time t, the number of patients being admitted or discharged at that time has to be less than or equal to the number of nurses present at the given time t, because a nurse can only discharge or admit one patient at a time.

$$w_t + \sum_k \sum_j \left(X_{kjt} + X_{kj(t-l_k+1)} \right) \leq Y_{tc} \qquad \forall c, \forall t \in T_c \tag{4.9}$$

  - At any given time the number of nurses has to be greater than or equal to e

$$Y_{tc} \geq e \qquad \forall c, \forall t \in T_c \tag{4.10}$$

  - At a given time t in a shift c, a single nurse can be assigned to at most s_c patients. This implies that at a given time t the number of patients present should be less than or equal to the number of nurses present, Y_{tc}, multiplied by the maximum number of patients they can be assigned to, s_c.

$$z_t + \sum_k \sum_j \sum_{\hat{t}=t-l_k+1}^{t} X_{kj\hat{t}} \leq s_c \cdot Y_{tc} \qquad \forall c, \forall t \in T_c \tag{4.11}$$

  - During a given shift c, the number of nurses present is constant.

$$Y_{tc} - Y_{\hat{t}c} = 0 \qquad \forall c, \forall t, \hat{t} \in T_c \tag{4.12}$$

- Number of appointments
  - In the blueprint schedule, μ_k appointments should be scheduled of type k.

$$\sum_j \sum_t X_{kjt} = \mu_k \qquad \forall k \tag{4.13}$$

- Variables
  - The following restrictions lie on the variables

$$X_{kjt} \in \{0, 1\} \tag{4.14}$$

$$Y_t \in \mathbb{Z}^+ \tag{4.15}$$

4.3.2 Objective Function

In choosing the objective function one chooses what is the best blueprint schedule and hence answers the first question of Section 4.2. The purpose of constructing a blueprint schedule is to be able to schedule the appointments for a Short-Stay Unit in such a way that with minimal capacity and resources, patients can be seen within their required access times. To this end the objectives of the blueprint schedule should take into consideration the number of nurses that are required and spreading out appointments of the same type as equally as possible across the different days of the schedule. This is expressed in objectives as follows:

Required nurses

Since for the Short-Stay Unit it is not efficient to have more nurses working than necessary, given the constraints formulated in (4.9), (4.10), (4.11) and (4.12) the number of working nurses should be kept to a minimum. To this end, the maximum difference between the number of patients that can be treated with the number of nurses present and the actual number of patients present during a shift should be minimized. Define the variable E to denote this difference:

$$E \geq \left(s_c \cdot Y_{tc} - \left(z_t + \sum_k \sum_j \sum_{\hat{t}=t-l_k+1}^{t} X_{kj\hat{t}} \right) \right) \qquad \forall c, \forall t \in T_c \tag{4.16}$$

$$E \in \mathbb{Z}^+ \tag{4.17}$$

Homogeneous distribution of appointment types

By distributing appointments of the same type as homogeneously as possible over the blueprint schedule, two aspects are taken into account: First, it is assumed that patient preferences are spread among the days of the week rather than among times of a day, so by spreading out the appointments of a given type, the probability increases that one of the assigned blocks for that appointment type in the blueprint will satisfy the patient preferences. This assumption is also used in order to define the assignment rules in Section 4.4.5. Secondly, the arrival process of the appointment requests of a given type per day is independent of the day of the week and so the homogeneous distribution increases the probability that, whenever an appointment request arrives, a slot for the corresponding appointment type will be available in the blueprint. Let this probability be denoted by p_s and the variance of the distribution of the blocks of a type by σ_d.

Lemma 4.1. *p_s is monotone decreasing in σ_d.*

Proof. The arrival process of appointment requests of a certain type is independent of the day. This implies that every day appointments of a given type arrive according to the same stochastic process. So the probability of being able to place an appointment depends only on the distribution of the appointment blocks in the blueprint. With increasing σ_d, there are days with a higher number of blocks of a given type, and days with a lower number of blocks of that type. But due to the rolling horizon approach, blocks on days with a high number may remain unused since the appointments arrive with the same process every day, whereas days with a lower number of blocks may not provide enough blocks for the arriving requests. So by spreading out the appointments homogeneously, i.e. with σ_d as small as possible, p_s increases. □

Therefore, let for every appointment type k the minimum and maximum number of blocks per day in the blueprint horizon be denoted by the variables N_k and M_k.

$$N_k \leq \sum_j \sum_{t \in T_f} X_{kjt} \qquad \forall f, \forall k \tag{4.18}$$

$$M_k \geq \sum_j \sum_{t \in T_f} X_{kjt} \qquad \forall f, \forall k \tag{4.19}$$

$$N_k, M_k \in \mathbb{Z}^+ \tag{4.20}$$

If appointments should be spread as equally as possible over the days, the difference between the minimum and the maximum number of appointments per day should be minimized. Hence let

$$V_k = M_k - N_k \text{ and} \tag{4.21}$$

$$V \geq V_k \qquad \forall k \tag{4.22}$$

$$V_k, V \in \mathbb{Z}^+ \tag{4.23}$$

denote that difference per appointment type k and the total difference over all appointment types respectively. For every appointment type k, this difference should be minimized. Defining the variables in this way ensures the linearity of the model.

Overall objective

These two aspects are combined into one scheduling objective for the blueprint schedule. Table 4.5 gives an overview of the notation for the objective.

factor	objective	weight
E	min	γ
V	min	β

Table 4.5: Overview of objectives

Finally, the complete LP to obtain the blueprint schedule can be stated and is given Figure 4.6.

$$
\begin{array}{ll}
\min \gamma \cdot E + \beta \cdot V & \\
 & \\
\sum_{j \in J_S} X_{kjt} \leq a_t^S \cdot d_{t+l_k-1}^S & \forall t, \forall k \\
\sum_{j \in J_N} X_{kjt} \leq a_t^N \cdot d_{t+l_k-1}^N & \forall t, \forall k \\
X_{kjt} + \sum_{\hat{k} \neq k} \sum_{\hat{t}=t}^{t+l_k-1} X_{\hat{k}j\hat{t}} \leq 1 & \forall k, \forall j, \forall t \\
X_{kjt} + \sum_{\hat{t}=t}^{t+l_k-1} X_{kj\hat{t}} \leq 2 & \forall k, \forall j, \forall t \\
l_k \cdot X_{kjt} \leq \sum_{\hat{t}=t}^{t+l_k-1} f_{jt} & \forall k, \forall j, \forall t \\
w_t + \sum_k \sum_j \left(X_{kjt} + X_{kj(t-l_k+1)} \right) \leq Y_{tc} & \forall c, \forall t \in T_c \\
Y_{tc} \geq e & \forall c, \forall t \in T_c \\
z_t + \sum_k \sum_j \sum_{\hat{t}=t-l_k+1}^{t} X_{kj\hat{t}} \leq s_c \cdot Y_{tc} & \forall c, \forall t \in T_c \\
Y_{tc} - Y_{\hat{t}c} = 0 & \forall c, \forall t, \hat{t} \in T_c \\
\sum_j \sum_t X_{kjt} = \mu_k & \forall k \\
B \geq \left(s_c \cdot Y_{tc} - \left(z_t + \sum_k \sum_j \sum_{\hat{t}=t-l_k+1}^{t} X_{kj\hat{t}} \right) \right) & \forall c, \forall t \in T_c \\
N_k \leq \sum_j \sum_{t \in T_f} X_{kjt} & \forall f, \forall k \\
M_k \geq \sum_j \sum_{t \in T_f} X_{kjt} & \forall f, \forall k \\
V \geq M_k - N_k & \forall k \\
B & \in \mathbb{Z}^+ \\
N_k & \in \mathbb{Z}^+ \\
M_k & \in \mathbb{Z}^+ \\
V_k & \in \mathbb{Z}^+ \\
V & \in \mathbb{Z}^+ \\
X_{kjt} & \in \{0,1\} \\
Y_{tc} & \in \mathbb{Z}^+
\end{array}
$$

Table 4.6: Linear program to obtain blueprint schedule

4.4 Assignment Rules

In this section, answer to the second question of Section 4.2 is given, i.e. how appointments should be assigned to reserved blocks of the blueprint. The following subsections evaluate aspects that lead to an efficient schedule.

4.4.1 Blocks Adjacent to Scheduled Appointments

To make efficient use of the available beds, it is best to schedule appointments on beds where other appointments take place prior to and after the current appointment. In doing so, gaps in the schedule are avoided if possible. So the assignment rule should give higher priority to blocks in the blueprint schedule, that are in between already scheduled appointments. If there is no such block, blocks that follow up on a scheduled appointment and blocks that are followed by a scheduled appointment should be preferred. There is no straight forward argument to determine which of these two cases should be preferred, but for simplicity, preference is given to appointments that follow up on a scheduled appointment. This is illustrated in Figure 4.2. The figure shows four beds with four blocks reserved for the appointment that needs to be scheduled. Time progresses from top to bottom of the figure, i.e. the top time slot of each bed is the earliest. In this figure, the reserved block at bed 1) would be preferred over a block at the other beds, because it is adjacent at the beginning and end to another appointment. The four blocks reserved for the appointment type are prioritized as 1), 2), 3), 4).

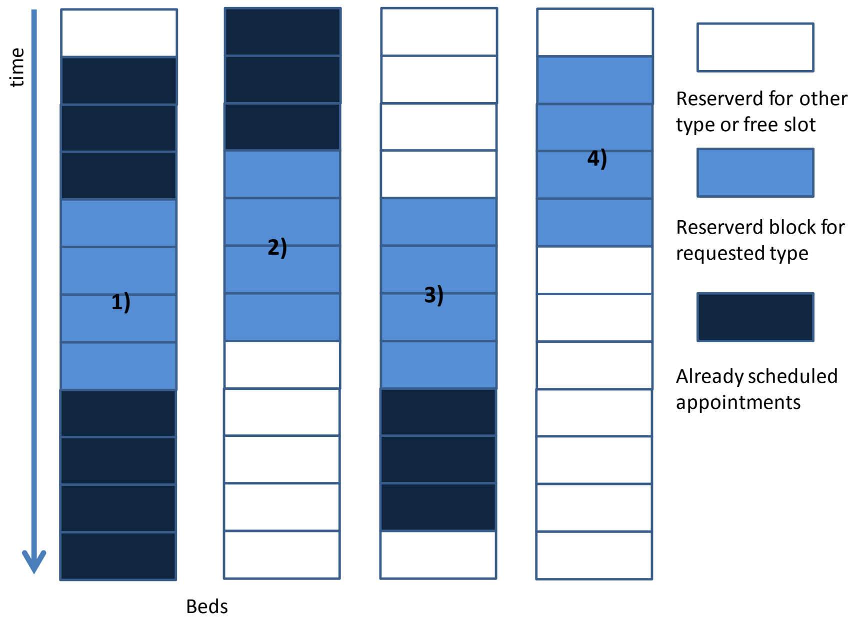

Figure 4.2: Preferred blocks

To see why this rule is optimal consider Figure 4.3. In this figure, a bed is depicted for a given time period where two appointments are already scheduled (dark blue) and there are two choices for scheduling an appointment of a given type (light blue). The resulting schedules of these two choices are depicted below. The white blocks denote unused, free time slots where other appointments can potentially be scheduled. Since with any choice, the same amount of time will be scheduled, the total amount of unused time slots, i.e. the total white area in the figure, is the same. However, it can be seen that the first choice leads to a larger connected white area, i.e. the free time slots are forming one large period whereas the second choice leads to small unconnected free time slots. With the next iteration of the heuristic, another blueprint will be made and it will become more difficult to 'squeeze' appointments in the free time slots if the free period is unconnected and broken into small pieces. With choice 1, a long appointment can still be scheduled, but not with choice 2. On the other hand, small appointments can be scheduled with any choice. Note that this not only holds for scheduling a request adjacent to appointments, but also for blocks adjacent to time slots where the unit is closed because the same argument applies.

Lemma 4.2. *Choosing blocks adjacent to already scheduled appointments increases the probability to be able to schedule further requests.*

Proof. Let g denote the largest connected period of unused time slots in the current schedule. Let l_R denote the length of the current request. If $g = l_R$ then the only option to schedule the current request is in between two already scheduled appointments (or time slots where the unit is closed), because otherwise there would be a larger connected period. If $g \leq l_R$ it is not possible to schedule the request. So assume $g \geq l_R$ and assume that there is another connected free period h between already scheduled appointments of length l_R. Now choice 1 corresponds to choosing h for the request and choice 2 to choosing g. Choice 1 results in g staying the same size, hence still being the largest connected free period in the next state, i.e. $\bar{g} = g$. But choice 2 reduces the size of g, hence the largest connected period of free time slots after making the choice, $\bar{g}$, is either equal or less than g, $\bar{g} \leq g$. Now consider the next request, $\bar{R}$. The type, and hence the length of this request is stochastic and so the probability that there is enough free space in the schedule to place the request is $P\left(L_{\bar{R}} = l_{\bar{R}}, \bar{g} \geq l_{\bar{R}}\right)$, that is the probability that the request has a certain length and that the largest connected free period is at least as long as that length. Consequently it follows that $P_{choice2}\left(L_{\bar{R}} = l_{\bar{R}}, \bar{g} \geq l_{\bar{R}}\right) \leq P_{choice1}\left(L_{\bar{R}} = l_{\bar{R}}, \bar{g} \geq l_{\bar{R}}\right)$, and hence that it is optimal to prefer adjacent blocks. □

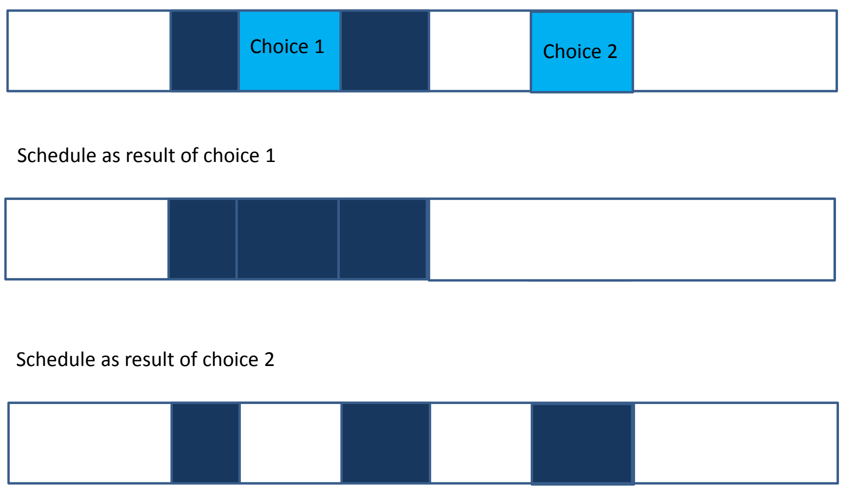

Figure 4.3: Optimality of appointment in between other appointments

4.4.2 Thresholds for Urgent Requests

Short Stay Units also receive urgent requests. In order to be able to schedule these requests, non-urgent appointments that could also be scheduled later, should not occupy the urgent blocks. On the other hand, reserving all blocks for urgent patients could lead to unused capacity in case no urgent requests arrive. Therefore, a threshold denoting the number of blocks that should be reserved for urgent appointments is defined for each day, ω_f, based on the statistics of urgent requests. By defining a threshold for each day, each unit can individually define what urgent means. For some Short-Stay Units an urgent request may be one that needs to be scheduled within two days, for some it may be within three days. Due to the rolling horizon approach it is necessary for the thresholds to be in increasing order, i.e. $\omega_0 \leq \omega_1 \leq \omega_2$.... To see this, assume the current day is denoted as day zero and $\omega_1 = 4$ and $\omega_2 = 3$. Now if all but the three threshold blocks of day two are filled up with appointments, when the heuristic moves to the next day, day two will be considered as day one and it will be impossible to have a threshold of four blocks. To this end, if a day is not considered as relevant for urgent requests, the threshold for this day should be set to the maximum of all thresholds of preceding days and so set $\omega_f = max_{\hat{f} \leq f} \left(\bar{\omega}_f, \omega_{\hat{f}} \right)$, where $\bar{\omega}_f$ denotes the threshold based on data, and ω_f the threshold with respect to the increasing order constraint.

4.4.3 Patient Preferences

Patient preferences are an essential part of scheduling appointments for a Short-Stay Unit. Taking these preferences into account is a service for patients and leads to increased patient satisfaction. It may also reduce the risk of no-shows. At the same time a planning based on patient preferences only is most likely not efficient, because the preferences of a single patient consider a single appointment and not the overall schedule. A solution to this is to give patients several options for their appointment and let them choose, so patients can still express their preferences and feel that they have a say in the decision, but the options can be chosen so that they do not interfere with the efficiency of the schedule. To this end, a maximum number of options that can be given has to be defined, which can be unit specific. Let B denote the maximum number of options.

4.4.4 First Blocks First

When several blocks are available within a priority class (e.g. if there are more than B blocks available adjacent to other appointments), spread across the length of the blueprint period, blocks at the beginning of the period (if feasible with the urgency thresholds) should be preferred. To see this, assume a block at the last day of the blueprint period is chosen instead of one at the first day. When the horizon of the heuristic shifts one day forward, the block at the first day will no longer be available. The block at the last day however, which is now the next to last day, would still be within the blueprint period. So the block at the first day, which is not chosen, will remain empty in the overall schedule and so the probability that the block of the last day would have been chosen for other requests is larger than that for the first day. Hence blocks at the beginning of the blueprint period should be preferred.

4.4.5 Selecting Different Days

Here, the assumption is made that patients prefer to be given options that differ from each other, i.e. they prefer to be given three options on three different days (if that is possible), instead of three options starting at different time slots on the same day. This assumption is also used in defining the objective function of the LP, in Section 4.3.2. This assumption is arbitrary in a way, because patient preferences are hard to be made specific and to quantify. However, this assumption can easily be changed in the model. Therefore for the remainder of this report, the assignment rule will work with this assumption.

4.4.6 Assignment Steps

Combining these aspects leads to the following rule:

1. List all available blocks for the appointment type of the request
   (a) total
   (b) per day
2. Check for each day from the release date until the due date of the request if the number of available blocks of the corresponding day is smaller than the defined thresholds for urgent requests. If so, these days will not be considered anymore.
3. For all remaining days, look for blocks that are adjacent to already scheduled appointments as described in Section 4.4.1 (see Figure 4.2).
   (a) First, blocks that are adjacent at the beginning and the end of the block.
   (b) Then blocks that follow an already scheduled appointment.
   (c) Then blocks that are followed by an already scheduled appointment.

   If the number of blocks exceeds B, mark the chronologically first blocks as options. If B is not reached, continue:
4. As long as B is not exceeded (or there are no more available blocks), chronologically go from day to day and pick the first available block, then move on to the next day.
5. The result is a number of options, less than or equal to B, for the appointment request, from which the patient can choose.

4.5 Conclusions

In this chapter the scheduling model is introduced. A heuristic is developed that combines a rolling horizon approach with advance planning. At the core of the heuristic is the LP that is used to obtain a blueprint schedule, where blocks are reserved for the different appointment types. Assignment rules then specify to which of the reserved blocks an appointment request should be assigned. The optimization problem is hence broken down into two parts: First, of all possible blueprints, the best blueprint has to be found, which is achieved by choosing an appropriate objective function for the LP. Second, the assignment rules have to ensure efficiency of the schedule. Both the LP and the assignment rules are designed so that they represent the scheduling procedure of Short-Stay Units in general. When the heuristic is applied to a certain unit, the parameters have to be defined in order to represent the characteristics of the unit. The next chapter will address the simulation model that is used to evaluate the developed heuristic.

Chapter 5

Simulation

This chapter deals with the simulation of the previously described scheduling heuristic. Computer simulation is a technique to test and evaluate a model. In most real life situations, it is for various reasons not possible to experiment or test an actual system. On the basis of a mathematical model of the system, in a simulation this system is imitated and numerical results of experiments can be obtained, [22]. For this project, a simulation that captures the scheduling of appointments with the scheduling heuristic is developed. To this end, first the simulation model will be explained in Section 5.1 and the case study of the AMC Short-Stay Unit will be discussed in Section 5.2. The experiments that will be conducted with this simulation model are described in Section 5.3 and the conclusions of this chapter are given in Section 5.4.

5.1 Simulation Model

Figure 5.1 shows a graphical representation of the simulation model of the scheduling system. The scheduling heuristic has been described in detail in Chapter 4, so this section addresses how the appointment requests will be generated and how choosing an option by a patient is modeled.

5.1.1 Generating Appointment Requests

In order to simulate the scheduling heuristic the arrival of appointment requests is modeled in three steps. First, using an empirical probability distribution obtained from the AMC Short-Stay Unit, a random number denoting the number of requests will be generated. Let one iteration denote the time between generating two blueprints, i.e. during one iteration a new blueprint is made and appointment requests that arrive in the period up to the next iteration will be scheduled. Hence for each iteration of the scheduling heuristic, a random number according to the distribution based on the data of the Short-Stay Unit will be drawn that denotes the number of requests that need to be scheduled in that period. Second, for each request the appointment code of that request is determined from a distribution derived from the historical data of the Short-Stay Unit. Third, depending on the appointment code, a duration and a release and due date will be determined. For the last step, per appointment code the durations of the appointments are investigated. The durations center around a certain number of time slots, with only few outliers. Therefore, per appointment code the most frequent duration is chosen. For the release and due date, it is important to keep in mind that only the realized

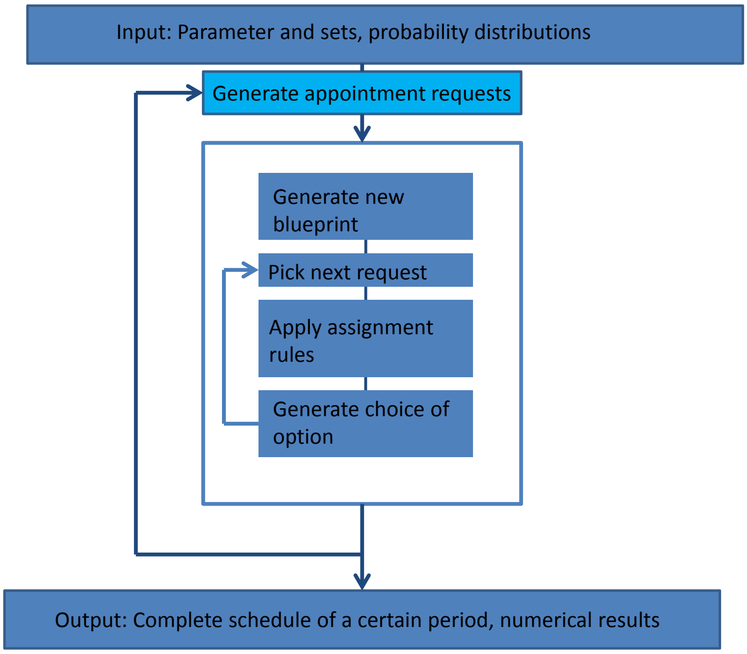

Figure 5.1: Schematic representation of the simulation model

access time is measured, not the actual required access time. However the nurse manager and the planner of the AMC Short-Stay Unit confirmed that it rarely happened that patients could not be scheduled on time. Hence it is assumed that the realized access times can be used as an estimation of the actual required access times. To obtain a release and a due date from the realized access time, the 10^{th} and 90^{th} percentile of the realized access times in the historical data are taken per appointment code. In that way, the variability of the access times among the different appointment codes is reflected.

5.1.2 Choosing an Option

Each time the assignment rules of the scheduling heuristic are applied to an appointment request, the result is a certain number of options from which the patient can choose an appointment. For the simulation a mechanism is needed to imitate the patient's choice. Because patient preferences are hard to model and there is no data available on that matter, one of the options will simply be selected at random, that is a uniform distribution between one and the available number of options will be used to determine which option is chosen.

5.1.3 Implementation of the Simulation Model

Data of the Short-Stay Unit in the AMC will be used as input for parameters and sets, as well as the distributions required to generate the appointment requests. The simulation will terminate after a specified period, with a complete schedule as output from which numerical results of performance measures can be calculated. This simulation model is implemented in

AIMMS[1] and Excel[2]. AIMMS is mainly used to solve the LP that determines the blueprint schedule, and several Excel macros will update the parameters and simulate the assignment rules.

5.2 Case Study

For this research, the AMC Short-Stay Unit is used as a case study. This section describes how the available data of the Short-Stay Unit is used as input to simulate this specific case. Most parameters and sets follow directly from the organization of the Short-Stay Unit. These will not be discussed in this section, but an overview is given in Appendix D.

5.2.1 Parameters and Sets for the LP

Here the parameters and sets used as input for the LP are discussed.

Blueprint horizon

In choosing the blueprint schedule horizon δ three aspects have to be taken into account:

- Access times of appointments
  The access times of appointments vary from a day up to three months. So in order to be able to schedule all these requests with the blueprint, one would like a long horizon.
- Occurrences of appointments
  A long horizon is also desirable when considering the number of appointments of a given type that occur in a given period. If the period is chosen too small, some appointment types do not occur on average.
- Computational time
  On the other hand, the time it takes to compute a solution to the LP depends mainly on the number of time slots within the blueprint schedule. To see this, consider X_{kjt}, resulting in $|K| \cdot |J| \cdot |T|$ variables. So choosing δ to be one week (7 days with 24 time slots, 168 time slots) or two weeks (14 days, 24 time slots, 336 time slots) has a great impact on the size of the problem.

Because the Short-Stay Unit closes every fortnight for the weekend, a multiple of 14 days would be a desirable choice for δ. However, due to time constraints with respect to computing, a blueprint period of seven days is chosen.

Objective function

In Section 4.3.2, the objective function in order to obtain the blueprint is defined as min $\gamma E + \beta V$. In order to choose γ and β appropriately, first the objective variables have to be normalized. This can be achieved by reasoning what the minimum and maximum values for these variables are. The normalization, which can be found in Appendix C, leads to $\gamma = \frac{\bar{\gamma}}{18}$ and $\beta = \frac{\bar{\beta}}{220}$. $\bar{\gamma}$ and $\bar{\beta}$ have to be chosen according to the preferences of the unit. Because the effects of these weights are hard to estimate, first experiments are conducted, to see what the effect of only focusing on V or E is.

[1] AIMMS 3.13, Paragon Decision Technology
[2] Excel 2010, Microsoft Office Professional Plus 2010

Unit of time slots

The Short-Stay Unit at the AMC works with time slots of 30 minutes, which leads to 48 time slots per day. However, the number of time slots contributes not only to the solving time of the LP but also to the time it takes to assign an appointment. To see this, consider an appointment type for which no blocks are reserved in the blueprint schedule. If the assignment rules are applied for such a request, the computer program iterates through all available time slots between release and due date of the request, so increasing the size of the time slots implies less iterations. Setting the time slot unit, ζ, to 1 hour reduces the number of variables in the LP almost to half of the size compared to the case where 30 minutes time slots are used; this simplifying choice is made. This leads to the modification in the blueprint LP, that now a single nurse can discharge or admit two patients during one time slot. Constraint 4.9 hence changes to

$$\frac{1}{2}\left(w_t + \sum_k \sum_j \left(X_{kjt} + X_{kj(t-l_k+1)}\right)\right) \leq Y_{tc} \qquad \forall c, \forall t \in T_c \tag{5.1}$$

Appointment types

For the LP it does not matter how the appointments are grouped into types. From a planning perspective however the most important aspect of an appointment is its duration for whether a four hour appointment is a blood transfusion or an antibiotics treatment does (in the case of most appointment types) not matter. What is important is the duration. Any other specifications related to the appointment code are taken into account when actually assigning an appointment, but not when designing the blueprint. Furthermore, the 80 different appointment codes would cause a high number of variables. Therefore it is chosen to define the appointment types by the duration of the appointments in time slots. Because of some outliers not the whole range of durations from the historical data could be used (this would lead to 87 types, contradicting the purpose of keeping the model small). When limiting the appointment types to appointments with a maximum duration of 13 hours (13 time slots = 13 appointment types), 90% of all appointments are included. This is found acceptable. Hence $|K| = 13$. Note that this limitation only applies to designing the blueprint. When actually generating appointment requests, the whole range of durations is considered.

Occurrences of appointments

From historical data, the exact number of appointments of each type within the period from January 2013 to September 2013 is known. But when choosing the blueprint horizon to be shorter than this period, the average number of occurrences has to be calculated for that period. Unfortunately these averages are not always integer. But since the parameter μ_k is required to be integer, first the average number of occurrences of each type per blueprint period is calculated. The resulting numbers are then rounded to the nearest integer (e.g. 1.4 would be rounded to 1 while 1.5 would be rounded to 2). To see how far from reality these values are, it is calculated backwards how many appointments of each type would occur in the period from January to September 2013 based on these rounded numbers. Looking at all appointments the relative difference between the actual and calculated number of appointments is 5%.

5.2.2 Assignment Rules

In order to apply the heuristic to the AMC Short-Stay Unit, necessary exceptions to the assignment rule are defined and the number of options that is offered to the patient needs to be specified.

Exceptions to the assignment rule

For the case study of the AMC Short-Stay Unit, the assignment rule described in Section 4.4 is used as a basis, but for this specific case modifications have to be made. There are three exceptions which are listed below, along with the required modifications:

1. The AMC Short-Stay Unit has several appointments that have special scheduling requirements (e.g. a specific room or a specific time).
   The modification of the rule is straight forward in this case: In step 1 of the standard assignment rule, only those blocks are listed that meet the scheduling requirements. If no such blocks exist, the first available block of time slots within the release and due date is taken, that meets the requirements and is feasible with respect to previously scheduled appointments, opening hours and admission and discharge hours. A list of these appointment types and their special requirements can be found in Appendix D.

2. The blueprint horizon for this case study is set to 7 days, but when a request is generated, also appointment types are included of which the due date exceeds the blueprint horizon. Consider the blueprint schedule that has just been calculated. And suppose a request arrives for an appointment with a release date that is one day beyond the scope of the blueprint. This request cannot be planned with the current blueprint schedule. The solution is to shift the blueprint schedule δ time slots forward. Because of the different opening hours during the weekend, the blueprint has to be modified so that the opening hours are taken into account, which means that blocks that are (as a whole or partly) scheduled during hours where the unit is closed will be deleted from the blueprint.

3. For the blueprint 13 different appointment types are considered, which include 90% of all appointments. But when a request is generated, all appointments of the Short-Stay Unit are taken into account, so it can occur that a request is longer than any of the reserved blocks in the blueprint.
   To handle this exception, first it is checked whether it is possible to schedule the appointment within its release and due date at a feasible time that is not reserved with blocks. If that is not possible, the first available block of time slots within the release and due date, that is feasible with respect to previously scheduled appointments, opening hours and admission and discharge hours, is taken, regardless of whether it overlaps with a block of the blueprint.

4. Thresholds.
   The thresholds for urgent appointments are based on the historical data of the Short-Stay Unit and can be found in Appendix D.

As a final rule, if no blocks can be found for an appointment request within the blueprint, the appointment will be scheduled at the first available block on the first available bed of time slots within the release and due date, that is feasible with respect to previously scheduled appointments, opening hours and admission and discharge hours. Only in the case where there are no more free time slots for that request on any bed between the release and due date, the appointment will not be scheduled at all. The simulation will keep track of the number of

appointments where this is the case.
While in the process analysis of the Short-Stay Unit four special types of requests are listed, urgent requests, overnight requests, combination requests and sequential requests, the scheduling heuristic only deals with two of these cases explicitly. Urgent requests are taken into account by the thresholds, and overnight requests are realized by generating appointments with long durations. Sequential requests are taken into account indirectly, each appointment was listed individually and hence contributed to the data set used for the empirical probability distributions. In practice, this could be realized by specifying a tight release and due date for the follow up appointments, so that they have to be scheduled at a fixed distance of each other. In the heuristic, they are not explicitly modeled. Combination requests are not considered, because scheduling these appointments requires the planners to contact the staff of other departments, which is beyond the scope of this model.

Maximum number of options

The maximum number of options offered to the patient is set to $B = 3$.

5.2.3 General Settings of the Heuristic

With the input for the LP and the settings of the assignment rules defined, what remains is to decide how often a new blueprint should be generated.

Iteration frequency

Technically, it is possible to generate a new blueprint every time a single appointment has been scheduled. However this implies that in practice, the LP has to be solved every time the planners want to schedule a single appointment. Solving the LP is very time consuming and hence for practical reasons the blueprint is updated every week, resulting in a lower iteration frequency, denoted by ρ.

5.2.4 Summary of the Chosen Parameters

Table 5.1 summarizes the most important parameter choices. For further notation let ϵ denote

Parameter	Description	Value
ρ	Iteration frequency	once in 7 days
δ	Blueprint period	168 time slots
ζ	Unit of time slots	1 hour
B	Maximum number of options	3

Table 5.1: Choices of model parameters

the number of time slots per day. In this case $\epsilon = 24$.

5.3 Experimental Setup

The purpose of the simulation model is to compare the performance of the heuristic to the current practice and to experiment with input of the scheduling heuristic in order to see what the effects of these changes on the resulting schedule are. The following factors are to be investigated with the simulation model:

- Patient preferences
  What is the effect of not giving three options to the patient, but just one appointment date and time?
- Decreasing capacity
  - Number of beds
    The results of the data analysis of Section 2.6 show that currently, the beds of the AMC Short-Stay Unit are not efficiently used and the question remains whether it would be possible to use less beds and still be able to see patients within their access times. To this end, the effect of decreasing the number of beds will be investigated.
  - Opening hours
    The data analysis also showed that the utilization during the weekend was very low. What would be the effect of closing the unit every weekend, instead of every fortnight? What would be the effect of closing more beds at night?
- Increasing demand
  What would happen when the demand increases? How many appointment requests can not be scheduled within their access times?

Let the input parameters and model settings as described above denote the baseline scenario. Unless stated otherwise, this scenario will be used as input. In Appendix E an overview of the changes in the input parameters for the experiments can be found.

5.4 Conclusions

In order to test the scheduling heuristic a simulation model is developed. The simulation model is constituted of three parts: First, the arrival process of appointment requests is modeled, using the historical data of the AMC Short-Stay Unit. Then, the heuristic schedules these requests according to the blueprint and the assignment rules. Finally, one of the options that are generated by the heuristic will be chosen at random, in order to imitate the patient's preferences. Most parameters for the AMC Short-Stay Unit case can be chosen straight forward according to the Unit's organization. For some parameters and the assignment rules however, simplifications or extra rules had to be defined to properly model the Unit's characteristics. Due to the large number of variables in the blueprint LP further simplifications had to be made and model parameters had to be chosen in order to keep the computing time to a manageable amount. With the simulation model the effect of certain changes in the input will be investigated. To see how the schedule changes under different scenarios, decreasing the bed capacity, changing the opening hours, the way patient preferences are taken into account and increasing demand will be evaluated with the simulation model.

Chapter 6

Output Analysis

This chapter deals with the analysis of the output obtained from simulating the planning process at the AMC Short-Stay Unit, using the scheduling heuristic. Section 6.1 deals with the statistical analysis of the output and addresses the issue of choosing the warming up period and the number of runs. The validation and verification of the simulation model are described in Section 6.2 and Section 6.3 summarizes the conclusions of this chapter.

6.1 Statistical Output Analysis

This section deals with the analysis of the simulation output. First, the output of the simulation is discussed in Section 6.1.1 after which the number of simulation runs and the length of the warming up period are addressed in Section 6.1.2.

6.1.1 Output of the simulation

The goal of the simulation is to quantify the effects of applying the developed scheduling heuristic at the AMC Short-Stay Unit. The outcomes of a single simulation run are just one realization of the underlying stochastic variables, so in order to draw conclusions, statistical analysis of the results is necessary. Each run produces as output a complete schedule for a specified period of time. In order to answer the research question of this study, the performance measures that will be collected should relate to the following two areas: access times of patients and resource utilization, where resources can be divided into beds and nurses.

- U - Total realized bed utilization
  In order to have a performance measure related to bed utilization that does not depend on a shift or day, the total realized bed utilization U, denoted in %, is calculated as the total amount of realized appointment hours divided by the total amount of available bed hours.

- $U_{c,d}$ - Average bed utilization during shift c and day d
  The average bed utilization per shift and day measured and denoted as $U_{c,d}$ in %.

- W - Total realized nurse patient ratio
  As for the bed utilization, it is desirable to have a performance measure independent of shifts and days that indicates the proportion of the number of nurses working and the number of patients present. To this end, let 1:W denote the total realized nurse patient

ratio, where W is calculated as the total amount realized appointment hours divided by the total amount of available nursing hours, based on the calculated number of required nurses.

- $V_{c,d}$ - Average number of required nurses during shift c and day d
  The average number of required nurses per shift and day of the week is calculated on the basis of the admission and discharge moments and the patient load.
- θ - Fraction of requests that could not be scheduled within the required access time
  Whenever an appointment request could not be scheduled within the required access time of that appointment, the appointment is not scheduled at all. θ denotes the number of not scheduled appointment requests divided by the total number of scheduled appointments in the observed period, and will be stated in %.

Note that except for θ, all performance measures have been calculated for the current situation at the AMC Short-Stay Unit in Section 2.6. Because the actual required access times were only registered on the paper-based appointment request forms, calculating θ from historical data would be a cumbersome and time-consuming task. However, interviews with Short-Stay Unit staff give the indication that almost all appointments could be scheduled within the required access times, hence θ is approximately zero in the current situation.

6.1.2 Simulation Runs and Warming Up Period

In the following the procedures and methods used to obtain the experimental setup are described. In order to determine the experimental setup all performance measures have to be taken into account and hence all procedures are conducted for each measure individually. For simplicity of notation however, the performance measure U will be used to describe the applied procedures. Therefore, let U_{ji} be the i^{th} observation of the j^{th} replication of the total bed utilization.
The simulation starts with an empty schedule. In order to eliminate the effect of the initial state on the results, a warming up period will be determined so that after that period, the transient means of the stochastic variables that are measured will converge to the steady state means [22]. Once the length of this period is chosen appropriately, the observations of that period are deleted, and only the remaining observations are used to determine the means. The graphical method of Welch is used to determine the warming up period, as described in [22] and [35].
Eight runs of the simulation are executed, each of length six months (that is 24 iterations per run, because each week a new blueprint is calculated), hence the number of runs is $n = 8$ and the number of observations per run $m = 24$. Consider U_{ji}. As a first step, the process is averaged per observation, i.e. $\bar{U}_i = \sum_{j=1}^{n} U_{ji}/n$ is calculated for all i. Second, the moving average of the averaged process is obtained as follows: Let $w \leq \lfloor \frac{m}{4} \rfloor$; here $w = 5$ is chosen, which is the window of the moving average. The moving average is then calculated as follows:

$$\bar{U}_i(w) = \begin{cases} \frac{\sum_{s=-w}^{w} \bar{U}_{i+s}}{2w+1} & \text{if } i = w+1, ..., m-w \\ \frac{\sum_{s=-(i-1)}^{i-1} \bar{U}_{i+s}}{2i-1} & \text{if } i = 1, ..., w \end{cases} \tag{6.1}$$

Finally, $\bar{U}_i(w)$ is plotted and the length of the warming up period is chosen as the point in time from where the graph seems to have converged. The method of Welch is applied to each performance measure, and the maximum of all individual warming up periods is taken, to be sure the system is in steady state. This maximum is obtained at $l = 14$ weeks, which is chosen as the warming up period. The performance measure for which this maximum is obtained is θ. Figure 6.1 shows the moving average of the averaged process with a window $w = 5$.

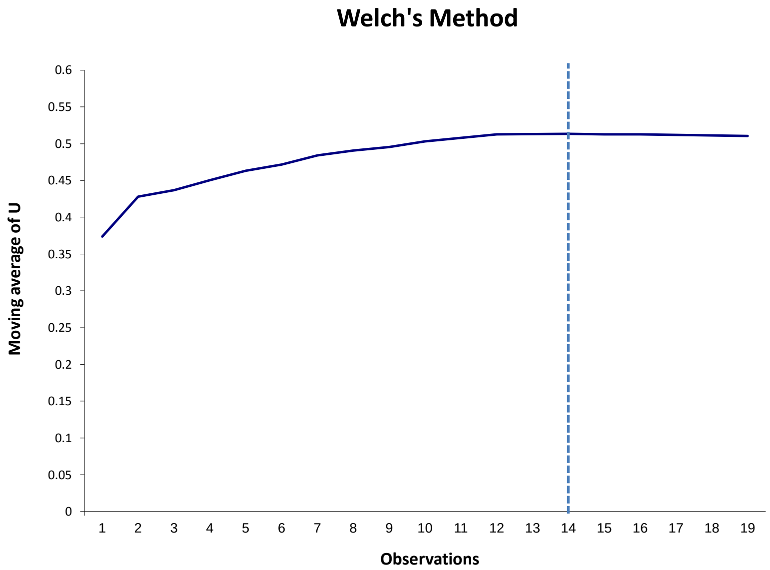

Figure 6.1: Moving average of averaged process according to Welch's method for U

As a next step, the length of each individual run has to be determined. In [32], Robinson describes an indicative measure, the convergence, that can be used to determine the run length. The convergence measure is calculated as follows on the basis of three simulation runs (again, U is used):

$$\hat{C}_i = \frac{max\,(U_{1i}, U_{2i}, U_{3i}) - min\,(U_{1i}, U_{2i}, U_{3i})}{min\,(U_{1i}, U_{2i}, U_{3i})} \forall i \tag{6.2}$$

According to Robinson, the run length should be selected so that the convergence reaches a steady level of under 5%. Figure 6.2 shows the results of the bed utilization U of three runs and the convergence measure $\hat{C}_i$. It can be seen that after 45 observations this level is reached. This procedure is repeated for each performance measure, and the maximum number of observations where a level of under 5% is reached for each measure, is taken as the number of observations per run. These calculations yield that for W, the maximum of all performance measures is reached with a run length of 50 observations, i.e. 50 weeks, so $m' = 50$.

Robinson [35] also states a rule of thumb by Banks, indicating that the length of a single run should be at least 10 times the warming up period. However to simulate 120 weeks with the simulation model, approximately 23 hours are needed. Thus to be able to perform various experiments in a reasonable time $m' = 50$ is a reasonable choice. When l and m' are chosen, the replication/deletion approach can be used to obtain the means of the stochastic variables of interest. This approach implies that n' runs are performed of m' observations. The warming up period is deleted and the remaining observations of the replications are used to define confidence intervals (CI's) for the stochastic variable. Define U_j as

$$U_j = \frac{\sum_{i=l+1}^{m'} U_{ji}}{m' - l} \text{for } j = 1, 2, ..., n' \tag{6.3}$$

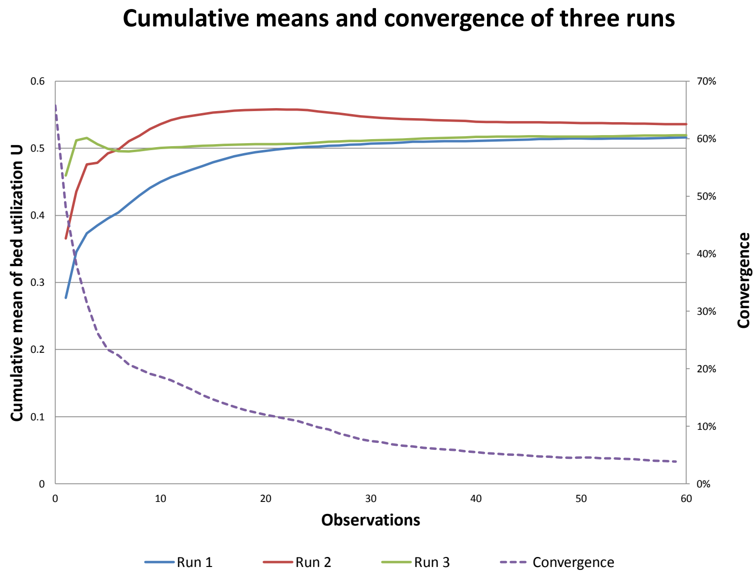

Figure 6.2: Results of three runs and the corresponding convergence measure

By the independence of the runs, the U_j's are independent and identically distributed variables. So a CI can be obtained with the following expression:

$$[\bar{U}(n') - \psi_{n'-1,1-\frac{\alpha}{2}} \cdot \sqrt{S^2/n'} \; ; \bar{U}(n') + \psi_{n'-1,1-\frac{\alpha}{2}} \cdot \sqrt{S^2/n'}], \tag{6.4}$$

where ψ has to be taken from the Student t distribution and α can be chosen in order to obtain a two-sided $100(1-\alpha)\%$ (CI). It is desirable that the results have a certain relative precision, i.e. the width of the CI is not too broad compared to the size of the $\bar{U}(n')$.
Law et al. [22] and Robinson [32] describe a procedure to determine the number of runs, i.e. n', to obtain the desired precision. Suppose the desired precision is κ, then first make n_0 replications and check whether

$$\frac{\psi_{n_0-1,1-\frac{\alpha}{2}} \cdot \sqrt{S^2/n_0}}{|\bar{U}(n_0)|} \leq \kappa \tag{6.5}$$

If the relation holds, n_0 is the required number of runs, if not, set $n_1 = n_0 + 1$ and repeat the procedure. Figure 6.3 shows the two sided 95% CI of the cumulative average of the bed utilization on a day shift on a weekday of eight runs. Again, all performance measures are considered and the maximum number of runs, obtained for θ, is taken so that the CI's of all performance measures reach a relative precision of 5%. This procedure yields $n' = 14$ as the required number of runs.
Table 6.1 summarizes the experimental setup that will be used for all experiments.

6.2 Verification and Validation of the Model

This section deals with the questions whether the developed computer program is an accurate representation of the conceptual model and whether the model is valid. Answering the first

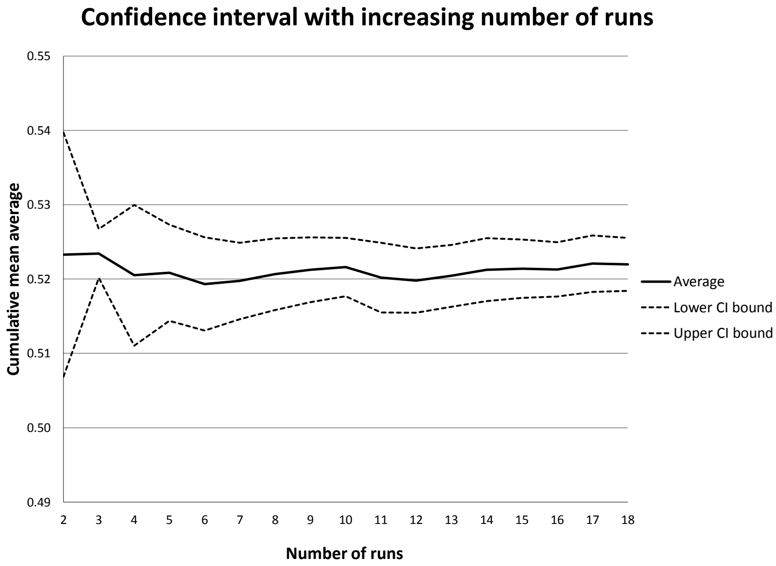

Figure 6.3: Two sided 95% CI of bed utilization U with cumulative mean

Notation	Description	Value
n'	Number of runs	14
l'	Length of warm up period in weeks	14
m'	Length of run in weeks	50
α	Significance level of the CI	0.05
κ	Desired relative precision	0.05

Table 6.1: Experimental Setup

question is the verification of the simulation program and the second question is the validation of the model, [22].

6.2.1 Verification

Verification is the process of determining whether the developed computer program is a correct translation of the conceptual model. The scheduling heuristic is implemented in AIMMS and Excel. The linear program is solved by AIMMS, and several macros in Excel carry out the assignment rules and update the input for the program. Each subroutine of the program was debugged individually using the AIMMS debugging tool, which makes it easy to trace all steps of the program during the sequential iterations. Finally the program as a whole was debugged. Additionally, for simple settings and small instances, it is verified that the outcome of the model is reasonable.

6.2.2 Validation

In order to make sure that the simulation model accurately captures the actual processes, three different models have to be considered: the LP, that creates the blueprint schedule, the scheduling heuristic and the simulation model.

The linear program

The parameters, sets and constraints of the linear program are the result of the process and data analysis in Chapter 2. Together with nursing staff and planners of the AMC Short-Stay Unit the data is reviewed in order to make sure the data reflects the actual process.

The scheduling heuristic

Because the scheduling heuristic is not the representation of an actual, existing system but rather a model of a proposed scheduling system it cannot be validated with an actual system.

The simulation model

The simulation model contains the first two models, the LP and the heuristic, and additionally imitates the arrival process of appointment requests at the Short-Stay Unit. To validate the results of the simulation with the actual hospital data, the scheduling heuristic is replaced by a model of the currently applied scheduling procedure at the AMC Short-Stay Unit. In that way, the performance measures obtained from historical data can be compared to the performance measures obtained by the simulation. Since in Section 2.4.2 a detailed description of the current scheduling procedure is given, the model, with some limitations, follows straight forward from that description and can easily be implemented in the framework of the simulation model. A brief description of this model is given in Appendix F.1. The output of the validation model is obtained as described in 6.1.2. First the arrival process is investigated. To see whether the distribution of the different appointment codes is correctly modeled, the percentage of appointments of a given code is compared to the actual hospital data. In Appendix F.1, Tables 14 and 15 give the average percentage of appointments of a given code of the simulation, compared to the historical data. It can be seen that for all appointment types, the relative difference in the average percentage of appointments of a given code to the historical data is less than 5%. led, the percentage of appointments of a given code is compared to the actual hospital data. In Appendix F.1, Tables 14 and 15 give the average percentage of appointments of a given code of the simulation, compared to the historical data. It can be seen that for all appointment types, the relative difference in the average percentage of appointments of a given code to the historical data is less than 5%. Furthermore, the relevant performance measures are compared to the historical data. To simplify notation, here the average values of the outcomes are given. For a complete overview of the results given as confidence intervals, see Appendix F.2. The validation runs yield an average overall bed utilization of $U = 52.7\%$ and an average overall nurse patient ratio of $V = 1 : 2.49$. Note that while this ratio might seem high, keep in mind that during the night shift there are always two nurses present while often due to the nurse patient ratios fewer nurses would be required. In all runs, every appointment request could be scheduled on time, so the average fraction of requests that could not be scheduled within their access time is $\theta = 0$. Table 6.2 shows the validation results and the equivalent values from the historical data.

Table 6.3 gives the results of $U_{c,d}$.

When compared to the results of the data analysis, see Table 2.13, it can be seen that the bed utilization is more homogeneously distributed among the shifts and weeks than the actual data reveals. Especially the weekend shows a higher utilization compared to the actual hospital data. The reason for this lies in the model of the current scheduling method, where patient preferences are not taken into account. According to the planners of the Short-Stay

Measure	Validation	Historical data
U	52.7%	52.9%
W	2.49	2.41
θ	0%	0%

Table 6.2: Validation results and historical data values of performance measures

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	62.9	63.9	62.3	57.7	50.5	53.3	49.5
Evening	61.6	57.8	55.1	46.5	35.1	45.1	45.2
Night	32.0	46.9	45.6	41.4	32.8	41.4	33.7

Table 6.3: Average bed utilization per day in %

Unit the weekend is not a preferred time for patients to schedule appointments. It can be seen however that the average total bed utilization obtained by the validation $U = 52.7\%$ is within 3.7% relative error of the total utilization obtained from the historical data.
As for the average number of required nurses per shift and day, first the average number of required nurses based on the number of admissions and discharges, then the average number of required nurses based on the patient load is given and finally, by taking the maximum of those values and bearing in mind that a minimum of two nurses is required at all times, the overall required number of nurses is derived and shown in the lower part of Table 6.4.

Required number of nurses based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.0	4.3	4.4	4.4	4.4	1.8	2.4
Evening	3.1	2.8	3.0	3.0	3.0	0.7	0.7
Night	2.1	2.2	2.1	2.2	2.2	0.7	0.7
Required number of nurses based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	3.5	3.5	3.4	3.2	2.7	1.6	1.4
Evening	1.4	1.4	1.3	1.1	0.8	0.9	0.9
Night	0.3	0.5	0.5	0.4	0.3	0.4	0.3
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.0	4.3	4.4	4.4	4.4	2.0	2.4
Evening	3.1	2.8	3.0	3.0	3.0	2.0	2.0
Night	2.1	2.2	2.1	2.2	2.2	2.0	2.0

Table 6.4: Average number of required nurses

Since the bed utilization varies from the historical data (which can be found in Section 2.6), it is no surprise that the number of required nurses differs, too, which can be seen when comparing the results to Tables 2.15-2.17. The validation yields an realized nurse patient ratio of $V = 1 : 2.49$. Compared to the actual total nurse patient ratio of 2.41, the relative error is 3.3%. Hence all performance that look at the performance on a general level, not in detail for days and shifts, are within 5% relative error of the observed values from historical data.

6.3 Conclusions

The computer model has been verified and by replacing the scheduling heuristic with a model of the current scheduling procedure, the model has been validated. The distribution of appointment codes and the average number of appointment requests per day, as well as the average overall bed utilization, are within 5% relative error from the actual data. When looking at the bed utilization per day and shift, it can be seen that the model of the current scheduling method has shortcomings. It does not correctly capture the distribution of appointments among days of the week and shifts, which can be explained since in the model of the current method patient preferences are not taken into account. This can also be seen when looking at the required number of nurses and the total realized nurse patient ratio. However, concluding from the overall bed utilization and the distribution of the appointment codes, the arrival process of requests is correctly modeled. Since the aim was not to build an accurate model of the current scheduling procedure, but merely a model of the current procedure that indicates whether the mechanisms of the simulation model that are also used when simulating the scheduling heuristic are valid, it can be concluded that the model is valid for the purpose of this study.

Chapter 7

Results

This chapter presents the results obtained from simulating the scheduling heuristic with the AMC Short-Stay case as input. Section 7.1 discusses the results of preliminary experiments with which the weights of the objective function of the blueprint LP are determined. Results of experiments with the baseline and in which the setting of the Short-Stay Unit is modified are provided in Section 7.2 and in Section 7.3 conclusions are drawn from the experiments.

7.1 Weights of the Objective Function

In Section 5.2 and Appendix C the normalization of β and γ is given. Now the normalized weights have to be chosen. These weights determine the effect of the objective variables on the overall schedule obtained by applying the heuristic. Two experiments have been conducted where for each experiment the weight of one objective variable is set zero, and the other is set one. For more details on the choice of the weights, the reader is referred to Appendix G. All results of further experiments are obtained with the following resulting objective function in the blueprint LP:

$$\begin{aligned}
&\min \gamma \cdot E + \beta \cdot V && (7.1)\\
=&\min \frac{\bar{\gamma}}{18} \cdot E + \frac{\bar{\beta}}{220} \cdot V && (7.2)\\
=&\min \frac{0.3}{18} \cdot E + \frac{0.7}{220} \cdot V && (7.3)
\end{aligned}$$

7.2 Numerical Results

In this section the numerical results of the experiments with the simulation model of the scheduling heuristic are provided. First, the results of the baseline scenario are presented in Section 7.2.1. Experiments in which the bed capacity is reduced or the opening hours are modified will be considered in Section 7.2.2, after which in Section 7.2.3 an experiment in which the demand is increased is discussed. Finally, experimenting with the influence of patient preferences is addressed in Section 7.2.4. To simplify notation, all results are presented as average values. For a complete overview of the confidence intervals of each performance measure, the reader is referred Appendix H.

7.2.1 Baseline

This section provides the results of the baseline scenario, that is the scenario in which the current settings of the AMC Short-Stay Unit (number of beds, opening hours etc.) are used, but the scheduling heuristic developed in this report is used to schedule the appointments. Table 7.1 provides an overview of the general performance measures θ, U and W. The average total bed utilization equals the validation results, since the same capacity and the same patient load are applied in this scenario.

Measure	Average
θ	0.00069
U	52.5
W	2.66

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	72.5	65.4	61.1	59.1	52.4	75.4	75.8
Evening	70.4	61.2	57.4	53.8	30.9	60.6	50.0
Night	18.0	39.5	40.5	38.3	31.4	35.6	36.3

Table 7.1: Average values of θ, U, W and $U_{c,d}$

The bed utilization per shift and day of the week however, which is given in Table 7.1, differs from the validation results. The bed utilization during weekends and during most evening shifts is higher, while the utilization during the night shifts is lower than in the validation results (which can be found in Tables 6.2-6.4 in Section 6.2.2). Table 7.1 shows that the average overall realized nurse patient ratio for the baseline scenario is almost 7% higher than in the results of the validation, which indicates that with the scheduling heuristic, slightly fewer nurses are required while the patient load is the same. This can also be seen in Table 7.2. While the required number of nurses is slightly higher than in the validation results during the day shift on a Monday, almost all evening and night shifts require only two nurses. This is in almost every case the result of the hospital requirement that at least two nurses have to be present during all shifts. This can be seen since the required number of nurses based on the number of patients and the number of admissions and discharges is lower than two. The peak in the admissions and discharges during Monday day shifts causes also a peak in the required number of nurses during the Monday day shifts. Except for the night shifts, this shift is the only shift where the current staffing level of the Short-Stay Unit, see Table 2.5, is reached. Other shifts require less nurses than the current staffing level prescribes. What is more, the required number of nurses is determined by the number of admissions and discharges for each shift.

Required number of nurses							
Based on admission and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.3	4.8	4.3	4.5	4.3	2.8	2.8
Evening	2.1	2.1	1.9	1.8	1.9	1.9	2.1
Night	0.8	1.3	0.8	1.0	0.9	1.0	1.0
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	3.6	3.3	3.0	2.9	2.6	2.2	2.3
Evening	1.4	1.2	1.1	1.1	0.6	1.2	1.0
Night	0.2	0.4	0.4	0.4	0.3	0.4	0.4
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.3	4.8	4.3	4.5	4.3	2.8	2.8
Evening	2.1	2.1	2.0	2.0	2.0	2.0	2.1
Night	2.0	2.0	2.0	2.0	2.0	2.0	2.0

Table 7.2: Average number of required nurses

As can be seen in Table 7.1, with the scheduling heuristic not all appointment requests could be scheduled within their required access times. The percentage of all requests arriving during the simulated period of 36 weeks that could not be scheduled within the required access times is 0.07%. When looking at the appointments that could not be scheduled, the type of the appointment is investigated, to see whether the length or the required access time of the request is the cause for this. The latter is the case: appointments with short access times, that is mostly appointments that need to be scheduled within the same day, are more likely not to be scheduled. Of all appointments that need to be scheduled within the same day of the request, 21% could not be scheduled on time. For all other access times this percentage is smaller. Figure 7.1 depicts the average percentage of requests with a given required access time that could not be scheduled within those times. Also when looking into appointment types with access times longer than 2 days, the duration of the appointments seems of no influence on the percentage of appointments that could not be scheduled.

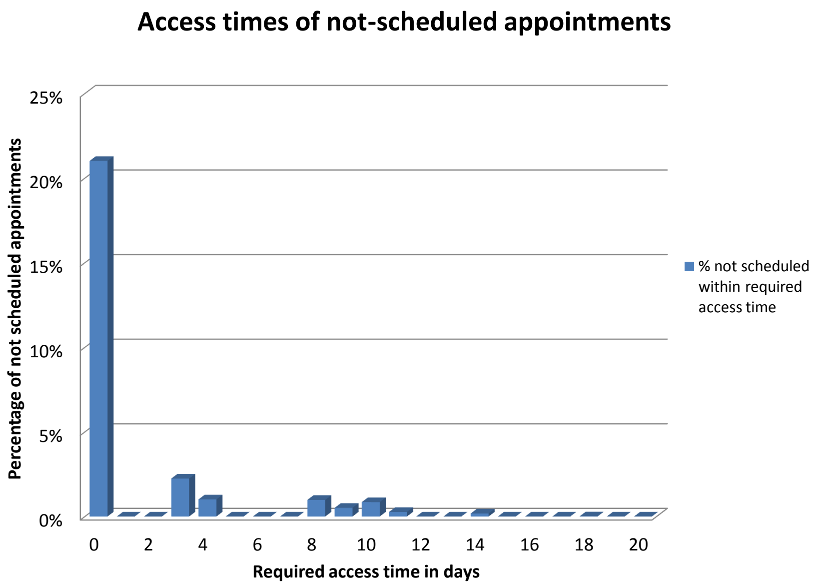

Figure 7.1: Percentage of not scheduled requests with given required access times

Figures 7.2-7.4 provide an overview of the three general performance indicators, U, W and θ for all conducted experiments.

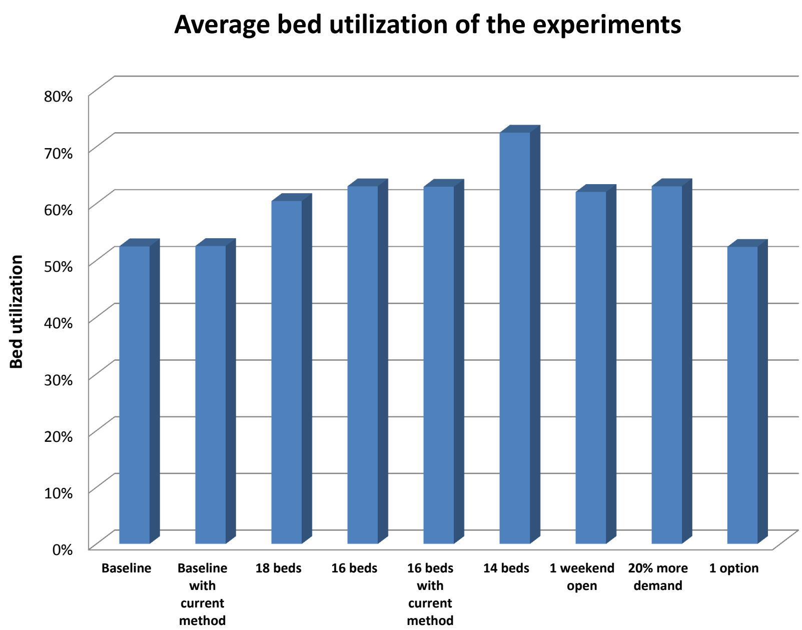

Figure 7.2: Performance measure U for all experiments

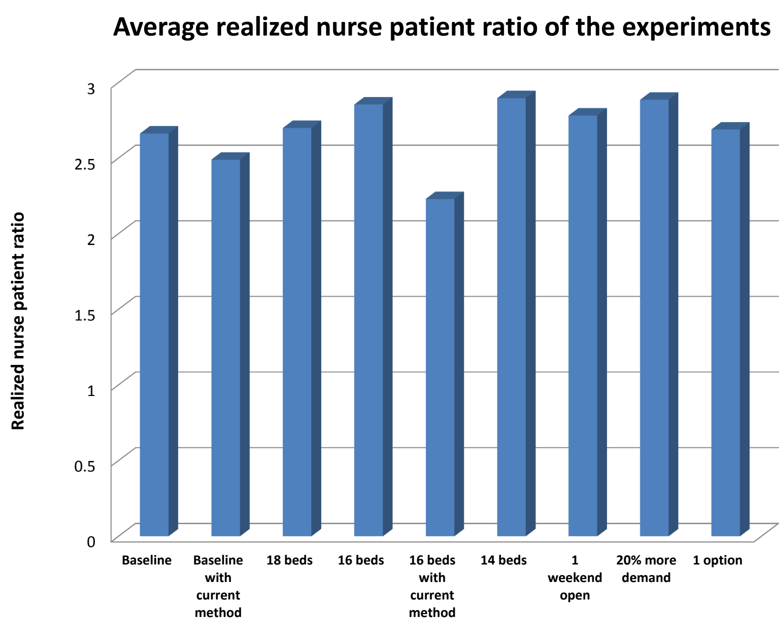

Figure 7.3: Performance measure W for all experiments

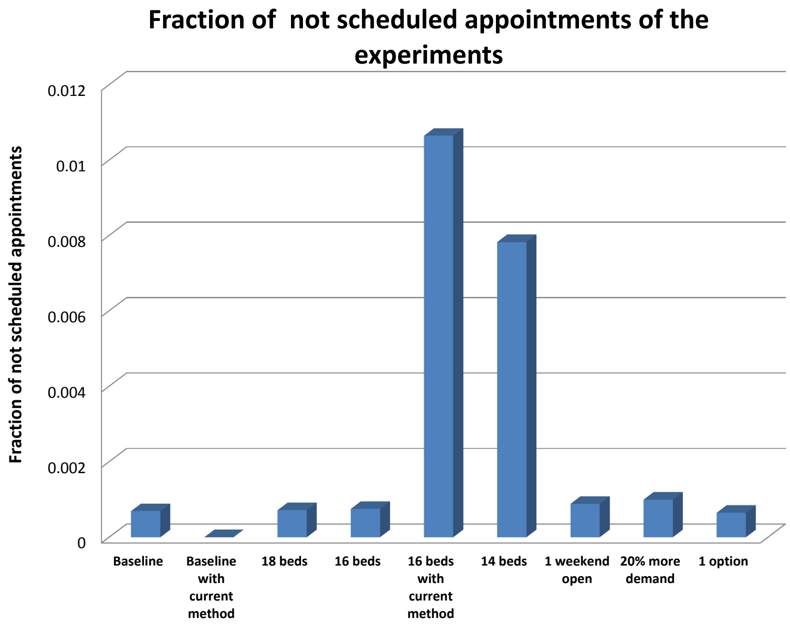

Figure 7.4: Performance measure θ for all experiments

Whenever an experiments refers to the current method, in this experiment the model of the current scheduling method is used during the simulation. The results of the experiments are discussed in the following sections.

7.2.2 Decreased Bed Capacity

Since the data analysis revealed that the Unit could operate with less capacity, experiments are conducted to see how far the bed capacity can be reduced so that, with the scheduling heuristic, still almost all patients can be seen within their required access times.

Experiment: 18 beds

The bed utilization of the baseline scenario is low, especially during the night shifts, hence in the first experiment the capacity of the unit is be decreased by 2 beds. Additionally, the proportion between the number of beds that close during the night and those that are open during the night is changed: in this scenario the unit operates with 18 beds during the week day shifts, and with 9 beds during the weekend and all evening and night shifts. From Figures 7.2-7.4 it can be seen that the overall utilization and the realized nurse patient ratio as well as θ slightly increase. Looking closer at the bed utilization per shift and per day, see Table 29 in Appendix H, it can be seen that mostly the night and evening shifts are higher utilized than in the baseline scenario. However, the overall utilization is still only at an average of 60.4% and none of the shifts have a higher utilization than 75.0%. For this reason, in the next experiment the number of beds is reduced even further. The number of required nurses, as well as the overall realized nurse patient ratio do not significantly differ from the baseline scenario.

Experiment: 16 beds

This experiment investigates the situation in which the unit operates with 16 beds during the day shifts, and 10 beds during the evening shifts, night shifts and during the weekend. It is chosen to leave 10 beds open during the evening and night shifts, because compared to the previous scenario these shifts might become more utilized as the overall bed capacity is further decreased. Compared to the baseline, the results show a slight increase of 8.7% in θ and of 7.2% in W, and a stronger increase of 20.1% in the bed utilization U, as can be seen in Figures 7.2-7.4. The bed utilization per shift and day of the week, Table 32 in Appendix H, reflects the overall increase in the bed utilization. The increase is almost equally distributed among all shifts and the peak in the Monday day shift remains. The night shifts remain the least utilized shifts in terms of beds and also nurses. Even with 16 beds, neither the patient load nor the number of admissions and discharges require more than two nurses during the week evening shifts, see Table 33 in Appendix H. In order to see whether the Short-Stay Unit could reduce the bed capacity to 16 beds using their current scheduling method and reach similar results, the simulation model of the current scheduling method that is used for validation purposes in Section 6.2.2, is modified so that the units capacity is reduced to 16 beds. The complete results of this experiment are given in Appendix H. Figures 7.2-7.4 clearly show that the currently applied method is outperformed by the heuristic. While naturally U remains unchanged, the overall nurse patient ratio is lower than with the scheduling heuristic. Remarkably, while with 20 beds and the current method, all requests could be scheduled within the required access times, with only 16 beds the current method fails to schedule 1.1% of all appointment requests, for the heuristic this percentage with 16 beds is only 0.075%. The results also show that the additional bed during the evening and night shifts compared to the previous experiment is not required, since the utilization during these shifts is still low, see Table 32.

Experiment: 14 beds

The results of the experiment with 16 beds provide motivation to go even further and reduce the number of beds to 14 beds, where 8 beds remain open during the night, evening and weekend shifts. With regard to the fraction of appointment requests that cannot be scheduled within their required access times, this scenario marks a breaking point: While during all former experiments θ remained under 0.1%, now almost 0.8% cannot be scheduled within the required access times. The overall bed utilization reaches 72% and even the night shifts are now on average above 50% bed utilization. With 14 beds the highest realized nurse patient ratio of all experiments, with 2.89, is reached.

Experiment: 1 weekend open

Another way to decrease the bed capacity of the unit is to alter the opening hours of the unit. In the current situation the unit is open during the weekend every fortnight. In Table 2.13 in Appendix H it can be seen that currently this results in a low bed utilization during the weekend. Therefore the following experiment investigates the effect of closing the unit for all but one weekend a month. The results of this experiment show that the percentage of appointment requests that cannot be scheduled within their required access times increases from 0.07% (baseline) to 0.09%. Although θ is still very small, the increase can be explained considering that there are certain appointments that have a duration just longer than 5 days, so that these request have to be scheduled partly during the weekend. If this is not possible every fortnight, some of these requests cannot be scheduled within the required access times. Since the overall bed capacity is decreased by closing during all but one weekend a month, naturally compared to the baseline U increases. Table 41 in Appendix H shows that now the day shifts in the weekend are highly utilized and also the other weekend shifts increased in bed utilization. As for the required number of nurses, due to an increased number of admissions and discharges during the Sunday day shift, the required number of nurses during this shift slightly increased. During other weekend shifts, only two nurses are required, see Table 42 in Appendix H.

7.2.3 Increased Demand

While one way to deal with underutilized capacity is to decrease the capacity, another way is to increase the demand in order to achieve higher capacity utilization. For the Short-Stay Unit, this implies an increase in appointment requests, which is investigated in the next experiment.

Experiment: 20% more demand

In this experiment the number of arriving appointment requests is increased by 20%. It is assumed, that the distribution of appointment types stays equal to the current situation. The results of this experiment are similar to the results of the experiment with 16 beds. However the number of required nurses, see Table 45 in Appendix H, is slightly higher in this scenario, especially during the evening shifts at the beginning of the week, which is reflected in a slightly higher overall realized nurse patient ratio W, see Figure 7.3.

7.2.4 Patient Preferences

After having investigated decreased capacity and increased demand, the focus of the experiment in this section lies on patient preferences. In the heuristic patient preferences are taken into account by providing three options of appointment times, from which the patient can choose. In the following experiment, the heuristic is altered so that the patient is given just one appointment time.

Experiment: 1 option

The aim of this experiment is to see what the effect of taking patient preferences into account is on the performance of the scheduling system. To this end, in this scenario, the patient cannot choose from three different options but is simply given a single appointment time. It is assumed that patients do not decline an appointment. It is expected that this experiment scores slightly better on the performance indicators W and θ than the baseline scenario, because always the best block is chosen for a given appointment request. Indeed, this is the case. Naturally, U stays unchanged since capacity and the appointment load remains the same as in the baseline scenario but to the baseline, it can be seen in Figures 7.2-7.4 that there are slight differences in the general performance indicators: W increases from 2.66 to 2.69 and θ decreases from 0.07% to 0.06%. So not giving the patients options to choose from increases, although only very slightly, as expected the performance. This experiment is conducted with 20 beds. With decreasing bed capacity the difference in the results with and without options might increase further.

7.3 Conclusions

In this chapter the experiments, conducted with the simulation model were discussed. First, preliminary experiments were performed to define the weights of the objective function of the blueprint LP. With the definite objective function the other experiments were performed to test the effect of changes to the Short-Stay Unit setting on the performance. The experiments can be grouped into three categories:

- Experiments in which the Short-Stay Unit bed capacity is decreased

  With decreasing capacity, U the bed utilization increases as expected. Also, with decreasing capacity the overall realized nurse patient ratio increases, which implies that the scheduling heuristic manages to schedule the appointments in such a way that on average, nurses care for more patients.
  Unlike with the current scheduling method, with the scheduling heuristic not all appointment request can be scheduled within their required access times. The fraction of appointments that can not be scheduled is however very small. Looking into more detail, the results reveal that mostly appointments that have to be scheduled on the same day as the request cannot be scheduled. Of all those appointments, 21% cannot be scheduled. This observation, that appointments with smaller required access times are more likely not to be scheduled, remains unchanged throughout all experiments. In the experiment in which the Unit is open only once a month during the weekend, the bed utilization during the Saturday day shifts reaches 90%, which indicates that closing the Unit every weekend is not an option. Furthermore, this experiment shows a relatively large value of θ compared to other experiments, which can be explained by considering appointments with a duration of 5 days or longer. If the Unit is closed three weekends in a row, the appointment cannot be scheduled for three weeks, which might make it impossible to schedule that request within its required access time. In order to see whether the scheduling heuristic performs better than the current scheduling method, the experiment in which the bed capacity is reduced to 16 beds was also conducted with the simulation model of the current scheduling method. The results show that indeed, the scheduling heuristic performs better with respect to all performance measures, especially with respect to θ. The smallest capacity that was tested was 14 beds, where 8 beds remain open during the evening, night and weekend. In this scenario, the bed utilization during all day shifts is above 70% and above 50% during almost all night shifts.

- Experiments in which the demand of appointment requests is increased

  One experiment was conducted in which the arriving stream of appointment requests is increased by 20%, keeping the distribution of different appointments unchanged. The performance of this experiment is similar to the experiment with 16 beds.

- Experiments in which patient preferences are addressed

  While the heuristic mainly focuses on efficiency, patient service is an important aspect of the Unit. In the scheduling heuristic three options for an appointment are given to the patient from which he can choose, which means, that in some cases the patient will choose an option that is not optimal for the efficiency of the schedule. To see how great that effect is, an experiment was conducted in which the patient is not given three options but simply given an appointment (which, by assumption is not declined). The results show that the effect is only minor, and hence that to give the patient extra service, namely the possibility to choose from three options, does not imply a significantly less efficient schedule. However, further investigation to see if this result is affected with decreasing bed capacity is required.

Looking closer at the required number of nurses, it can be seen that while in the baseline scenario the number of required nurses was exclusively determined by the number of admissions and discharges, in other scenarios, this varies per shift and hence a better balance between patient load and number of admissions and discharges is achieved by the scheduling heuristic, which is also reflected in the increasing values of W.
From the required number of nurses that are calculated, one can derive the number of FTE's that are required if these staffing levels would be applied. Figure 7.5 gives an overview of the required number of FTE's if the staffing level based on the required number of nurses would be applied.

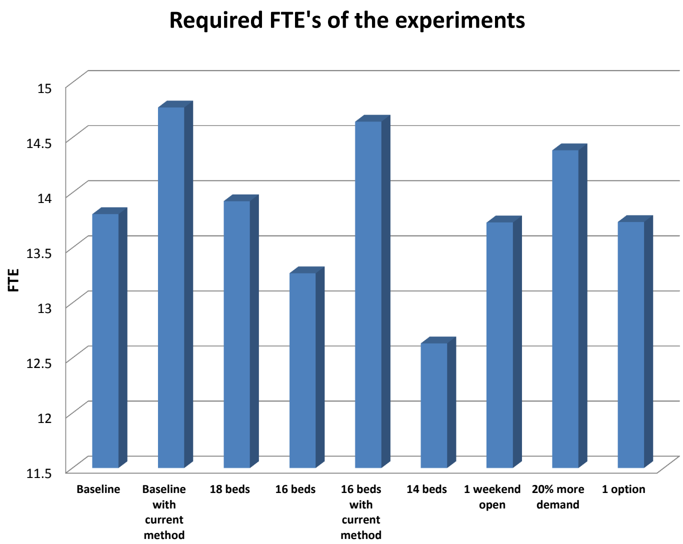

Figure 7.5: FTE's of the experiments

Currently, see Table 2.3, the Short-Stay Unit has 14.44 FTE's in patient care, which is also roughly the result the current scheduling method reaches. By simply applying the scheduling heuristic and not changing the setting of the unit, it can be seen that almost one FTE can be saved, which can be seen comparing the baseline with the heuristic to the baseline with the current method. When the capacity is reduced this difference increases even further: With 16 beds, the current scheduling method yields 14.6 FTE, while with the heuristic only 13.3 FTE are needed. Looking at the most extreme case, the experiment with 14 beds, based on these staffing levels the unit could save 1.8 FTE compared to the currently required number of FTE's.

Chapter 8

Conclusion

This chapter provides the conclusions of this report. First general conclusions are given in Sections 8.1 and recommendations based on this research are presented in Section 8.2. Finally, suggestions for further applications of the results of this study are made in Section 8.3.

8.1 Conclusion

The goal of this research was to develop a scheduling method for Short-Stay Units that aims at seeing patients within their required access times while maximizing the resource utilization.

8.1.1 Case Study of the AMC Short-Stay Unit

In order to reach the research goal, first insights into the processes relevant to scheduling appointments at Short-Stay Units had to be gained. This was achieved using the AMC Short-Stay Unit as a case study. A process and data analysis revealed three main aspects that have to be considered when evaluating scheduling methods for Short-Stay Units. These are the bed utilization, the required number of nurses and the fraction of all appointment requests that can not be scheduled within the required access times.

8.1.2 The Scheduling Heuristic

The process analysis of the Short-Stay Unit showed that the difficulty for the planners lies in the online fashion with which the appointments need to be scheduled. An appointment has to be scheduled without knowing exactly what other requests arrive. With the available historical data however, knowledge on the average number of occurrences of the various appointments can be used in order to address the challenge of online scheduling. A scheduling heuristic was developed that combines advance planning with a rolling horizon approach: the core of the heuristic is an LP which creates a blueprint schedule that reserves capacity for certain appointment types. Here the historical data is used to see how many appointments of a given type occur. The LP schedules these appointment blocks in such a way that the required number of nurses can be kept to a minimum and appointments of different types are evenly distributed among the different days. With assignment rules, the arriving requests are then assigned to the reserved blocks. The observation that it is optimal to schedule appointments in between other appointments if possible and thresholds for urgent appointments are applied in these assignment rules. The scheduling heuristic hence divides the optimization problem of finding the optimal schedule into two parts: First finding the optimal LP, which is done by defining an appropriate objective function, and by finding the optimal placement for an appointment within the blueprint, which is done with the assignment rules.

8.1.3 Performance of the Heuristic

With the aid of a simulation model of the scheduling heuristic as well as the currently applied scheduling method, the performance of the heuristic in different scenarios was evaluated.

With the current setting of the unit, the heuristic outperforms the current scheduling method

Results of the baseline scenario show that compared to the current scheduling method, the scheduling heuristic performs better with respect to the required number of nurses and the overall realized nurse patient ratio. On the other hand, the heuristic does not manage to schedule all patients within their required access times. A fraction of 0.07% of all appointments could not be scheduled on time. These are mainly appointments which have short access times. 21% of all appointments that need to be scheduled within the same day could not be scheduled, for appointments with larger access times this percentage is much smaller. This observation, that appointments with short access times are more likely not to be scheduled within their required access times, holds throughout all experiments.

Heuristic performs well in experiments with decreased capacity

Experiments in which either the bed capacity of the unit is decreased or the demand of arriving appointment requests is increased show that the scheduling heuristic manages to schedule the same amount of appointments as in the baseline scenario with less capacity which results in a higher bed utilization and higher realized nurse patient ratios. In the most extreme experiment the bed capacity was reduced to 14 beds. Here it can be seen that there is a breaking point: In all other scenarios the fraction of not scheduled appointments never exceeded 0.1%, but in this experiment 0.8% of all appointments could not be scheduled. However, 0.8% is still a very low percentage. In this scenario the bed utilization during most day shifts reaches almost 90%.

With decreased capacity the heuristic outperforms the current scheduling method

Direct comparison between the heuristic and the current scheduling method can be made based on the scenario in which the unit operates with 16 beds: the current method could not schedule 1.1% of all appointments while with the heuristic this percentage was less than 0.1%. Looking at the required number of nurses, the scheduling heuristic outperforms the current method: the current method yields an even lower realized nurse patient ratio than in the baseline scenario. With the heuristic however, the realized nurse patient ratio is 15% higher than in the baseline scenario. These results enforce the conclusion that if the unit will reduce capacity in order to reach higher resource utilization, a more efficient scheduling method is required than the currently applied scheduling method.

Further investigation on providing appointment options required

Results of the experiment in which the patient is not given three appointment options to choose from, show that this modification does not lead to a significantly more efficient schedule. Hence, in this scenario, it is possible to provide this service to the patient without cutting back on efficiency. However this experiment was conducted with 20 beds. It needs to be investigated whether this observation holds with less capacity.

Savings for Short-Stay Unit

From the results of the required number of nurses, the required number of FTE's can be derived. By applying the scheduling heuristic in the current setting the Short-Stay Unit could save one FTE, comparing to the current staffing level. When the units capacity is reduced to 14 beds, 1.8 FTE's could be saved. The current overall amount of FTE of the Short-Stay Unit is 16.84, so 1.8 FTE amounts to 10.7% of the current staffing level. Assuming one FTE for a nurse amounts to 52.000 Euro, with the staffing levels resulting from the scheduling heuristic, up to 93.600 Euro can be saved.

From these results, the conclusion can be drawn that the developed scheduling heuristic performs well in the investigated scenarios and can provide a more efficient schedule for the Short-Stay Unit.

8.2 Recommendations

On the basis of this research, several recommendations can be made, concerning the Short-Stay Unit, further development of the scheduling model, and further research in general.

8.2.1 Recommendations to the AMC Short-Stay Unit

Staffing level

The data analysis of the Short-Stay Unit at the AMC revealed that the current staffing level of the nurses is not in accordance with the nurse patient ratios. Currently during the day and evening shifts of the week one additional nurse is working that would not be required by strictly applying the nurse patient ratios. It is hence recommended to investigate whether one additional nurse is really required.

Capacity reduction

The simulation experiments clearly show that it is possible to reduce capacity for the AMC Short-Stay Unit. It is hence recommended that management of the Unit investigates possible ways to do so. The experiments conducted with the simulation model merely give an indication of what is possible. In order to determine which intervention would be the most suitable for the AMC Short-Stay Unit, more interventions and the cross-effects, that is combining interventions (e.g. reduce the number of beds and close the unit during all but one weekend a month) need to be tested. Along with this, it might be worth to investigate the way in which patient preferences are taken into account. In the heuristic the patient is given options from which he can choose. Even without the heuristic, it might be worth using such a system since it still provides service to the patient but leaves more room for the planners to create a more efficient schedule.

Workload of nurses

When decreasing capacity, a point of discussion is the nursing work load. The results of the simulation show that with less beds a higher realized nurse to patient ratio can be achieved, which implies that nurses have to care for more patients at a time than in the current situation. When calculating the number of required nurses only the number of admission and discharges that occur during the same time slot, and the number of patients at the unit are taken into account. Although all times the nurse patient ratios that are prescribed by the AMC are applied and hence it can be assumed that the work load for the nurses is still at a manageable level, the nurses will have to be prepared for this change.

Apply basic principles

The scheduling heuristic is not a finished decision support tool. The implementation in AIMMS and Excel has no user interface and is not designed as scheduling software for the daily use yet. It is however the basis to develop such a tool. Two basic principles that are used in the scheduling model can directly be applied which is recommended to the Short-Stay Unit: If possible, schedule appointments in between other appointments and define thresholds for urgent appointments. It has to be noted that with the heuristic, 21% of all appointments that needed to be scheduled within the same day could not be scheduled. This indicates that the estimation of the thresholds might need modification. On the other hand, it has to be noted that this result can not fairly be compared to historical hospital data. The required access times of patients were not available digitally, so no detailed analysis of the performance of the Unit with respect to this performance measure was possible.

Appointment durations

The data analysis showed that currently the durations that are used to plan appointments, underestimate the realized appointment durations. Since the utilization of the unit is low, the difference in planned and realized appointment durations in the current situation can be managed since in almost all cases there is available capacity if a patient needs to stay longer than planned. If the unit were to decrease its capacity however, it is crucial that the durations of the appointments are known correctly. Therefore it is recommended that per appointment type the realized durations are investigated and that these results are applied by the planners when making the schedule.

Access times

What is more, also the required access times of appointment requests require further investigation. Currently these times are only recorded on paper. If this data were available digitally, the performance of the Short-Stay Unit with respect to the required access times could be monitored in detail.

8.2.2 Recommendations for Further Model Development

Parameters of the scheduling heuristic

The scheduling heuristic was tested with input of the AMC Short-Stay Unit as a case study. Due to a high number of variables in the LP, computation time of the scheduling model was very long. With the chosen settings, a single run took approximately 9 hours. In order to keep the computation time to a manageable level, simplifying choices about the parameters

of the heuristic had to be made. These parameters are the length of the blueprint schedule, the frequency with which the blueprint is updated and the length of a time slot.
When the length of the blueprint period is increased, the occurrences of appointments of the different types can more accurately be modeled, and hence a better blueprint with respect to the occurrences of appointments can be made.
Considering the iteration frequency, that is the frequency with which a new blueprint is calculated, it is expected that with a higher frequency, the scheduling heuristic achieves better results. Suppose the blueprint would be generated every time an appointment request has been scheduled, then every change in the current schedule can be taken into account and anticipated with the new blueprint. In this study the frequency is set to once a week, so the same blueprint is used for scheduling multiple appointments. With a higher frequency the schedule will supposedly become more efficient.
The length of a time slot is of great influence on the number of variables of the LP. While the AMC Short-Stay Unit works with time slots of 30 minutes, in this research slots of one hour are used in order to reduce the number of variables by half, and hence to reduce the computation time. Time slots of 30 minutes are however desirable because the duration of appointments can more accurately be represented which improves the planning. In order to quantify the influence of these parameters on the overall schedule, further experiments with the simulation model of the scheduling heuristic are required. It has to be noted however, that the large computing time is mainly an issue for the simulation study and not for solving the LP: in order to obtain statistically significant results a long period of time has to be simulated repeatedly. In practice, the blueprint could be calculated over night and no experiments would have to be conducted that require repeated runs of the model. Hence in practice, the long computation time is not such a big issue.
Based on these observations it is recommended to conduct a detailed sensitivity analysis of these parameters, in order to see what the effect of changing the parameters on the overall schedule is.

Assignment rules for requests that are scheduled without the blueprint

With the LP the expected number of appointments to occur in a given period are scheduled in a blueprint. To assign requests to a block in the blueprint the assignment rules are used. Whenever for a given request no block is available in the blueprint schedule, currently the first available time slot at the first available bed that is feasible with the opening hours and admission and discharge times is given to this request. It would be worthwhile investigating whether for these requests rules similar to the assignment rules could be established.

Combination requests

In the process analysis of the AMC Short-Stay Unit four types of special appointments are revealed: Urgent requests, overnight requests, combination requests and sequential requests. Urgent and overnight requests are directly considered in the scheduling heuristic. Sequential requests can be considered indirectly: The period between the individual appointments of a series can be translated to modified release and due dates, so that the appointments can be individually scheduled with the heuristic but will lie at a fixed distance from each other. Combination requests are beyond the scope of this study. In the data analysis briefly the period that patients of the Short-Stay Unit leave the Unit and spend at other departments for their combination appointment is investigated. With detailed information on this period per appointment type, combination appointments could be included into the blueprint by splitting these appointment requests in two parts (the two time periods the patient actually is present at the Short-Stay Unit) and leave the period between these parts (where the patient is at another department) available for other appointments. This would lead to an even more efficient schedule since the period in between can be used for other appointments.

Dynamic rules to reject appointment requests

The results of the simulation experiments show that currently only a very small fraction of appointments could not be scheduled. A higher percentage of not scheduled appointments might still be tolerable. If together with management of the Short-Stay and possibly other departments a norm about the percentage of not scheduled appointments could be established the scheduling heuristic could adapt the assignment rules to this norm by providing the option to reject an appointment request, even though it would be possible to schedule the request within the required access times, if the rejecting the requests leads to a significantly more efficient schedule. This aspect is directly linked to recommendations for further research, which are addressed in the following section.

8.2.3 Recommendations for Further Research

Evaluation functions

In the literature review, evaluation functions are briefly mentioned. These are functions that (in chess) assign values to all possible states of a system and indicate which state is better than another. In chess these functions indicate the value of a given setting of the chess board. These functions are constructed of evaluation features which relate to different aspects of the system. By combining these features into a function, the value of the function can be seen as a score that assesses a state with respect to all aspects of the system. Such evaluation functions are an interesting approach in the field of online scheduling. In the assignment rules of the developed scheduling heuristic, indirectly one of these features, namely that it is best to schedule an appointment in between other appointments, is introduced and used. Designing evaluation functions is a cumbersome and time consuming task, as Buro points out in [5]. Hence in this research a more straight forward approach is followed, combining advance planning and a rolling horizon approach. Further research in the area of applying evaluation functions to scheduling problems is however promising. It would provide a powerful tool to directly, in an online fashion, assess possible placements of an appointment in a schedule. The features of the function would have to be related to the three main performance measures of this study: Bed utilization, realized nurse to patient ratio and the fraction of not scheduled appointments. But while these measures are calculated retrospectively in this study, the evaluation features need to relate to these measures at a more local, online level: For example with respect to the nurses, such a feature needs to express whether the placement of an appointment request might require an additional nurse for that shift. Once a evaluation function for the Short-Stay scheduling problem is developed, it can be linked to the idea of dynamic rules to either schedule or reject an appointment request: If the value of the evaluation function of all possible placements of the request in the current schedule is low, the request could be rejected in order to ensure an efficient schedule. Defining what a "low" value is that would justify a request rejection and an acceptable percentage of rejected requests are further issues that need to be investigated.

Nurse staffing

In the process analysis it was revealed that the nurse rooster is made roughly a month in advance. Since the scheduling of the appointments for the Unit is done online, the exact workload of a given day is not exactly known even on the day before. So making the nurse roster several weeks in advance can not take into account the actual workload of a given day. Hence research that aims at linking the scheduling of appointments to rostering the nurses is recommended in order to prevent over- or understaffing. One possible direction might be working with flexible nurses, so that on short notice the staffing level can be adapted if necessary. The nurse manager of the AMC Short-Stay Unit also briefly mentioned that it might be worthwhile to think about combining the nursing work during the night shifts with other departments. This might indeed be an interesting approach since the results of the simulation experiments show that especially during the night and weekend shifts, often no two nurses are required based on the patient load and admission and discharge times. Hence adapting the requirement of two nurses per shift considering combining departments might be another possible direction.

8.3 Further Applications

The motivation of this research came from Short-Stay Units but the developed scheduling heuristic can be applied to other situations. What is important is that the heuristic is designed to deal with an online scheduling problem, where information on the number of occurrences of different appointment types is available. The assignment rules are designed for the specific context of Short-Stay Units, but can be modified to other contexts as well. Possible applications are not limited to hospital departments or other medical facilities but can include various facilities that work on appointment basis and make the appointments online. Important is that the duration of these appointments has to be known in advance. Take as an example municipality offices, where citizens make appointments to deal with legal issues or apply for documents such as passports. If the appointment planning is done online, and if the duration of these appointments is fixed, these appointments can be grouped into different appointment types and based on historical data on the appointments, a blueprint can reserve time slots for certain appointment types.

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Appendices

A Admission Request Forms

Here, in Figures 1 and 2, the admission request forms are included. The extra form is only for patients who need a blood transfusion or a pre/post hydration treatment.

Aanvraagformulier opname Short Stay F5 **FAXNUMMER: 020 56 69321** A - kant

TEL PLANNING: 020 56 66049

Naam aanvragend arts/sein................................./................

Datum aanvraag..

Plaats hier afdruk gegevens patiënt

Diagnose ....

Specialisme ....

- ❍ Gewenste datum/data klinische behandeling op Short Stay — datum ....
- ❍ Thuiszorg afgesproken na opname (PEG, PTC-drain) — ja/nvt
- ❍ Verrichting door arts (drain, punctie) — naam arts... sein:...........................
- ❍ Overige (o.a ADL ondersteuning nodig?) — ....
- ❍ Vervolg afspraak poli/short stay (omcirkel) — datum ....

➢ **INDIEN BLOEDTRANSFUSIE/PRE-POST HYDRATIE: witte formulier 'Short Stay/Behandelkamer Q2 Opdracht'**

	Specialisme	**Behandeling**	**Verblijfsduur**	**Afspraak code**
	END	Vastenproef	max 80 uur	VAST
	END	Dorstproef	2 dagen	DORST
	END	Metyrapone	1 nacht	METYRAPONE
	END	Houdingsproef	1 nacht	HOUDINGSPRF
	END	Nachtelijke Cortisolmeting	1 nacht	NACHTCORTMT
	GER	Valpreventie	5 uur	VALPREV
	GER	Onderzoek	tijd en duur aangeven	ONDERZ
	GER	APD	150 min	APD
	HEM	Antibiotica iv	2 uur	ABIV
	HEM	IVIG	.... uur .... dag(en)	IVIG
	HEM	Ferese patiënten na oogsten	1 dag met overnachting	FERESEPT
	HEM	R-Chop (eerste keer)	7 uur	CHOPMAB/I
	HEM	R-Chop (tweede keer)	210 min	CHOPMAB_II
	HEM	Rituximab	5 uur	RITUXIMAB
	HEM	Ofatumumab	6 uur	OFATUMAB
	HEM	BMspreekuur geen dormicum	1 uur	BPM
	HEM	BMspreekuur wel dormicum	4 uur	BPMDOR
	IMM/NIZ	Cyclofosfamide	...... uur	CYCLOFOSF
	IMM/NIZ	MPS	2, 3 of 6 uur ....dag(en)	MPSKUUR
	INT	Antibiotica iv	2 uur	ABIV
	INT	Observatie na onderzoek	6 uur	OBSNAONDERZ
	INT	Klinische voorbereiding coloscopie	1 dag met overnachting	VBCOSCOPIE
	INT	Angiografie	8 uur	ANGIOGRAFI
	INT	Gaucher	1 dagdeel	GAUCHER
	INT	Fabry	1 dag	FABRY
	LON	OSAS/Slaaponderzoek	1 nacht	OSAS
	LON	Groot onderzoek CF	1 dag	GRONDERZCF
	LON	Onderzoeksdag pat. Topreferente zorg	1 dag met overnachting	TOPREFONDERZ
	LON	MPS kuur	2, 3 of 6 uur ...... dag(en)	MPS KUUR
	LON	IVIG	.... uur .... dag(en)	IVIG
	LON	Infliximab	4 uur	INFLIXIMAB

AEH versie 1 dd 6/12/12

Aanvraagformulier opname Short Stay F5 **FAXNUMMER: 020 56 69321** B – kant

TEL PLANNING: 020 56 66049

Naam aanvragend arts/sein................................./................

Datum aanvraag..

Plaats hier afdruk gegevens patiënt

Diagnose ....

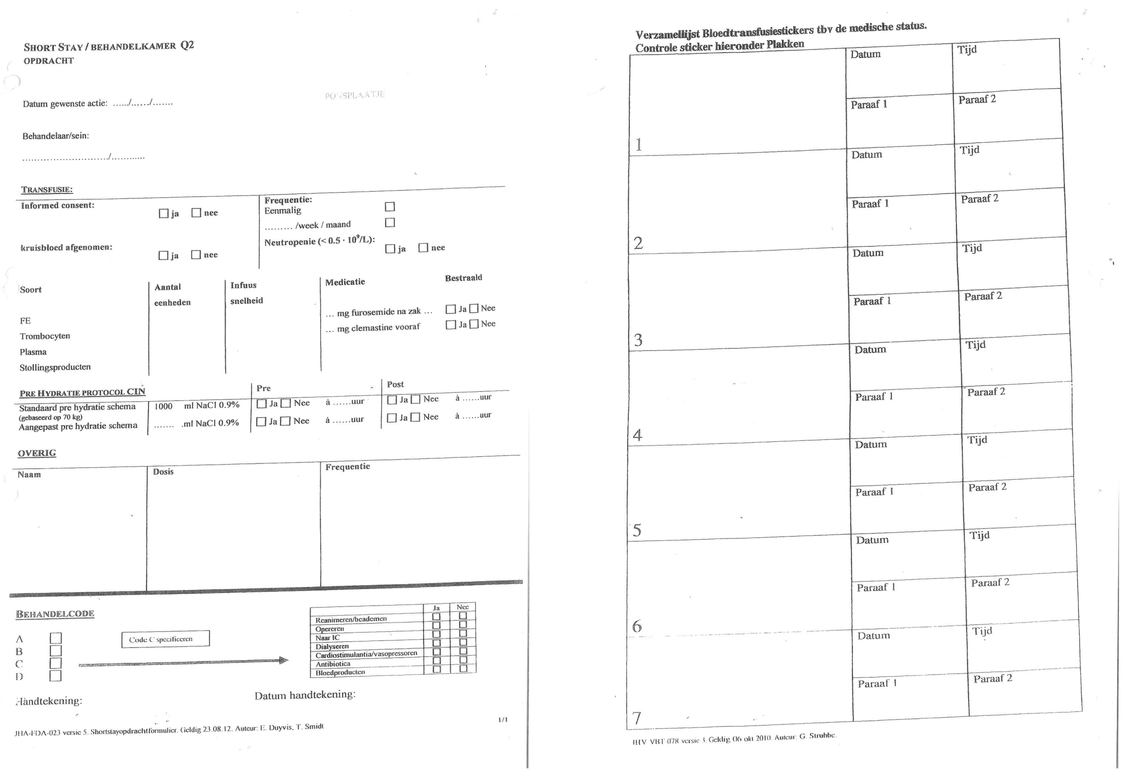
Specialisme ....

- ❍ Gewenste startdatum/data klinische behandeling op Short Stay — datum ....
- ❍ Thuiszorg afgesproken na opname (PEG, PTC-drain) — ja/nvt
- ❍ Verrichting door arts (drain, punctie) — naam arts... sein:...........................
- ❍ Overige (o.a ADL ondersteuning nodig?) — ....
- ❍ Vervolg afspraak poli/short stay (omcirkel) — datum ....

➢ **INDIEN BLOEDTRANSFUSIE/PRE-POST HYDRATIE: witte formulier 'Short Stay/Behandelkamer Q2 Opdracht'**

	Specialisme	**Behandeling**	**Verblijfsduur**	**Afspraak code**
	MDL	Observatie na endoscopische ingrepen (EMR, ERCP, PEG, POEM)	met overnachting	OBSNAONDERZ
	MDL	Leverscreening	3 nachten	LEVERSCR
	MDL/RDD	Scleroseren cyste	1 dag met overnachting	SCLCYSTE
	MDL	Ferro	5 uur	FERRO
	MDL	Infliximab	4 uur	INFLIXIMAB
	MDL	Leverbiopsie	8 uur	LEVERBIOP
	MDL	Ascites drainage	6 uur	OVERIG
	MDL/RDD	PTC drain	1 nacht	PTCDOPNAME
	MDL/OTH/RDD	RFA	1 nacht	RFAPOST01
	MDL/OTH/RDD	SIRT	1 nacht	SIRTOPNAME/SIRTPOST02
	MDL/OTH/RDD	TACE	1 nacht	TACEOPNAME/TACEPOST01/TACEPOST02
	NIT	Curve (spiegel)	4 of 8 uur	CURVE SPGL
	NIT	Geclusterd onderzoek	8 uur	GECLONDERZ
	NIT	MPS kuur	2, 3 of 6 uur ....dag(en)	MPSKUUR
	NIT	Antibiotica iv	2 uur	ABIV
	NIT	SOLIRIS iv	2,5 uur	SOLARISIV
	NIT	IVIG	.... uur .... dag(en)	IVIG
	NIT	Rituximab	5 uur	RITUXIMAB
	NIT	Ferro	5 uur	FERRO
	NIT	NB tx	5 uur	NBTX
	NIZ	NB eigen nier	1.5 dag	NBEIGEN
	NIZ	CPD Tenckhoff katheter	2 dagen	TENCKHOFF
	NIZ	Angiografie	8 uur	ANGIOGRAFI
	OTH	APD	150 min	APD
	OTH	Ascites drainage	6 uur	OVERIGE
	OTH/GER/RDD	Vertebro plastiek	8 uur	VERTOPNAME/VERTPOST01
	REU	Abatacept	120 min	ABATACEPT
	REU	Cyclofosfamide	...... uur	CYCLOFOSF
	REU	IVIG	.... uur .... dag(en)	IVIG
	REU	Infliximab	4 uur	INFLIXIMAB
	REU	MPS kuur	2, 3 of 6 uur ....dag(en)	MPSKUUR
	REU	Rituximab	5 uur	RITUXIMAB
	REU	Tocilizumab	120 min	TOCILIZUMA

Figure 1: Admission request form Short-Stay Unit



SHORT STAY / BEHANDELKAMER Q2
OPDRACHT

Datum gewenste actie: ...../....../.......

Behandelaar/sein:
............................/...........

TRANSFUSIE:
Informed consent: ☐ ja ☐ nee
Frequentie: Eenmalig ☐
.... /week / maand ☐
Neutropenie (< 0.5 · 10⁹/L): ☐ ja ☐ nee
kruisbloed afgenomen: ☐ ja ☐ nee

Soort	Aantal eenheden	Infuus snelheid	Medicatie	Bestraald
FE			... mg furosemide na zak ...	☐ Ja ☐ Nee
Trombocyten			... mg clemastine vooraf	☐ Ja ☐ Nee
Plasma				
Stollingsproducten				

PRE HYDRATIE PROTOCOL CIN		Pre		Post	
Standaard pre hydratie schema (gebaseerd op 70 kg)	1000 ml NaCl 0.9%	☐ Ja ☐ Nee	à ......uur	☐ Ja ☐ Nee	à ......uur
Aangepast pre hydratie schema	.... ml NaCl 0.9%	☐ Ja ☐ Nee	à ......uur	☐ Ja ☐ Nee	à ......uur

OVERIG

Naam	Dosis	Frequentie

BEHANDELCODE
A ☐
B ☐
C ☐
D ☐
Code specificeren

	Ja	Nee
Reanimeren/beademen	☐	☐
Opereren	☐	☐
Naar IC	☐	☐
Dialyseren	☐	☐
Cardiostimulantia/vasopressoren	☐	☐
Antibiotica	☐	☐
Bloedproducten	☐	☐

Handtekening: Datum handtekening:

JHA-FDA-023 versie 5. Shortstayopdrachtformulier. Geldig 23.08.12. Auteur: E. Duyvis, T. Smidt 1/1

Verzamellijst Bloedtransfusiestickers tbv de medische status.
Controle sticker hieronder Plakken

	Datum	Tijd
1	Paraaf 1	Paraaf 2
	Datum	Tijd
2	Paraaf 1	Paraaf 2
	Datum	Tijd
3	Paraaf 1	Paraaf 2
	Datum	Tijd
4	Paraaf 1	Paraaf 2
	Datum	Tijd
5	Paraaf 1	Paraaf 2
	Datum	Tijd
6	Paraaf 1	Paraaf 2
	Datum	Tijd
7	Paraaf 1	Paraaf 2

HEV VBT 078 versie 3. Geldig 06 okt 2010. Auteur: G. Strubbe

Figure 2: Supplement admission request form

B Data Analysis

This section provides additional information of the data analysis of Section 2.6. Again, the available data consisted of the period of 1^{st} of January to 1^{st} of September 2013.
Table 1 shows the complete number of appointments, per appointment type and per admitting specialism. The original Dutch appointment codes are used.

Treatment code	Specialism ANS	CAR	CHI	END	GER	HEM	IMM	INT	LON	MDL	NEU	NIT	NIZ	NUC	OTH	RDD	REU	RTH	URO	VAS	Total
ABATASEPT																	92				92
ABIV						97		130		8		14	8								257
APD				2	1	4		11		2							1				21
ASCITESDRA								1													1
BLDTRS2						7		8	1						1			1			18
BLDTRS4					2	73		95	5	2					7		1	1			186
BLDTRS6					5	54		69	1			1	1		12			1			144
BLDTRS8					1	21		24							5		1				52
BLOEDTRF					1	5		17													23
BLOEDTRFKB		1			12	34		59	1	5					6			1			119
BLOEDTRNSF								2													2
BLTRANSF															1						1
CHOPMAB.I								2													2
CHOPMAB.II								1													1
CRVE SPGL4								6													6
CRVE SPGL6								13				20	1								34
CRVE SPGL8								5									2				7
CYCLOFOSF											1						3				4
DIVCHEMO								1													1
DORST				4																	4
FABRY2				1				3													4
FABRY4				1				3													4
FERINJECT				8	1			12		43											64
FERRO			1	2	1			15		60		2	3								84
GAMMAGLOB						33		92	33			2	15				1				176
GAUCHER								9													9
INFLIXIMAB									10	181							15				206
IVIG						22	1	19	1			4	7								54
KRSBLD						4		1													5
LEVERBIOS						1		2		50											53
LEVERSCR										3											3
METYRAP				22				18													40
MPS						3		28	44	2		8	8				46				139
MPS KUUR									1				1				2				4
MPSV1									4								3				7
MPSV2							1		4								2				7
NACHTCORT				2																	2
NBEIGEN								17					3								20
NBEIGENV								1													1
NBTX								31				24									55
OBSNAOND		1	1	2	2	3		23	8	75		1	2		2		2	1	2	1	126
OBSNAONDZ								16	1	22		4	2		1		1		1	4	52
OFATUMAB						5		10													15
ONDERZ					24	1		35		2							1				63
OSAS								5	189	1											195
OSASV									1												1
OVERIG					1	1		24		13		2	3		3	1	3				51
OVERIGE1					1	2		16	5	8											32
OVERIGE10						1		1													2
OVERIGE2				1	4	4		9		2		3	3				2				28
OVERIGE3										1											1
OVERIGE4						3		11		4					3		1				22
OVERIGE6			1					11	2	31			1		5						51
OVERIGE8				2	1			4		3							3				13
PEG								1													1
POSTCT								1		1											2
PRECT				1	2	16		58	15	5		3		2	18			3			123
PRESIRTOPN								1		2					5						8
PRESIRTP01															1						1
PTCDOPNAME			2					3		28											33
PTCDPOST01										1											1
REMICADEC								2	6	838							28				874
REMICADER								1	1	1							54				57
RFAOPNAME								2		13						1		1			17
RFAPOST01										1											1
RITUXIHEMI						3		5													8
RITUXIHEMV						7		2													9
RITUXIMAB						11		28				1					18				58
RITUXIREUI																	10				10
RITUXIREUV																	22				22
SCLCYSTE										3											3
SIRTOPNAME								1		1					2						4
SOLARISIV								12				10									22
TACEOPNAME								1		20					1	1					23
TACEPOST02										1											1
TENCKHOF													1								1
TOCILIZUMA								3		2							342				347
TOETROMB						15		1													16
VALPREV					2																2
VAST				3				2													5
VBCOSCOPIE										13											13
VENOFER								1		3											4
VERTOPNAME	1							3		1						3					8
Total	1	2	5	51	61	430	2	988	333	1452	1	99	59	2	73	6	656	9	3	5	4238

Table 1: Number of appointments per type and admitting specialism

Table 2 gives the minimum, maximum and average access times that could be calculated from hospital data, that is the number of days that lie between the request of an appointment and the appointment itself. The large negative values indicate, that these appointments have been added to the system after the appointment has taken place.

Appointment type	Min	Max	Av. realized access time
ABATASEPT	2.0	113.0	40.4
ABIV	0.0	54.0	9.2
APD	1.0	123.0	37.4
ASCITESDRA	2.0	2.0	2.0
BLDTRS2	0.0	37.0	13.2
BLDTRS4	-4.0	68.0	11.0
BLDTRS6	0.0	84.0	11.2
BLDTRS8	0.0	112.0	17.2
BLOEDTRF	1.0	175.0	52.5
BLOEDTRFKB	0.0	120.0	11.2
BLOEDTRNSF	-1.0	0.0	-0.5
BLTRANSF	2.0	2.0	2.0
CHOPMAB_I	5.0	8.0	6.5
CHOPMAB_II	14.0	14.0	14.0
CRVE SPGL4	1.0	29.0	10.3
CRVE SPGL6	1.0	71.0	14.0
CRVE SPGL8	1.0	56.0	13.9
CYCLOFOSF	3.0	22.0	9.8
DIVCHEMO	35.0	35.0	35.0
DORST	5.0	41.0	22.8
FABRY2	2.0	38.0	19.5
FABRY4	3.0	15.0	7.5
FERINJECT	0.0	40.0	8.5
FERRO	0.0	40.0	6.0
GAMMAGLOB	-276.0	142.0	32.4
GAUCHER	6.0	34.0	16.6
INFLIXIMAB	-264.0	112.0	22.5
IVIG	0.0	83.0	22.5
KRSBLD	13.0	41.0	27.6
LEVERBIOS	0.0	76.0	15.9
LEVERSCR	27.0	45.0	33.3
METYRAP	5.0	39.0	17.6
MPS	0.0	55.0	12.4
MPS KUUR	0.0	31.0	8.0
MPSV1	3.0	35.0	18.3
MPSV2	4.0	36.0	19.3
NACHTCORT	8.0	13.0	10.5
NBEIGEN	1.0	16.0	7.8
NBEIGENV	5.0	5.0	5.0
NBTX	0.0	49.0	10.7

Appointment type	Min	Max	Av. realized access time
OBSNAOND	-266.0	124.0	11.0
OBSNAONDZ	0.0	43.0	9.4
OFATUMAB	1.0	69.0	36.1
ONDERZ	-1.0	85.0	17.7
OSAS	-4.0	89.0	18.0
OSASV	-4.0	-4.0	-4.0
OVERIG	-10.0	41.0	6.3
OVERIGE1	0.0	42.0	14.8
OVERIGE10	-1.0	0.0	-0.5
OVERIGE2	-264.0	36.0	-0.1
OVERIGE3	12.0	12.0	12.0
OVERIGE4	0.0	64.0	16.2
OVERIGE6	0.0	46.0	5.5
OVERIGE8	0.0	40.0	8.9
PEG	4.0	4.0	4.0
POSTCT	4.0	7.0	5.5
PRECT	1.0	83.0	13.1
PRESIRTOPN	0.0	21.0	5.9
PRESIRTP01	7.0	7.0	7.0
PTCDOPNAME	0.0	43.0	8.0
PTCDPOST01	3.0	3.0	3.0
REMICADEC	0.0	167.0	35.5
REMICADER	-266.0	150.0	43.5
RFAOPNAME	6.0	32.0	13.1
RFAPOST01	6.0	6.0	6.0
RITUXIHEMI	3.0	39.0	15.9
RITUXIHEMV	2.0	28.0	11.4
RITUXIMAB	1.0	45.0	10.7
RITUXIREUI	2.0	119.0	26.8
RITUXIREUV	2.0	49.0	15.8
SCLCYSTE	12.0	16.0	13.3
SIRTOPNAME	10.0	15.0	13.0
SOLARISIV	-260.0	160.0	51.0
TACEOPNAME	6.0	30.0	13.3
TACEPOST02	23.0	23.0	23.0
TENCKHOF	1.0	1.0	1.0
TOCILIZUMA	0.0	168.0	41.6
TOETROMB	0.0	28.0	4.8
VALPREV	-270.0	-270.0	-270.0
VAST	0.0	20.0	13.6
VBCOSCOPIE	0.0	17.0	8.0
VENOFER	0.0	9.0	3.3
VERTOPNAME	2.0	16.0	11.0
Total	-276.0	175.0	22.18

Table 2: Hospital data access times in days

Table 3 gives the minimum, maximum and average average appointment lengths per appointment type in hours.

Appointment type	Min	Max	Average
ABATASEPT	1.5	2.5	2.0
ABIV	0.8	15.5	3.5
APD	2.3	3.0	2.5
ASCITESDRA	4.0	4.0	4.0
BLDTRS2	2.0	10.3	3.4
BLDTRS4	2.0	25.0	5.3
BLDTRS6	3.5	21.0	6.1
BLDTRS8	5.5	12.5	7.8
BLOEDTRF	7.5	12.0	8.7
BLOEDTRFKB	4.0	14.5	9.5
BLOEDTRNSF	0.5	5.5	3.0
BLTRANSF	7.0	7.0	7.0
CHOPMAB_I	7.0	7.0	7.0
CHOPMAB_II	4.0	4.0	4.0
CRVE SPGL4	3.0	7.0	4.0
CRVE SPGL6	5.5	12.0	6.2
CRVE SPGL8	5.0	13.5	7.6
CYCLOFOSF	9.0	14.5	11.1
DIVCHEMO	6.0	6.0	6.0
DORST	6.5	54.5	36.9
FABRY2	2.0	2.3	2.1
FABRY4	4.0	4.0	4.0
FERINJECT	2.0	6.0	2.3
FERRO	2.0	6.0	4.0
GAMMAGLOB	1.7	14.5	4.9
GAUCHER	3.0	5.0	3.8
INFLIXIMAB	1.5	4.5	3.1
IVIG	2.0	6.0	4.7
KRSBLD	0.2	0.3	0.3
LEVERBIOS	1.5	12.5	7.8
LEVERSCR	16.0	50.0	38.2
METYRAP	13.5	19.0	18.5
MPS	1.5	54.5	7.4
MPS KUUR	2.0	11.5	7.9
MPSV1	2.3	2.5	2.5
MPSV2	2.3	2.5	2.5
NACHTCORT	18.5	19.0	18.8
NBEIGEN	12.5	27.5	23.3
NBEIGENV	6.3	6.3	6.3
NBTX	3.0	7.0	5.0

Appointment type	Min	Max	Average
OBSNAOND	4.3	105.0	23.2
OBSNAONDZ	2.3	43.7	16.0
OFATUMAB	3.5	8.0	6.0
ONDERZ	0.5	13.5	4.5
OSAS	6.5	16.0	15.9
OSASV	16.0	16.0	16.0
OVERIG	0.5	59.5	8.3
OVERIGE1	0.5	49.0	7.0
OVERIGE10	1.5	13.5	7.5
OVERIGE2	2.0	10.5	3.1
OVERIGE3	3.0	3.0	3.0
OVERIGE4	0.2	14.5	4.7
OVERIGE6	2.7	12.5	6.3
OVERIGE8	6.0	12.0	8.8
PEG	11.5	11.5	11.5
POSTCT	6.5	18.5	12.5
PRECT	1.3	19.3	7.4
PRESIRTOPN	10.0	26.0	14.9
PRESIRTP01	4.7	4.7	4.7
PTCDOPNAME	10.7	60.0	25.6
PTCDPOST01	22.0	22.0	22.0
REMICADEC	2.0	9.0	2.5
REMICADER	2.5	14.5	2.7
RFAOPNAME	9.5	27.5	24.4
RFAPOST01	16.0	16.0	16.0
RITUXIHEMI	8.0	8.0	8.0
RITUXIHEMV	4.0	5.0	4.2
RITUXIMAB	2.0	8.0	5.0
RITUXIREUI	5.0	5.5	5.4
RITUXIREUV	6.0	7.0	6.9
SCLCYSTE	14.5	24.5	21.2
SIRTOPNAME	24.0	26.0	25.2
SOLARISIV	2.0	2.5	2.5
TACEOPNAME	13.7	37.0	25.5
TACEPOST02	16.0	16.0	16.0
TENCKHOF	48.0	48.0	48.0
TOCILIZUMA	1.0	2.5	2.1
TOETROMB	0.8	3.0	2.2
VALPREV	3.2	3.2	3.2
VAST	51.0	90.0	70.4
VBCOSCOPIE	5.3	25.7	14.8
VENOFER	2.0	3.5	2.6
VERTOPNAME	6.0	8.0	6.7

Table 3: Average, maximum and minimum appointment duration in h continued

Now looking at the difference between the planned and realized appointment durations in hours, Tables 4 and 5 provide an overview of all appointment codes.

Appointment code	less	-4	-3	-2	-1	1	2	3	4	more	Total #
ABATASEPT	0	0	0	0	4	82	5	0	1	0	92
ABIV	7	1	2	20	58	109	38	12	3	7	257
APD	0	0	0	0	7	10	2	2	0	0	21
ASCITESDRA	0	0	0	0	0	0	1	0	0	0	1
BLDTRS2	0	0	1	1	1	8	5	2	0	0	18
BLDTRS4	3	0	2	18	45	53	31	14	7	13	186
BLDTRS6	1	6	2	16	38	40	20	10	6	5	144
BLDTRS8	0	1	4	10	14	10	4	3	1	5	52
BLOEDTRF	0	1	4	3	7	5	1	0	1	1	23
BLOEDTRFKB	16	7	15	9	23	17	15	6	3	8	119
BLOEDTRNSF	0	0	0	0	0	0	1	0	0	1	2
BLTRANSF	0	0	0	0	0	1	0	0	0	0	1
CHOPMAB_I	0	0	0	1	0	0	0	1	0	0	2
CHOPMAB_II	0	0	0	0	0	0	1	0	0	0	1
CRVE SPGL4	0	0	0	0	1	2	1	0	2	0	6
CRVE SPGL6	1	3	1	1	2	14	8	3	0	1	34
CRVE SPGL8	0	0	0	2	0	1	2	0	0	2	7
CYCLOFOSF	0	0	0	0	0	2	1	0	0	1	4
DIVCHEMO	0	0	0	0	1	0	0	0	0	0	1
DORST	1	1	0	0	0	0	1	0	0	1	4
FABRY2	0	0	0	0	0	3	1	0	0	0	4
FABRY4	0	0	0	1	3	0	0	0	0	0	4
FERINJECT	0	0	1	0	9	41	7	2	1	3	64
FERRO	0	0	21	11	20	24	5	1	1	1	84
GAMMAGLOB	0	1	35	37	52	31	9	1	2	8	176
GAUCHER	0	0	0	2	5	1	0	1	0	0	9
INFLIXIMAB	0	0	0	20	80	76	21	8	1	0	206
IVIG	0	11	6	8	12	12	0	0	2	3	54
KRSBLD	0	0	0	0	0	0	2	2	1	0	5
LEVERBIOS	2	9	10	16	6	6	1	1	0	2	53
LEVERSCR	3	0	0	0	0	0	0	0	0	0	3
METYRAP	0	0	0	2	16	15	4	1	1	1	40
MPS	3	2	1	2	14	53	44	9	3	8	139
MPS KUUR	0	0	0	0	0	1	0	0	0	3	4
MPSV1	0	0	0	0	4	2	1	0	0	0	7
MPSV2	0	0	0	0	6	1	0	0	0	0	7
NACHTCORT	0	0	0	0	1	1	0	0	0	0	2
NBEIGEN	0	0	1	0	2	5	4	4	0	4	20
NBEIGENV	0	0	0	0	0	0	0	0	0	1	1
NBTX	1	0	6	5	17	13	7	2	1	3	55

Table 4: Difference between planned and realized appointment durations in hours, per appointment code

Appointment code	less	-4	-3	-2	-1	1	2	3	4	more	Total #
OBSNAOND	12	6	10	16	12	10	11	8	7	34	126
OBSNAONDZ	2	1	2	2	6	8	7	0	4	20	52
OFATUMAB	0	0	0	2	2	6	3	2	0	0	15
ONDERZ	0	1	0	1	16	20	6	2	3	14	63
OSAS	1	2	0	5	21	110	39	8	4	5	195
OSASV	0	0	0	0	0	1	0	0	0	0	1
OVERIG	5	0	1	1	7	10	1	1	0	25	51
OVERIGE1	0	0	0	2	8	6	6	1	1	8	32
OVERIGE10	0	0	0	0	0	0	0	0	0	2	2
OVERIGE2	0	0	0	0	7	17	2	0	0	2	28
OVERIGE3	0	0	0	0	1	0	0	0	0	0	1
OVERIGE4	0	0	1	2	7	7	2	0	0	3	22
OVERIGE6	1	6	2	6	14	7	7	0	0	8	51
OVERIGE8	0	3	2	1	4	1	0	1	0	1	13
PEG	0	0	0	0	0	0	0	0	0	1	1
POSTCT	0	0	0	0	0	0	0	0	0	2	2
PRECT	0	1	3	8	24	45	24	9	1	8	123
PRESIRTOPN	0	0	2	1	1	3	1	0	0	0	8
PRESIRTP01	0	0	0	0	0	0	0	0	0	1	1
PTCDOPNAME	5	0	0	4	3	6	6	2	1	6	33
PTCDPOST01	0	0	0	0	0	0	0	0	0	1	1
REMICADEC	1	1	0	1	202	481	105	52	19	12	874
REMICADER	0	0	0	0	12	26	14	3	0	2	57
RFAOPNAME	0	1	0	3	3	4	1	3	0	2	17
RFAPOST01	0	0	0	0	0	0	0	0	0	1	1
RITUXIHEMI	0	1	1	1	0	1	3	1	0	0	8
RITUXIHEMV	0	0	0	1	3	2	1	2	0	0	9
RITUXIMAB	0	0	4	5	15	12	5	6	5	6	58
RITUXIREUI	0	0	0	1	2	6	0	1	0	0	10
RITUXIREUV	0	0	1	10	6	3	1	0	1	0	22
SCLCYSTE	0	0	0	0	0	1	0	0	0	2	3
SIRTOPNAME	0	0	0	0	2	0	2	0	0	0	4
SOLARISIV	0	0	0	0	7	14	1	0	0	0	22
TACEOPNAME	0	1	0	1	5	3	6	1	1	5	23
TACEPOST02	0	0	0	0	0	0	0	0	0	1	1
TENCKHOF	0	0	0	0	0	0	0	0	0	1	1
TOCILIZUMA	0	0	0	0	40	252	32	11	10	2	347
TOETROMB	0	0	0	0	0	6	5	1	2	2	16
VALPREV	0	0	0	0	2	0	0	0	0	0	2
VAST	0	0	0	0	1	0	2	0	0	2	5
VBCOSCOPIE	1	0	0	0	1	2	0	0	1	8	13
VENOFER	0	0	0	0	0	2	2	0	0	0	4
VERTOPNAME	0	0	0	2	1	3	2	0	0	0	8
Total	66	67	141	261	883	1714	540	200	97	269	4238

Table 5: Difference between planned and realized appointment durations in hours, per appointment code, continued

C Normalization of the Objective Function Coefficients

The coefficients of the objective function variables have to be normalized in order to appropriately choose γ and β to represent the preferences of the Short-Stay Unit. E represents the maximum difference between the number of patients that can be treated by the nurses that are present at that time, and the actual number of patients that are present. Suppose there are no patients present but for every bed a nurse is available. In that case $E = 18 = 20 - 2$ since there always needs to be a minimum of two nurses. In the ideal case, and assuming that at always at least the required amount of nurses to handle the workload is present, the minimum value is $E = 0$. V is the maximum of the difference between the minimum and maximum number of blocks in the blueprint of a given appointment type per day, over all appointment types. Suppose of a given type k no blocks are scheduled on one day, but on another day, on every bed only appointments of that type are scheduled. This is the worst case. The smallest appointment type has a duration of one hour. So in the worst case $12 \cdot 13 + 8 \cdot 8 = 220$ appointments could be scheduled (At the south wing, on 8 beds 8 appointments can be scheduled per day, and at the north wing 13 appointments on 12 beds, because of the admission and discharge time restrictions), leading to a difference of $V = 220$. In the best case, all appointments are evenly distributed among the days, so $V = 0$. Normalization leads to $\gamma = \frac{\bar{\gamma}}{18}$ and $\beta = \frac{\bar{\beta}}{220}$. $\bar{\gamma}$ and $\bar{\beta}$ have to be chosen according to the preferences of the unit.

D Input for Short-Stay Unit AMC

In this section, the parameter values and sets that are not addressed in Section 5.2, used to model the AMC Short-Stay Unit, are summarized.
First of all, as time slot unit 1 hour is used. Hence a day is divided into 24 time slots.

D.1 Sets

Notation	Description	Elements
K	Set of all appointment types	1, 2, ..., 13
J	Set of all beds	1, 2, ..., 20
T	Set of all time slots in the scheduling horizon[1]	$i, i+1, ..., i+\delta-1$
S	Set of all shifts	Day, Evening, Night
F	Set of all days[2]	$d, d+1, ..., d+\frac{\delta}{\epsilon}-1$
T_f	Set of all time slots belonging to day f[3]	$r, r+1, ..., r+\epsilon-1$
J_N	Set of all beds located on the north wing	1, 2, ..., 12
J_S	Set of all beds located on the south wing	13, 14, ..., 20

Table 6: Set elements

To calculate the time slots belonging to each shift, the following times for shifts are used:

- Day shift: 8:00-15:00
- Evening shift: 15:00-23:00
- Night shift: 23:00-8:00

Note that these are not the exact times of the shifts as described in Section 2.5.1. Here the overlap between the shifts it is taken into account as well as the fact that the model works with time slots of one hour. To be able to make quantitative statements about the performance of the unit without counting patients twice in two different shifts, the shift hours stated above are used.
As for admitting and discharge times, the times indicated in Table 2.2 are used.

D.2 Parameters

Table 7 shows which parameters can directly be given as input. In Table 8 the specifications

Notation	Description	Values
ζ	Unit of time slots	1h
δ	Length of the blueprint schedule period in time slots	$7 \cdot \epsilon = 168$
e	The minimum number of nurses that has to be present	2

Table 7: Parameters

[1]This varies due to the rolling horizon approach, for simplicity of notation, let i denote the first time slot of the blueprint period

[2]This varies due to the rolling horizon approach, for simplicity of notation, let d denote the first time slot of the blueprint period

[3]This varies due to the rolling horizon approach, for simplicity of notation, let r denote the first time slot of a given day f

for the appointment types are given, that is the number of appointments of the type that have to be scheduled, μ_k, and the length of an appointment of that type in time slots, l_k. The

k	l_k	μ_k
1	1	1
2	2	6
3	3	16
4	4	8
5	5	3
6	6	8
7	7	3
8	8	3
9	9	1
10	10	1
11	11	0
12	12	2
13	13	1

Table 8: Appointment parameters

nurse-patient ratios, that is the maximum number of patients one nurse can be assigned to during is shift are given in Table 2.6. The values of the parameters w_t and z_t are initially set to zero, but as the heuristic iterates, these values will change and represent the number of admissions/discharges and the number of patients at the unit respectively.
The parameters a_t^S, a_t^N, d_t^S, d_t^N are initialized so that they represent the admission and discharge times represented in Table 2.2. As for f_{jt}, initially the opening hours of Table 9 are used, but as the heuristic iterates, the parameter will change and indicate time slots as not available where previously appointments have been scheduled.

Wing	Week 1	Week 2
North	Mon 8am - Fri 4pm	Mon 8am - Mon 8am
South	Mon-Fri, 8am - 4pm	Mon-Fri, 8am - 4pm

Table 9: Opening hours of the unit over two weeks

D.3 Probability Distributions

As input for the simulation model, probability distributions are needed to model the appointment requests. First, the arrival process, i.e. how many appointment requests arrive per day, has to be modeled. The probability distribution of the number of requests per day is given in Figure 2.3. Tables 10 and 11 show the probability distribution of the different appointment codes. Per appointment code, the (cumulative) probability is given, together with the duration of the appointment in time slots (1 time slot equals 1 hour), and the release and due date in days, counting from $\delta = 0$. The expected due date is calculated as the 90th percentile of the realized access times and the release date as the 10th percentile of these times.

D.4 Thresholds for Urgent Appointments

In Section 4.4, thresholds for urgent appointment are introduced. They are used by the assignment rule to make sure that there will be enough capacity left for urgent appointments. In order to determine the thresholds for the AMC Short-Stay Unit the number of appointments with required access times of $0, 1, ..., 6$ days are investigated, which covers a whole blueprint period of seven days. Per appointment code, first the percentage of appointments with the corresponding access times is calculated. These percentages are then multiplied with the average number of occurrences of that appointment code per blueprint period. This is the average number of appointments of a given code with the corresponding access time, and is set as the threshold ω_f. It turns out, that there are only few appointment types where this leads to a threshold greater than 0. These are summarized in Table 12, which first gives the threshold purely based on the data of the Short-Stay Unit, ω_f and then the thresholds where the increasing order constraint is taken into account, $\bar{\omega}_f$.

D.5 Appointments with Special Assignment Rules

In Section 5.2.2 it is mentioned that some appointment types of the Short-Stay Unit have extra scheduling constraints. These types are listed in Table 13. While the constraint for all Rituximab appointments arises from the drug that is given during the appointment, the reason that a the preparation for a coloscopy (VBCOSCOPIE) has to be performed in a single bed room is simply the privacy of the patient. For the thirst and hunger test (DORST and VAST respectively), the patient needs to be alone in a room because he or she is not allowed to drink or eat for a long time, and the room has to be cleared of all drinks, water and food. OSAS is the code for sleep research, and since the patient is monitored during sleep, it is important that the patient is alone in the room. Furthermore, because this appointment type has to be scheduled after 8pm.

Code	Probability in %	Cumulative	Duration in time slots	Release date in days	Due date in days
ABATASEPT	2.17	0.00	3	11	84
ABIV	6.06	0.02	3	1	19
APD	0.50	0.08	3	4	73
ASCITESDRA	0.02	0.09	4	2	2
BLDTRS2	0.42	0.09	3	0	30
BLDTRS4	4.39	0.09	4	0	35
BLDTRS6	3.40	0.14	6	0	34
BLDTRS8	1.23	0.17	8	1	42
BLOEDTRF	0.54	0.18	9	2	130
BLOEDTRFKB	2.81	0.19	12	1	28
BLOEDTRNSF	0.05	0.22	6	0	0
BLTRANSF	0.02	0.22	8	2	2
CHOPMAB_I	0.05	0.22	7	5	8
CHOPMAB_II	0.02	0.22	4	14	14
CRVE SPGL4	0.14	0.22	3	3	21
CRVE SPGL6	0.80	0.22	6	2	24
CRVE SPGL8	0.17	0.23	6	1	33
CYCLOFOSF	0.09	0.23	10	4	18
DIVCHEMO	0.02	0.23	6	35	35
DORST	0.09	0.23	42	7	38
FABRY2	0.09	0.23	3	6	34
FABRY4	0.09	0.23	5	4	12
FERINJECT	1.51	0.23	3	2	19
FERRO	1.98	0.25	3	1	11
GAMMAGLOB	4.15	0.27	6	8	63
GAUCHER	0.21	0.31	5	6	30
INFLIXIMAB	4.86	0.31	3	3	49
IVIG	1.27	0.36	6	3	47
KRSBLD	0.12	0.37	1	14	41
LEVERBIOS	1.25	0.37	8	1	35
LEVERSCR	0.07	0.39	49	27	42
METYRAP	0.94	0.39	19	7	30
MPS	3.28	0.40	2	1	28
MPS KUUR	0.09	0.43	9	0	22
MPSV1	0.17	0.43	3	4	31
MPSV2	0.17	0.43	3	5	32
NACHTCORT	0.05	0.43	19	9	13
NBEIGEN	0.47	0.43	27	4	13
NBEIGENV	0.02	0.44	7	5	5
NBTX	1.30	0.44	6	2	25

Table 10: Distribution of appointment codes with duration, release and due date

Code	Probability in %	Cumulative	Duration in time slots	Release date in days	Due date in days
OBSNAOND	2.97	0.45	21	0	28
OBSNAONDZ	1.23	0.48	6	0	28
OFATUMAB	0.35	0.49	6	9	60
ONDERZ	1.49	0.50	7	1	49
OSAS	4.60	0.51	17	7	32
OSASV	0.02	0.56	16	7	32
OVERIG	1.20	0.56	3	0	29
OVERIGE1	0.76	0.57	1	1	35
OVERIGE10	0.05	0.58	2	0	0
OVERIGE2	0.66	0.58	3	1	25
OVERIGE3	0.02	0.58	3	12	12
OVERIGE4	0.52	0.58	5	1	35
OVERIGE6	1.20	0.59	6	0	14
OVERIGE8	0.31	0.60	7	0	23
PEG	0.02	0.61	12	4	4
POSTCT	0.05	0.61	7	4	7
PRECT	2.90	0.61	6	2	27
PRESIRTOPN	0.19	0.63	13	1	12
PRESIRTP01	0.02	0.64	5	7	7
PTCDOPNAME	0.78	0.64	27	1	17
PTCDPOST01	0.02	0.64	23	3	3
REMICADEC	20.62	0.64	3	5	57
REMICADER	1.34	0.85	3	11	86
RFAOPNAME	0.40	0.86	27	6	22
RFAPOST01	0.02	0.87	16	6	6
RITUXIHEMI	0.19	0.87	9	5	37
RITUXIHEMV	0.21	0.87	5	4	22
RITUXIMAB	1.37	0.87	6	3	22
RITUXIREUI	0.24	0.89	6	5	51
RITUXIREUV	0.52	0.89	7	2	37
SCLCYSTE	0.07	0.89	25	12	15
SIRTOPNAME	0.09	0.89	26	11	15
SOLARISIV	0.52	0.90	3	12	146
TACEOPNAME	0.54	0.90	27	6	23
TACEPOST02	0.02	0.91	17	23	23
TENCKHOF	0.02	0.91	48	1	1
TOCILIZUMA	8.19	0.91	3	9	84
TOETROMB	0.38	0.99	3	0	14
VALPREV	0.05	0.99	4	3	3
VAST	0.12	0.99	90	4	20
VBCOSCOPIE	0.31	0.99	6	1	15
VENOFER	0.09	1.00	3	1	7
VERTOPNAME	0.19	1.00	7	4	16

Table 11: Distribution of appointment codes with duration, release and due date, continued

ω_f							
Code	ω_0	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6
ABIV	0	1	1	1	1	0	0
BLDTRS4	1	1	0	1	0	0	0
OBSNAOND	1	0	0	0	0	0	0
REMICADEC	0	0	0	1	1	1	1
$\bar{\omega}_f$							
Code	$\bar{\omega}_0$	$\bar{\omega}_1$	$\bar{\omega}_2$	$\bar{\omega}_3$	$\bar{\omega}_4$	$\bar{\omega}_5$	$\bar{\omega}_6$
ABIV	1	1	1	1	1	1	1
BLDTRS4	1	1	1	1	1	1	1
OBSNAOND	1	1	1	1	1	1	1
REMICADEC	1	1	1	1	1	1	1

Table 12: Thresholds of the different appointment codes

Code	Constraint
DORST	Single bed room
OSAS	Single bed room and after 8pm
RITUXIHEMI	after 10 am
RITUXIHEMIV	after 10 am
RITUXIMAB	after 10 am
RITUXIREUI	after 10 am
RITUXIREUV	after 10 am
VAST	single bed room
VBCOSCOPIE	single bed room

Table 13: Special scheduling appointment constraints per appointment code

E Input for Simulation Scenarios

This section describes the input that is used for the simulation of the different scenarios. As a standard, the baseline scenario is considered, and only those parameters that are changed will be noted here.

1. Bed capacity
   (a) 18 beds, 9 on F5NO and 9 on F5ZU
   (b) 16 beds, 10 on F5NO and 6 on F5ZU
   (c) 14 beds, 8 on F5NO and 6 on F5ZU
2. Opening hours
   (a) Close the unit during the weekend once a month
3. Patient preferences
   (a) B=1, i.e. the request is assigned to an appointment without letting the patient choose from several options
4. Increasing demand
   (a) Increase the arriving stream of appointment requests by 20%, assuming the distribution among appointment codes stays the same. This is realized by increasing the number of requests per day. While in the baseline scenario the average number of requests per day was 22.7, in this scenario it is 27.1.

F Validation

F.1 Model of the Current Scheduling Method

In Section 2.4.2 a detailed description of the currently applied scheduling method at the AMC Short-Stay Unit is given. For the purpose of validation, the current method is implemented in Excel, however, the following limitations have to be noted:

- It is stated that the planners take patient preferences into account, by checking with the patient whether the appointment date and time suit him or her, and in some cases the patient even plans an appointment directly with the planners. The patient preferences are not included in the model since no data is available on these preferences.
- In case an appointment has to be planned in combination with an appointment at another department, the appointment is scheduled in consultation department. Because including the schedules of other departments is beyond the scope of this study, these cases are neglected.
- If an appointment can not be scheduled within the access time of the patients, the planners would contact the physician and consult with him if it can be planned later in the schedule. This is excluded from the model and appointments beyond their access time are not scheduled. (Note that this event did not occur in any of the validation runs).

With these limitations the current scheduling method reduces to the following steps:

1. If the appointment duration is longer than 8 hours, the appointment will be scheduled at F5NO, otherwise F5ZU is tried first, before moving on to beds of F5NO.
2. Only days between the release and due date are considered.
3. Search the schedule first through all feasible appointment times at the first bed (either F5NO or F5ZU), then move on along the different beds, and finally among the different days.

F.2 Validation Results

To validate the model of the current scheduling procedure, the distribution of appointments among the different codes of the simulation is compared to the historical data. Table 14 shows the average % of appointments of a given code of the simulation, compared to the % of appointments of a given code obtained from historical data, and their relative difference.

Table 16 gives the CI's of θ, U and W, obtained by the validation simulation model.

The CI's for the bed utilization and the required number of nurses per shift and day of the week are given in Tables 17 and 18 respectively. Table 18 first gives the required number of nurses based on admissions and discharges, then based on patient load, and finally combines both values and the requirement that two nurses have to be present at all times.

Code	Simulation % of all appointments	Historical data % of all appointments	Relative difference %
ABATASEPT	2.17	2.27	4.53
ABIV	6.06	5.76	5
APD	0.50	0.47	4.47
ASCITESDRA	0.02	0.02	4.11
BLDTRS2	0.42	0.44	4.35
BLDTRS4	4.39	4.20	4.39
BLDTRS6	3.40	3.23	4.82
BLDTRS8	1.23	1.27	3.77
BLOEDTRF	0.54	0.52	4.91
BLOEDTRFKB	2.81	2.91	3.74
BLOEDTRNSF	0.05	0.05	4.49
BLTRANSF	0.02	0.02	3.82
CHOPMAB_I	0.05	0.05	3.97
CHOPMAB_II	0.02	0.02	4.99
CRVE SPGL4	0.14	0.15	3.71
CRVE SPGL6	0.80	0.77	4.26
CRVE SPGL8	0.17	0.17	3.53
CYCLOFOSF	0.09	0.10	4.91
DIVCHEMO	0.02	0.02	3.54
DORST	0.09	0.09	4.05
FABRY2	0.09	0.09	4.34
FABRY4	0.09	0.09	3.97
FERINJECT	1.51	1.57	4.17
FERRO	1.98	2.07	4.45
GAMMAGLOB	4.15	4.32	4
GAUCHER	0.21	0.20	4.29
INFLIXIMAB	4.86	4.63	4.66
IVIG	1.27	1.23	3.66
KRSBLD	0.12	0.11	4.1
LEVERBIOS	1.25	1.20	3.94
LEVERSCR	0.07	0.07	4.76
METYRAP	0.94	0.98	3.56
MPS	3.28	3.41	3.84
MPS KUUR	0.09	0.09	4.17
MPSV1	0.17	0.17	4.39
MPSV2	0.17	0.16	3.63
NACHTCORT	0.05	0.05	3.61
NBEIGEN	0.47	0.45	4.98
NBEIGENV	0.02	0.02	4.86
NBTX	1.30	1.36	4.95

Table 14: Distribution of appointment codes in %: Simulation and historical data

Code	Simulation % of all appointments	Historical data % of all appointments	Relative difference %
OBSNAOND	2.97	3.10	4.38
OBSNAONDZ	1.23	1.17	4.57
OFATUMAB	0.35	0.37	3.81
ONDERZ	1.49	1.56	4.64
OSAS	4.60	4.82	4.84
OSASV	0.02	0.02	4.23
OVERIG	1.20	1.15	4.41
OVERIGE1	0.76	0.78	3.78
OVERIGE10	0.05	0.05	3.51
OVERIGE2	0.66	0.69	4.18
OVERIGE3	0.02	0.02	4.61
OVERIGE4	0.52	0.54	4.91
OVERIGE6	1.20	1.16	3.79
OVERIGE8	0.31	0.29	4.47
PEG	0.02	0.02	4.56
POSTCT	0.05	0.05	4.74
PRECT	2.90	3.05	4.97
PRESIRTOPN	0.19	0.20	3.96
PRESIRTP01	0.02	0.02	3.57
PTCDOPNAME	0.78	0.81	4.59
PTCDPOST01	0.02	0.02	4.43
REMICADEC	20.62	21.61	4.77
REMICADER	1.34	1.41	4.55
RFAOPNAME	0.40	0.42	4.57
RFAPOST01	0.02	0.02	3.91
RITUXIHEMI	0.19	0.20	4.35
RITUXIHEMV	0.21	0.22	3.5
RITUXIMAB	1.37	1.44	4.9
RITUXIREUI	0.24	0.24	3.8
RITUXIREUV	0.52	0.54	3.63
SCLCYSTE	0.07	0.07	4.83
SIRTOPNAME	0.09	0.10	4.06
SOLARISIV	0.52	0.50	4.16
TACEOPNAME	0.54	0.57	4.16
TACEPOST02	0.02	0.02	4.86
TENCKHOF	0.02	0.02	3.8
TOCILIZUMA	8.19	8.54	4.34
TOETROMB	0.38	0.39	4.55
VALPREV	0.05	0.05	3.92
VAST	0.12	0.12	4.07
VBCOSCOPIE	0.31	0.32	4.19
VENOFER	0.09	0.09	4.63
VERTOPNAME	0.19	0.20	4.56

Table 15: Distribution of appointment codes in %: Simulation and historical data, continued

Performance indicator	CI
θ	0 ; 0
U	52.4 ; 52.6
V	2.48 ; 2.50

Table 16: CI's of θ, total bed utilization and nurse patient ratio

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	62.9 ; 62.9	63.9 ; 63.9	62.3 ; 62.3	57.7 ; 57.7	50.5 ; 50.5	53.3 ; 53.3	49.5 ; 49.5
Evening	61.6 ; 61.6	57.8 ; 57.8	55.1 ; 55.1	46.5 ; 46.5	35.1 ; 35.2	45.1 ; 45.1	45.2 ; 45.3
Night	32.0 ; 32.0	46.9 ; 46.9	45.6 ; 45.6	41.4 ; 41.4	32.8 ; 32.8	41.4 ; 41.4	33.7 ; 33.7

Table 17: CI's of bed utilization

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	5.9 ; 6.1	4.3 ; 4.3	4.4 ; 4.4	4.4 ; 4.4	4.4 ; 4.4	1.8 ; 1.8	2.3 ; 2.4
Evening	3.0 ; 3.1	2.8 ; 2.8	3.0 ; 3.0	3.0 ; 3.0	3.0 ; 3.0	0.7 ; 0.7	0.7 ; 0.7
Night	2.0 ; 2.2	2.1 ; 2.2	2.0 ; 2.2	2.1 ; 2.3	2.1 ; 2.3	0.7 ; 0.7	0.7 ; 0.8
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	3.5 ; 3.5	3.5 ; 3.6	3.4 ; 3.4	3.2 ; 3.2	2.7 ; 2.7	1.6 ; 1.6	1.4 ; 1.5
Evening	1.4 ; 1.5	1.4 ; 1.4	1.3 ; 1.3	1.1 ; 1.1	0.8 ; 0.8	0.9 ; 0.9	0.9 ; 0.9
Night	0.3 ; 0.3	0.5 ; 0.5	0.5 ; 0.5	0.4 ; 0.4	0.3 ; 0.3	0.4 ; 0.4	0.3 ; 0.3
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.0 ; 6.1	4.3 ; 4.3	4.4 ; 4.4	4.4 ; 4.4	4.4 ; 4.4	2.0 ; 2.0	2.3 ; 2.4
Evening	3.0 ; 3.1	2.8 ; 2.8	3.0 ; 3.0	3.0 ; 3.0	3.0 ; 3.0	2.0 ; 2.0	2.0 ; 2.0
Night	2.0 ; 2.1	2.1 ; 2.2	2.1 ; 2.2	2.2 ; 2.2	2.2 ; 2.3	2.0 ; 2.0	2.0 ; 2.0

Table 18: CI's of required number of nurses

G Choice of Weights of Objective Variables

The objective function of the blueprint LP consists of two objective variables, V and E. Their weights, β and γ respectively, determine their influence on the overall objective. In Section 5.2 and Appendix C, the normalization of β and γ is given. Still the normalized weights $\bar{\beta}$ and $\bar{\gamma}$ have to be chosen. Interviews with the Short-Stay Unit staff give the indication, that while a low number of required nurses, which relates to $\gamma \cdot V$, is desirable, the Unit wishes to be able to schedule an appointment for almost all patients within their access times, which is related to $\beta \cdot E$. Hence E is slightly prioritized over V. With this indication in mind, two experiments are conducted with the simulation model to see how this can be translated to the values of $\bar{\beta}$ and $\bar{\gamma}$: one where $\bar{\beta} = 0$ and the other one with $\bar{\gamma} = 0$.

G.1 Simulation Experiments

In this section, the results of the experiments to determine the weights of the objective variables in the blueprint LP are given.

$\bar{\beta} = 1$, $\bar{\gamma} = 0$

Table 19 provides the results for θ, U and V when the objective variable in the blueprint LP focuses only on spreading out the appointment blocks of different appointments evenly among different days. Tables 20 and Tables 21 provide the bed utilization and the required number of nurses per shift and day.

Performance indicator	CI
θ	0.00063 ; 0.00067
U	52.1 ; 52.9
V	2.50 ; 2.53

Table 19: CI's of θ, total bed utilization and nurse patient ratio

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	84.8 ; 85.2	64.2 ; 65.1	54.5 ; 55.2	53.3 ; 54.0	50.7 ; 51.2	84.6 ; 85.7	88.2 ; 89.1
Evening	77.6 ; 78.1	51.2 ; 52.4	38.0 ; 39.0	35.5 ; 36.4	21.7 ; 22.2	43.6 ; 44.5	42.3 ; 43.0
Night	11.4 ; 11.6	31.3 ; 31.7	22.7 ; 23.2	19.8 ; 20.3	16.6 ; 17.0	18.3 ; 18.6	16.6 ; 17.1

Table 20: CI's of bed utilization

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.4 ; 6.4	4.4 ; 4.5	4.4 ; 4.5	4.4 ; 4.5	4.2 ; 4.3	3.5 ; 3.5	3.6 ; 3.6
Evening	1.5 ; 1.6	0.9 ; 1.0	0.6 ; 0.6	0.5 ; 0.5	0.7 ; 0.7	0.8 ; 0.8	0.9 ; 0.9
Night	0.8 ; 0.8	1.5 ; 1.6	0.8 ; 0.9	0.9 ; 0.9	0.8 ; 0.9	0.9 ; 0.9	0.9 ; 0.9
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	4.0 ; 4.0	3.1 ; 3.1	2.6 ; 2.6	2.5 ; 2.6	2.4 ; 2.4	2.3 ; 2.4	2.4 ; 2.5
Evening	1.4 ; 1.4	0.9 ; 1.0	0.7 ; 0.7	0.7 ; 0.7	0.4 ; 0.4	0.8 ; 0.8	0.8 ; 0.8
Night	0.1 ; 0.1	0.3 ; 0.3	0.2 ; 0.2	0.2 ; 0.2	0.2 ; 0.2	0.2 ; 0.2	0.2 ; 0.2
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.4 ; 6.4	4.4 ; 4.5	4.4 ; 4.5	4.4 ; 4.5	4.2 ; 4.3	3.5 ; 3.5	3.6 ; 3.6
Evening	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0
Night	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0

Table 21: CI's of required number of nurses

$\bar{\beta} = 0$, $\bar{\gamma} = 1$

Now the scenario where the objective variable in the blueprint LP only relates to the required number of nurses is investigated. Table 22 provides the results of θ, V and U, while Tables 23 gives the bed utilization and the required number of nurses per shift and day of the week.

Performance indicator	CI
θ	0.00072 ; 0.0074
U	52.1 ; 52.9
V	2.70 ; 2.72

Table 22: CI's of θ, total bed utilization and nurse patient ratio

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	84.9 ; 85.5	62.9 ; 63.6	55.2 ; 56.2	53.0 ; 53.8	50.9 ; 51.5	84.1 ; 85.1	86.8 ; 88.0
Evening	73.7 ; 74.3	47.9 ; 49.2	37.9 ; 39.1	33.7 ; 34.6	21.6 ; 22.2	41.8 ; 43.0	39.0 ; 40.0
Night	11.1 ; 11.3	28.5 ; 28.9	21.8 ; 22.4	20.0 ; 20.5	16.5 ; 16.8	16.8 ; 17.3	17.5 ; 17.9

Table 23: CI's of bed utilization

G.2 Conclusions

When $\bar{\beta} = 0$, the objective function is only linked to the required number of nurses, and the average value of V, the overall nurse patient ratio, is approximately 8% higher than in the case where $\bar{\beta} = 0$. On the other hand, the average value of θ, the fraction of requests that could not be scheduled within the required access times, is 12% higher when $\bar{\beta} = 0$ compared to $\bar{\beta} = 1$. So the influence of the weights is greater on θ, which is related to V, than on the required number of nurses, which relates to E. So in order to level out this effect and giving V and E equal weight, the weights are chosen $\bar{\gamma} = \frac{0.08}{0.08+0.12} = 0.4$ and $\bar{\beta} = \frac{0.12}{0.08+0.12} = 0.6$. Finally, to do the preference of the Short-Stay Unit staff justice, the value of $\bar{\gamma}$ is slightly decreased to 0.3 while $\bar{\beta}$ slightly increased to 0.7. Combining with the results of the normalization, all experiments are conducted with the following objective function in the LP: $\frac{0.3}{18} \cdot V + \frac{0.7}{220} \cdot E$.

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	5.4 ; 5.4	3.9 ; 3.9	3.6 ; 3.7	3.6 ; 3.6	3.7 ; 3.7	3.1 ; 3.1	2.9 ; 3.0
Evening	2.3 ; 2.3	1.5 ; 1.6	1.2 ; 1.2	0.9 ; 1.0	1.3 ; 1.3	1.3 ; 1.3	1.3 ; 1.3
Night	0.8 ; 0.8	1.3 ; 1.3	0.9 ; 0.9	0.9 ; 0.9	0.8 ; 0.8	0.8 ; 0.8	0.8 ; 0.8
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	4.2 ; 4.3	3.1 ; 3.2	2.8 ; 2.8	2.7 ; 2.7	2.5 ; 2.6	2.5 ; 2.6	2.6 ; 2.6
Evening	1.5 ; 1.5	1.0 ; 1.0	0.8 ; 0.8	0.7 ; 0.7	0.4 ; 0.4	0.8 ; 0.9	0.8 ; 0.8
Night	0.1 ; 0.1	0.3 ; 0.3	0.2 ; 0.2	0.2 ; 0.2	0.2 ; 0.2	0.2 ; 0.2	0.2 ; 0.2
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	5.4 ; 5.4	3.9 ; 3.9	3.6 ; 3.7	3.6 ; 3.6	3.7 ; 3.7	3.1 ; 3.1	2.9 ; 3.0
Evening	2.3 ; 2.3	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0
Night	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0

Table 24: CI's of required number of nurses

H Results of the Simulation Experiments

This sections provides the complete numerical results of the simulation experiments, given as confidence intervals. All results are obtained with the experimental setup given in Table 6.1.

H.1 Baseline

This section provides the results of simulating the current situation at the AMC Short-Stay Unit with the heuristic as scheduling method. Table 25 shows the results for the total bed utilization, the total nurse patient ratio and the fraction of all appointment requests that could not be scheduled within the required access times.

Performance indicator	CI
θ	0.00068 ; 0.00071
U	52.4 ; 52.5
V	2.63 ; 2.70

Table 25: CI's of θ, total bed utilization and nurse patient ratio

The results for the bed utilization and the number of required nurses per shift and day of the week are given in Tables 26 and 27 respectively.

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	72.4 ; 72.7	65.2 ; 65.7	60.8 ; 61.3	58.8 ; 59.4	52.1 ; 52.7	75.1 ; 75.6	75.6 ; 76.0
Evening	70.1 ; 70.8	60.9 ; 61.6	56.9 ; 57.9	53.4 ; 54.3	30.6 ; 31.3	60.1 ; 61.1	49.6 ; 50.5
Night	17.8 ; 18.2	39.2 ; 39.8	40.1 ; 40.8	37.9 ; 38.6	31.1 ; 31.7	35.2 ; 36.0	36.0 ; 36.6

Table 26: CI's of bed utilization

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.3 ; 6.3	4.8 ; 4.8	4.3 ; 4.3	4.5 ; 4.5	4.3 ; 4.4	2.8 ; 2.8	2.8 ; 2.8
Evening	2.1 ; 2.2	2.1 ; 2.1	1.9 ; 2.0	1.8 ; 1.8	1.9 ; 2.0	1.9 ; 1.9	2.0 ; 2.1
Night	0.8 ; 0.8	1.3 ; 1.3	0.8 ; 0.8	1.0 ; 1.0	0.9 ; 0.9	0.9 ; 1.0	0.9 ; 1.0
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	3.6 ; 3.6	3.2 ; 3.3	3.0 ; 3.0	2.9 ; 3.0	2.6 ; 2.6	2.2 ; 2.2	2.2 ; 2.3
Evening	1.4 ; 1.4	1.2 ; 1.2	1.1 ; 1.1	1.1 ; 1.1	0.6 ; 0.6	1.2 ; 1.2	1.0 ; 1.0
Night	0.2 ; 0.2	0.4 ; 0.4	0.4 ; 0.4	0.4 ; 0.4	0.3 ; 0.3	0.3 ; 0.4	0.4 ; 0.4
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.3 ; 6.3	4.8 ; 4.8	4.3 ; 4.3	4.5 ; 4.5	4.3 ; 4.4	2.8 ; 2.8	2.8 ; 2.8
Evening	2.1 ; 2.2	2.1 ; 2.1	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.1 ; 2.1
Night	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0

Table 27: CI's of required number of nurses

H.2 Experiment: 18 Beds

In this section, the results of the experiment in which the unit operates with 18 beds, half of which located on F5NO and half on F5ZU, i.e. nine beds are open during evening and night shifts. In Table 28 the results for the total bed utilization, the total nurse patient ratio and the fraction of all appointment requests that could not be scheduled within the required access times are presented.

Performance indicator	CI
θ	0.00069 ; 0.00078
U	60.0 ; 60.8
V	2.68 ; 2.71

Table 28: CI's of θ, total bed utilization and nurse patient ratio

Tables 29 and 30 provide and overview of the bed utilization and the required number of nurses per shift and day of the week.

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	75.2 ; 75.5	70.3 ; 70.9	66.9 ; 67.8	64.5 ; 65.6	59.8 ; 61.0	65.7 ; 65.9	66.0 ; 66.2
Evening	61.7 ; 62.0	64.4 ; 65.2	61.6 ; 62.6	59.1 ; 60.3	42.6 ; 43.5	61.8 ; 62.2	52.2 ; 52.4
Night	40.6 ; 41.1	52.6 ; 53.4	55.5 ; 56.5	50.3 ; 51.2	42.8 ; 43.5	54.5 ; 55.2	47.8 ; 48.6

Table 29: CI's of bed utilization

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.1 ; 6.1	4.9 ; 4.9	4.6 ; 4.6	4.9 ; 4.9	5.0 ; 5.0	2.0 ; 2.0	2.4 ; 2.4
Evening	1.5 ; 1.5	1.3 ; 1.3	1.1 ; 1.2	1.2 ; 1.2	1.1 ; 1.2	1.0 ; 1.0	0.8 ; 0.8
Night	0.5 ; 0.5	0.7 ; 0.7	0.5 ; 0.5	0.7 ; 0.7	0.6 ; 0.6	0.6 ; 0.6	0.7 ; 0.7
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	2.5 ; 2.5	2.3 ; 2.4	2.2 ; 2.3	2.2 ; 2.2	2.0 ; 2.0	1.3 ; 1.3	1.3 ; 1.3
Evening	1.9 ; 1.9	1.9 ; 2.0	1.8 ; 1.9	1.8 ; 1.8	1.3 ; 1.3	1.9 ; 1.9	1.6 ; 1.6
Night	0.4 ; 0.4	0.5 ; 0.5	0.6 ; 0.6	0.5 ; 0.5	0.4 ; 0.4	0.5 ; 0.6	0.5 ; 0.5
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.1 ; 6.1	4.9 ; 4.9	4.6 ; 4.6	4.9 ; 4.9	5.0 ; 5.0	2.0 ; 2.0	2.4 ; 2.4
Evening	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0
Night	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0

Table 30: CI's of required number of nurses

H.3 Experiment: 16 Beds

In this section, the results of the experiment in which the unit operates with 16 beds instead of 20 during the day shifts, and with 10 instead of 12 beds during night, evening and all weekend shifts, are presented. Table 31 shows the results for the total bed utilization, the total nurse patient ratio and the fraction of all appointment requests that could not be scheduled within the required access times.

Performance indicator	CI
θ	0.00073 ; 0.00077
U	62.9 ; 63.1
V	2.85 ; 2.86

Table 31: CI's of θ, total bed utilization and nurse patient ratio

Tables 32 and 33 provide and overview of the bed utilization and the required number of nurses per shift and day of the week.

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	76.4 ; 76.4	73.1 ; 73.3	73.7 ; 73.9	73.6 ; 73.8	73.1 ; 73.3	75.3 ; 75.4	72.0 ; 72.2
Evening	73.6 ; 73.8	68.8 ; 69.0	70.2 ; 70.4	70.1 ; 70.2	41.9 ; 42.0	65.8 ; 66.0	58.5 ; 58.9
Night	35.2 ; 35.5	49.8 ; 50.1	50.0 ; 50.3	46.2 ; 46.6	41.1 ; 41.5	49.5 ; 49.9	43.0 ; 43.3

Table 32: CI's of bed utilization

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.1 ; 6.2	4.1 ; 4.1	4.4 ; 4.5	5.0 ; 5.0	4.9 ; 4.9	1.6 ; 1.6	2.0 ; 2.0
Evening	1.9 ; 1.9	1.8 ; 1.8	1.6 ; 1.6	2.0 ; 2.0	2.0 ; 2.0	1.1 ; 1.1	1.4 ; 1.4
Night	0.8 ; 0.8	0.9 ; 0.9	0.8 ; 0.8	1.1 ; 1.1	0.8 ; 0.9	0.8 ; 0.8	0.8 ; 0.8
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	3.1 ; 3.1	2.9 ; 2.9	2.9 ; 3.0	2.9 ; 3.0	2.9 ; 2.9	1.9 ; 1.9	1.8 ; 1.8
Evening	1.2 ; 1.2	1.1 ; 1.1	1.2 ; 1.2	1.2 ; 1.2	0.7 ; 0.7	1.1 ; 1.1	1.0 ; 1.0
Night	0.3 ; 0.3	0.4 ; 0.4	0.4 ; 0.4	0.4 ; 0.4	0.3 ; 0.3	0.4 ; 0.4	0.4 ; 0.4
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.1 ; 6.2	4.1 ; 4.1	4.4 ; 4.5	5.0 ; 5.0	4.9 ; 4.9	2.0 ; 2.0	2.0 ; 2.0
Evening	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0
Night	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0

Table 33: CI's of required number of nurses

H.4 Experiment: 16 Beds with Current Scheduling Method

In this experiment, the simulation uses the model of the current scheduling method, described in Appendix F.1. Furthermore, the capacity of the unit is reduced to16 beds, as in Section H.3. Table 34 shows the confidence intervals of the general performance measures.

Performance indicator	CI
θ	0.00073 ; 0.00077
U	62.6 ; 63.3
V	2.22 ; 2.24

Table 34: CI's of θ, total bed utilization and nurse patient ratio

Tables 35 and 36 provide and overview of the bed utilization and the required number of nurses per shift and day of the week.

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	70.7 ; 70.9	71.4 ; 71.8	70.8 ; 71.2	67.7 ; 68.4	57.0 ; 57.6	76.8 ; 77.7	68.7 ; 69.7
Evening	74.5 ; 75.0	69.7 ; 70.5	68.6 ; 69.4	61.2 ; 62.3	41.9 ; 42.5	72.5 ; 73.6	66.8 ; 68.1
Night	39.2 ; 40.1	51.0 ; 51.7	53.5 ; 54.3	49.4 ; 50.1	41.3 ; 42.2	50.3 ; 51.3	45.5 ; 46.4

Table 35: CI's of bed utilization

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.3 ; 6.3	4.3 ; 4.4	4.4 ; 4.4	4.4 ; 4.4	4.5 ; 4.6	2.2 ; 2.2	2.8 ; 2.8
Evening	3.0 ; 3.0	2.8 ; 2.8	2.8 ; 2.8	2.8 ; 2.8	3.0 ; 3.0	0.8 ; 0.9	0.9 ; 0.9
Night	0.9 ; 0.9	1.6 ; 1.6	0.9 ; 0.9	1.1 ; 1.1	1.0 ; 1.0	0.9 ; 0.9	0.9 ; 0.9
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	2.8 ; 2.8	2.9 ; 2.9	2.8 ; 2.8	2.7 ; 2.7	2.3 ; 2.3	1.9 ; 1.9	1.7 ; 1.7
Evening	1.2 ; 1.3	1.2 ; 1.2	1.1 ; 1.2	1.0 ; 1.0	0.7 ; 0.7	1.2 ; 1.2	1.1 ; 1.1
Night	0.3 ; 0.3	0.4 ; 0.4	0.4 ; 0.5	0.4 ; 0.4	0.3 ; 0.4	0.4 ; 0.4	0.4 ; 0.4
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.3 ; 6.3	4.3 ; 4.4	4.4 ; 4.4	4.4 ; 4.4	4.5 ; 4.6	2.2 ; 2.2	2.8 ; 2.8
Evening	3.0 ; 3.0	2.8 ; 2.8	2.8 ; 2.8	2.8 ; 2.8	3.0 ; 3.0	2.0 ; 2.0	2.0 ; 2.0
Night	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0

Table 36: CI's of required number of nurses

H.5 Experiment: 14 Beds

The bed capacity is reduced even further in this experiment to 14 beds, where 6 beds are located on F5ZU and hence close during the evening, night and weekend shifts. The general performance measures are summarized in Table 37.

Performance indicator	CI
θ	0.00761 ; 0.00804
U	72.3 ; 72.7
V	2.88 ; 2.91

Table 37: CI's of θ, total bed utilization and nurse patient ratio

An overview of the bed utilization and the required number of nurses per shift and day of the week is given in Tables 38 and 39.

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	88.5 ; 88.7	88.4 ; 88.5	88.3 ; 88.5	88.4 ; 88.6	88.6 ; 88.7	76.7 ; 77.6	73.7 ; 74.4
Evening	82.4 ; 82.8	79.8 ; 80.4	80.3 ; 80.8	74.4 ; 74.6	45.8 ; 46.1	74.8 ; 75.4	71.5 ; 71.9
Night	35.0 ; 35.5	59.6 ; 60.4	59.6 ; 60.2	58.9 ; 59.5	54.6 ; 55.1	60.4 ; 61.2	58.0 ; 58.3

Table 38: CI's of bed utilization

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	5.3 ; 5.3	3.7 ; 3.7	3.8 ; 3.8	3.9 ; 3.9	3.9 ; 4.0	1.4 ; 1.4	1.2 ; 1.2
Evening	2.2 ; 2.2	1.9 ; 1.9	1.8 ; 1.8	1.9 ; 1.9	2.3 ; 2.3	1.3 ; 1.3	1.3 ; 1.3
Night	1.5 ; 1.5	1.6 ; 1.6	1.3 ; 1.3	1.3 ; 1.3	1.3 ; 1.4	1.3 ; 1.3	1.3 ; 1.3
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	3.1 ; 3.1	3.1 ; 3.1	3.1 ; 3.1	3.1 ; 3.1	3.1 ; 3.1	1.5 ; 1.6	1.5 ; 1.5
Evening	1.1 ; 1.1	1.1 ; 1.1	1.1 ; 1.1	1.0 ; 1.0	0.6 ; 0.6	1.0 ; 1.0	1.0 ; 1.0
Night	0.2 ; 0.2	0.4 ; 0.4	0.4 ; 0.4	0.4 ; 0.4	0.4 ; 0.4	0.4 ; 0.4	0.4 ; 0.4
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	5.3 ; 5.3	3.7 ; 3.7	3.8 ; 3.8	3.9 ; 3.9	3.9 ; 4.0	2.0 ; 2.0	2.0 ; 2.0
Evening	2.2 ; 2.2	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.3 ; 2.3	2.0 ; 2.0	2.0 ; 2.0
Night	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0

Table 39: CI's of required number of nurses

H.6 Experiment: 1 Weekend Open

In this section, the results of the experiment in which the unit is open during only one weekend per month. In Table 40 the results for the total bed utilization, the total nurse patient ratio and the fraction of all appointment requests that could not be scheduled within the required access times are presented.

Performance indicator	CI
θ	0.00084 ; 0.00093
U	61.7 ; 62.4
V	2.77 ; 2.80

Table 40: CI's of θ, total bed utilization and nurse patient ratio

Tables 41 and 42 provide and overview of the bed utilization and the required number of nurses per shift and day of the week.

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	83.8 ; 84.2	78.9 ; 79.5	75.8 ; 76.5	73.7 ; 74.3	71.1 ; 71.9	90.5 ; 91.0	87.2 ; 87.8
Evening	85.0 ; 85.6	76.8 ; 77.8	76.0 ; 76.9	68.5 ; 69.4	54.7 ; 55.6	74.1 ; 75.1	42.3 ; 43.0
Night	22.1 ; 22.5	49.6 ; 50.1	52.9 ; 53.6	49.5 ; 50.1	41.4 ; 41.9	44.7 ; 45.5	34.8 ; 35.4

Table 41: CI's of bed utilization

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.0 ; 6.0	4.5 ; 4.6	4.2 ; 4.2	4.6 ; 4.7	4.5 ; 4.5	2.8 ; 2.8	3.0 ; 3.1
Evening	1.0 ; 1.1	0.9 ; 0.9	0.8 ; 0.9	0.8 ; 0.8	1.0 ; 1.0	1.0 ; 1.0	1.0 ; 1.0
Night	0.6 ; 0.6	0.8 ; 0.8	0.5 ; 0.5	0.8 ; 0.8	0.6 ; 0.6	0.6 ; 0.6	0.7 ; 0.7
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	2.1 ; 2.1	2.2 ; 2.3	2.2 ; 2.2	2.1 ; 2.1	2.0 ; 2.0	1.6 ; 1.6	1.5 ; 1.6
Evening	2.1 ; 2.1	1.9 ; 1.9	1.9 ; 1.9	1.7 ; 1.7	1.4 ; 1.4	1.8 ; 1.9	1.0 ; 1.1
Night	0.1 ; 0.1	0.4 ; 0.4	0.4 ; 0.4	0.4 ; 0.4	0.3 ; 0.3	0.4 ; 0.4	0.3 ; 0.3
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.0 ; 6.0	4.5 ; 4.6	4.2 ; 4.2	4.6 ; 4.7	4.5 ; 4.5	2.8 ; 2.8	3.0 ; 3.1
Evening	2.1 ; 2.1	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0
Night	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0

Table 42: CI's of required number of nurses

H.7 Experiment: 20% More Demand

In this section, the results of the experiment in which 20% more appointment requests arrive at the Short-Stay Unit. In Table 43 the results for the total bed utilization, the total nurse patient ratio and the fraction of all appointment requests that could not be scheduled within the required access times are presented.

Performance indicator	CI
θ	0.00095 ; 0.0010
U	62.8 ; 63.3
V	2.88 ; 2.89

Table 43: CI's of θ, total bed utilization and nurse patient ratio

Tables 44 and 45 provide and overview of the bed utilization and the required number of nurses per shift and day of the week.

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	77.1 ; 77.5	75.0 ; 75.4	73.9 ; 74.3	72.6 ; 73.1	68.3 ; 69.2	78.5 ; 78.8	78.0 ; 78.3
Evening	77.8 ; 78.2	74.6 ; 75.2	73.5 ; 74.1	65.1 ; 65.7	55.3 ; 55.7	68.0 ; 68.4	53.8 ; 54.3
Night	37.9 ; 38.1	55.6 ; 56.3	58.0 ; 58.8	51.4 ; 51.7	42.4 ; 42.7	53.6 ; 54.1	44.8 ; 45.3

Table 44: CI's of bed utilization

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.5 ; 6.6	4.7 ; 4.8	4.5 ; 4.5	5.1 ; 5.1	5.1 ; 5.1	2.3 ; 2.3	2.8 ; 2.8
Evening	1.8 ; 1.8	1.5 ; 1.5	1.5 ; 1.5	1.5 ; 1.5	1.6 ; 1.6	1.2 ; 1.2	1.1 ; 1.1
Night	0.6 ; 0.6	0.8 ; 0.8	0.6 ; 0.6	0.9 ; 0.9	0.7 ; 0.7	0.7 ; 0.7	0.7 ; 0.7
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	2.6 ; 2.6	2.5 ; 2.5	2.5 ; 2.5	2.4 ; 2.4	2.3 ; 2.3	1.6 ; 1.6	1.6 ; 1.6
Evening	2.3 ; 2.3	2.2 ; 2.3	2.2 ; 2.2	2.0 ; 2.0	1.7 ; 1.7	2.0 ; 2.1	1.6 ; 1.6
Night	0.4 ; 0.4	0.6 ; 0.6	0.6 ; 0.6	0.5 ; 0.5	0.4 ; 0.4	0.5 ; 0.5	0.4 ; 0.5
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.5 ; 6.6	4.7 ; 4.8	4.5 ; 4.5	5.1 ; 5.1	5.1 ; 5.1	2.3 ; 2.3	2.8 ; 2.8
Evening	2.3 ; 2.3	2.2 ; 2.3	2.2 ; 2.2	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0
Night	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0

Table 45: CI's of required number of nurses

H.8 Experiment: 1 Option

In this section, the results of the experiment in which the unit is open during only one weekend per month. In Table 46 the results for the total bed utilization, the total nurse patient ratio and the fraction of all appointment requests that could not be scheduled within the required access times are presented.

Performance indicator	CI
θ	0.00061 ; 0.00069
U	52.0 ; 52.7
V	2.67 ; 2.70

Table 46: CI's of θ, total bed utilization and nurse patient ratio

Tables 47 and 48 provide and overview of the bed utilization and the required number of nurses per shift and day of the week.

Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	68.8 ; 69.1	71.0 ; 71.5	67.0 ; 67.7	63.9 ; 64.5	57.5 ; 58.3	83.3 ; 83.8	83.2 ; 83.8
Evening	77.1 ; 77.8	68.9 ; 69.9	64.8 ; 66.0	57.3 ; 58.3	37.4 ; 38.1	66.7 ; 67.8	58.3 ; 59.0
Night	21.5 ; 21.7	43.6 ; 44.1	45.0 ; 45.8	41.0 ; 41.8	33.2 ; 33.9	44.8 ; 45.5	39.0 ; 39.7

Table 47: CI's of bed utilization

Required number of nurses							
Based on admissions and discharges							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.0 ; 6.0	4.6 ; 4.6	4.3 ; 4.3	4.5 ; 4.5	4.4 ; 4.4	2.5 ; 2.6	2.8 ; 2.8
Evening	1.4 ; 1.4	1.1 ; 1.1	0.9 ; 1.0	0.9 ; 0.9	0.9 ; 1.0	1.0 ; 1.0	1.0 ; 1.0
Night	0.6 ; 0.6	0.9 ; 0.9	0.6 ; 0.6	0.7 ; 0.7	0.6 ; 0.6	0.7 ; 0.7	0.7 ; 0.7
Based on patient load							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	2.3 ; 2.3	2.4 ; 2.4	2.2 ; 2.3	2.1 ; 2.2	1.9 ; 1.9	1.7 ; 1.7	1.7 ; 1.7
Evening	2.3 ; 2.3	2.1 ; 2.1	1.9 ; 2.0	1.7 ; 1.7	1.1 ; 1.1	2.0 ; 2.0	1.7 ; 1.8
Night	0.2 ; 0.2	0.4 ; 0.4	0.5 ; 0.5	0.4 ; 0.4	0.3 ; 0.3	0.4 ; 0.5	0.4 ; 0.4
Required number of nurses							
Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Day	6.0 ; 6.0	4.6 ; 4.6	4.3 ; 4.3	4.5 ; 4.5	4.4 ; 4.4	2.5 ; 2.6	2.8 ; 2.8
Evening	2.3 ; 2.3	2.1 ; 2.1	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0
Night	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0	2.0 ; 2.0

Table 48: CI's of required number of nurses

List of symbols

Symbol	Description	Section
a	Scheduling decision	4.1
A_s	Set of all feasible decisions in state s	4.1
A_S, A_N	Set of all time slots where patients can be admitted on the corresponding wing	4.3
a_t^S	Parameter indicating if time slot t is a time slot where patients can be admitted at the south wing	4.3
B	Maximum number of options offered to the patient	4.4
c	Subscript for shifts	4.3
C	Set of all shifts	4.3
$\hat{C}_i$	Convergence measure	6.1
D	Time in days	4.2
d_t^S	Parameter indicating if time slot t is a time slot where patients can be discharged at the south wing	4.3
D_S, D_N	Set of all time slots where patients can be discharged on the corresponding wing	4.3
e	The minimum number of nurses that has to be present	4.3
E	Maximum difference between required and actual number of nurses present	4.3
f	Subscript for days	4.3
f_{jt}	Parameter indicating if bed j is available at time t	4.3
F	Set of all days	4.3
g	Length of the largest connected free period in the current schedule	4.4
h	Length of a connected free period in the current schedule	4.4
j	Subscript for beds	4.3
J	Set of all beds	4.3
J_S, J_N	Set of all beds j located on the corresponding wing	4.3
k	Subscript for an appointment type	4.3
K	Set of all appointment types	4.3
l'	Length of the warming up period	6.1
l_k	Length of an appointment of type k in time slots	4.3
L_R	Length of the current appointment request	4.4
M_k	Maximum number of appointments per day of type k in the blueprint horizon	4.3
m'	Number of observations	6.1
n	Current schedule	4.1
n'	Number of runs	6.1
N_k	Minimum number of appointments per day of type k in the blueprint horizon	4.3

Table 49: List of used symbols in alphabetical order

Symbol	Description	Section
p_s	Probability that a block in the blueprint is available whenever an appointment request arrives	4.3
$p_{s,\bar{s}}$	Transition probability from state s to $\bar{s}$	4.1
r	Current appointment request	4.1
R	Assignment rule of the heuristic	4.2
s	State of the system	4.1
S^2	Sample variance corresponding to $\bar{U}(n')$	6.1
s_c	The maximum number of patients that one nurse can be assigned to during shift c	4.3
t	Subscript for time slots	4.3
T	Set of all time slots in the scheduling horizon	4.3
T_c	Set of all time slots belonging to shift c	4.3
T_f	Set of all time slots belonging to day f	4.3
U	Total bed utilization	6.1
U_{ji}	j^{th} observation of the i^{th} run of the bed utilization	6.1
$U_{c,d}$	Average bed utilization during shift c and day d	6.1
$\bar{U}(n')$	Sample mean of bed utilization obtained from n' runs with the replication/deletion approach	6.1
V	Maximum difference between M_k and N_k	4.3
$V_{c,d}$	Average number of required nurses during shift c and day d	6.1
w	Window of moving average	6.1
W	Total nurse patient ratio	6.1
w_t	The number of patients being admitted or discharged at time t	4.3
X	Current blueprint schedule	4.1
X_{kjt}	Variable denoting whether an appointment of type k is scheduled on bed j starting at time slot t	4.3
Y_{tc}	Number of nurses present at time t in shift c	4.3
z_t	The number of patients present at time t	4.3
α	Significance level of the confidence intervals	6.1
β	Weight in objective function for V	4.3
γ	Weight in objective function for E	4.3
δ	Length of the blueprint schedule period in time slots	4.3
ϵ	Number of time slots in a day	5.2
ζ	Unit of time slots of the schedule	5.2
θ	Fraction of requests that are not scheduled within their access times	6.1
κ	Desired relative precision of the CI	6.1
μ_k	Number of appointments of type k that have to be scheduled	4.3
ρ	Iteration frequency of the heuristic	5.2
σ_d	Variance of the distribution of appointment blocks among the different days in the blueprint	4.3
τ	Length of planning horizon	4.3
ψ	t value from Student's t-Distribution	6.1
ω_f	Threshold for urgent appointments on day f	4.4

Table 50: List of used symbols in alphabetical order continued