Erasmus University Rotterdam

Master's Thesis

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Handeling the flow of emergency patients at a hospital

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Abstract

When starting to read a paper on hospitals, a medical paper would directly come to mind, but this is not a medical paper. This paper explains and researches the average length of stay of three specialisms. It provides the reader a framework for thinking more detailed at the importance and difficulty on statistics on the length of stay. We have seen that there is a difference between different diagnoses, but these diagnoses can change during the stay. What do we need to assess an expected length of stay, other than a first diagnosis? In this research we have seen that we need an admission indication and more data for better results. We saw that there are patients with exaggerated length of stay, which we could not use to forecast length of stay. Not only will we discuss the length of stay, we will see that an Acute Admission Ward has added value to the current situation when we look at the process of admitting emergency patiennts.

Acknowledgements

This paper would not be written in this way if it was not for some other people. First, I would like to thank Prof. Dekker for supervising me during this research and for thinking with me during our feedback sessions. Second, I would like to thank Y. Lont as well, for helping me elaborating the research questions and contacting the right persons at the right time. Finally, I would like to thank Vincent Lansbergen for always supporting me and pushing me when I needed it.

Contents

1 Introduction

Due to the new clinical information system 'de Zorgsuite', or Health Information System (HIS), planning processes at the Erasmus University Medical Center will be equipped differently with respect to patient admission, bed planning, operational planning and scheduling. Two basic principles for this Health Information System will be integral resource planning and generic processes. Here, clinical capacity or simply the number of beds has to decrease significantly.

For a decrease in the number of beds, we need an overview in the current situation. Occupation of beds is one of the important factors for obtaining such overview. Bed occupancy is defined by the length of stay, or LoS, multiplied by the number of patients. It is therefore, also important to know what the LoS is of specific patients as it is to know the number of patients staying in the hospital. We will distinguish two different types of patients in this research. Elective patients are patients that can be planned an that are mostly on a waiting list, waiting at home or at another hospital or nursing home to retrieve surgery at the Erasmus University Medical Center. Because these surgeries are not emergencies, we can plan them efficiently to obtain higher occupancy and also less transferred patients. Another type of patients are emergency patients. These are patients that arrive at the emergency department of the Erasmus University Medical Center, or policlinical patients which have to be admitted immediately. When emergency patients have to stay, it is of high importance that beds are available at the specific department of that patient. When this is not the case, the patient has to be declined and transferred to another hospital. With an occupancy rate of approximately 60% it may not be necessary to decline patients. A current overview in bed capacity is therefore of great importance.

The focus of this research will be on two issues. The first issue is to forecast the expected length of stay (LoS). In the current situation, the physician determines the expected length of stay at the moment of a patient admission based on his observations. A request for surgery leads to a planned operation and automatically to a planned admission. The whole planning of this admission is based on the planning of surgery. Planning surgery is done at infinite capacity of beds for admission and the system does not check for available beds at a planned surgery. Besides admission due to requests for surgery, physicians can also request patient admissions without having surgery. Because of the new built site of the Erasmus Medical University Center, the number of beds has to be reduced and planning for the two types of admission will be much more important in the future. In this research we will answer the question what econometric methods can be used for forecasting LoS.

The second issue which is in the focus of this paper is that of clinical capacity. In which way can we make a fair consideration between minimizing costs and maximizing patient satisfaction. We could investigate whether we could have less costs and a better bed occupancy by combining all wards, but would this be a good advice? Every patient has its own specialism and nurses are not trained to work with all these specialisms. We thus, cannot simply say that every patient can go to each ward, because this is not easily feasible. In the current situation, there are pilots running combining different wards of certain specialisms, because in the new site of the Erasmus University Medical Center there are only one-bed rooms, which will result into having to share resources. This is still in progress and generally beds from different specialisms are not being shared at all. Questions that, thus, arrise are whether it is possible to assign capacity per specialism or to departments, themes or on hospital-level? We will also study the relationship between admission and planning in operations.

Before assigning a company for delivering the new HIS, a list of bottlenecks came through by means of workshops at the Erasmus University Medical Center. These workshops were given through the program DOK. The list of bottlenecks was provided to several players in the market for providing IT systems in health care. Based on these bottlenecks, the IT players had to indicate which requirements they could meet and which not. Our research questions are a direct result of some of the bottlenecks. We will analyse the data which is in the scope of these bottlenecks and create a model to give a better insight in how to organise the new system with respect to a more efficient planning of the clinical capacity.

We will distinguish two research questions. The first research question is whether econometric models can be used to forecast LoS. For our second topic, we will investigate emergency admissions. We will create a simulation model which provides different scenarios in hospital admission through the emergency department and will study which scenario performs best in different ways.

In the following sections, we will give an overview of how to approach this study. In Section 2, we will give a more detailed problem definition. We will address what constitutes our problem and which aspects we need to keep into account while performing this research. In Section 3, we will discuss the relevance and motivation of this our issue. We will discuss why this research is relevant and for whom. We will also explain whether this is only scientifically relevant or whether this research is also relevant for practical applications within the Erasmus University Medical Center. In this Section we will also address how this research will suffice for the issues described in Section 2. In Section 4, we will review the existing literature on this topic. In this section, we will discuss why our research relates to existing literature, and to what extend this research will contribute. Data, methods and results on the first research question will be discussed in Section 2.1. In Section 7 the second research question, regarding bed planning will be presented. We will discuss which models and techniques will be used in this research and why this is the most appropriate idea. We will give a short overview on what data we need and where data is available within the Erasmus University Medical Center.

2 Problem definition

All problems, as they are introduced in the Introduction, will be explained clearly and a possible approach will be stated. For each problem regarding bed planning, we will also investigate on what level decisions have to be made. Decision levels will be discussed in Section 4.1.

2.1 Length of Stay

The first issue is to find an appropriate modelling method to forecast the length of stay. In the current situation, the LoS is determined by the physician at the department. It can vary by physician what the LoS is for patients with the same condition. The current information system does not require expected LoS at the admission of a patient. Consequences are that a patient is planned to be in the hospital for an infinite amount of time. Planning patients on the bed in the future are now impossible. For this reason, one of the requirements for the new HIS is:

The Electronic Patient Record/HIS provides the possibility to plan patients based on historical data (median of mean of the historical LoS) or based on a profile, where a standard LoS is implemented

For this requirement, it is necessary to investigate whether a standard profile provides a good forecast or dynamic profiles, such as a moving average. Our research question regarding this topic will, thus, be:

In what way is it possible to forecast length of stay?

Within this question, we will use historical data to analyse three types of specialisms. We will use one surgical specialism, one non-surgical and one other specialism. The specialisms studied are Surgery, Internal Medicine and Pediatrics, respectively. These three specialisms are chosen to provide information on three different types of specialisms, so we can analyse whether there are different ways to assess the LoS for these different types. We will visualise differences of length of stay for these three specialisms with histograms and graphs based on historical data. For every specialism, we will compare different methods with our data to check whether this method can assess the data. We will answer the questions for which patient categories the admission can be estimated realistically and whether there are already existing algorithms which we can use to investigate the LoS or that this length is based on specialism or other factors. More on the methods will be discussed in Section 6.2

2.2 Bedplanning & the Emergency Department

When patients at the Emergency Department have to be admitted to a ward, an emergency physician has to make sure there is a bed for the patient at the ward of its specialism. If there are no available beds at the wards, the patient has to be transferred to another hospital. In the ideal situation it is already clear which wards have available beds, so the patient can be transferred to that ward immediately. In practice, unfortunately, this is not the case. Also the term 'available beds' differs within every ward. For one department there are no available beds when there are electives planned the next day, but for the other department there are no available beds when there are no physical available beds. A more overruling mechanism is needed to decide whether a department is really full. We will try to create decision rules in a way that we are able to simulate the current situation and comparing this scenario with two other scenarios to study if there are ways to admit patients from the emergency department more efficiently. We will, thus, test three different scenarios for admitting patients from the emergency department where our main question within this scope of the emergency department will be:

Is it desirable to set up another workflow for the admission of emergency patients?

For answering this question we will define workflow as one of the possible scenarios for admitting patients, where the default scenario will be the curren scenario, as is presented as Scenario 1. These three scenarios will be assessed by a simulation model:

1. The current situation, in which the nurses decide whether the patient can be admitted
2. The situation in which a planning coordinator decides whether the patient can be admitted
3. A situation where there is a Acute Admission Ward, where a patient can be admitted to for 48 hours before being transferred to the ward of its specialism. At this ward, patients of all specialisms may be admitted

We will simulate these scenarios on a specialism where there often are admissions from the emergency department: Cardiology. The decision rules for performing our simulations are made based on information from employees in the process. Based on historical data we will investigate what the occupancy level is at departments of these specialisms.
The decision rules and differences between scenarios will be presented in detail in Section 7.2.

3 Relevance and Motivation

At the DOK-project a new information system will be organized. For the organization of this system it is of high importance to have a good insight on how to organize the various groups within the program. By means of workshops to indicate bottlenecks in the current situation, one of these groups are on clinical capacity. What is the best and most efficient way of organizing the workflow of emergency patients within the system? How can we organize the overall planning of admission? Is it better to assign a planning coordinator or is the difference in efficiency negligible? Will it be better to organize the planning for hospital admission the way it is, based on OR-planning, or is there a way of implementing the bed capacity to the planning, without losing surgery time. All of these questions are questions regarding the organization of the HIS at DOK. There are seven phases within this project, which are shown in Figure 3 below. Phase 0 is based on starting the separate projects in which the project is split. Phase 1, specification, is based on training project- and maintenance workers. In this phase, process designs and specifications will be created for the organization of the new hospital information system. In Phase 2, organization, new applications, designed in Phase 1 are being tested. After this phase, the applications can be integrated in the software. For the progress of this project,

it is important to get a good insight in certain processes to help the decision making regarding the HIS.
The main motivation for this research is to perform a study on the practical

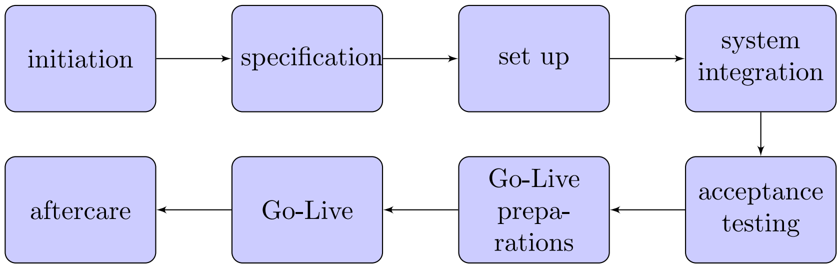


Figure 1: Here, all Phases of the DOK project are shown.

implications and to support the team generic processes in the decision making for the organization of the HIS. Within the Erasmus University Medical Center, there are already some other papers created as we have discussed in the previous section. We are going to combine some methods and assumptions for this research and expand them in a way where we can assist the team Generic Processes at the DOK project.

4 Literature

There is already some literature regarding the topic of Length of Stay and bed planning within hospitals. In this Section we will discuss literature on three different topics. Key words in this literature study are mainly: *Decision levels, Length of Stay, Bed Planning, Simulation.*

In this Section, first, we will introduce decision levels and in what way they will be important here. Second, we will look at papers on Length of Stay, which are usefull for this research. Finally we will discuss some relevant literature on bed planning.

4.1 Background and Decision Levels

According to Vissers et al. [2001] there are five levels in which decisions have to be made within a hospital. We will discuss them from bottom level to top according to Figure 2. We will see there is some overlap in managerial decision making, where there are three levels, namely strategic, tactical and operational level.

4.1.1 Patient Planning & Control

According to Adan and Vissers [2002] the main question arrising at this level is which patient is treated at what time. This type of decision making is on offline operational level, which means that decisions have to be made before the process start. Within this type of planning belongs scheduling of patient admissions, consultations and examinations. The planning of these components

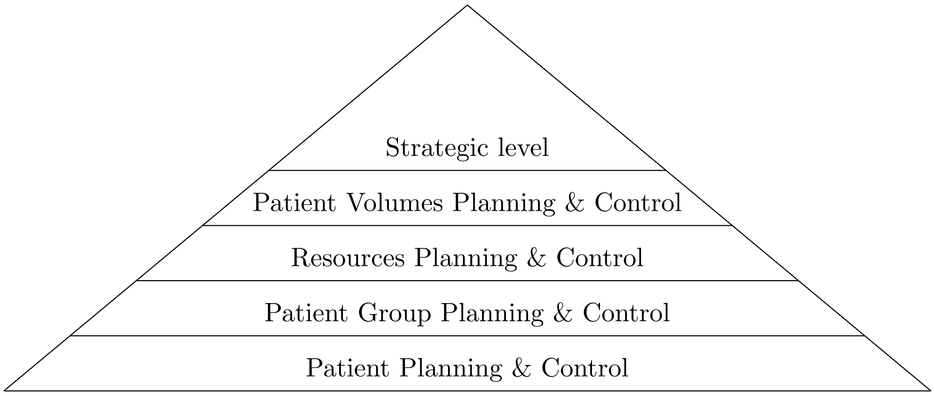


Figure 2: The hierarchical structure of decision levels within hospitals

is done by the operational management, which depend on the specialist, the officers and also the patients. This type of decision making depends on higher decision levels, in which is stated how resources are made available to different patient groups [Adan and Vissers, 2002].
Another type of operational planning is online operational planning. This is planning when the process has already started. An example of online operational planning is changing the planning when an emergency patient arrives. The horizon of this type of planning is on the day itself for online planning through a week for offline operational planning. There are various other papers on this topic, where lots of them refer to the papers of Adan and Vissers [2002].

4.1.2 Patient Group Planning & Control

Adan and Vissers [2002] refer to this type of planning as time-phased allocation. The major idea here is to ensure that the day-to-day schedule, provided in the previous section, is in line with the service requirements that are specified for different patient groups and on how many resources there are available for eacht of these patient groups. The horizon of this type of planning is approximately one week through three months.

4.1.3 Resources Planning & Control

The planning of resources is based on the allocation of resources to specialties or patient groups. We here, check whether the resources required can also be supplied by the hospital, based on the budget of the entire hospital. This is also of the type time-phased allocation.

4.1.4 Patient Volumes Planning & Control

This planning is more of the long term planning, with an horizon of approximately one to two years. Decisions here are made by the hospital management, which are more based on the fact that the hospital management has to make arrangements with parties outside the hospital on total amounts of annual resources. The main question here is what the development of hospital activities is in the next year. When in a year, numbers deviate, the management has to change direction to maintain the required amounts at the end of the year.

4.1.5 Strategic Planning

This is also planning by the hospital management at a horizon of two to five years. These are decisions regarding the investment of resources and the range in which services are being offered in the future.

4.2 Length of Stay

There are different types of paper in the field of Length of Stay. Because our goal here is to create methods to predict the Length of Stay we need to explore which literature is already available on this topic. We will discuss some relevant papers on this study to look at different methodologies to assess our question.

A widely cited paper on this topic is Wey et al. [1988], who use the LoS to compare different cases of nosocomial candidemia by means of the Wilcoxon signed rank test. Also Pittet et al. [1994] use the Wilcoxon signed rank test to check for differences in LoS between groups of nosocomial patients. In Gustafson [1968], five methodologies for predicting and explaining the LoS are being described and compared. Relevant methods used in this paper mainly are Regression Analysis, where factors in this model are a surgeon rate for predicting the length of stay, factors from literature that might influence the LoS and factors which are obtained by interviews with physicians. Also the historical mean was used as a method for predicting LoS. In their paper, they refer to Robinson et al. [1966]. In this paper, they analyse the frequency distributions of the hospital length of stay as they do on specific diseases. For the case of diseases they distinguish the length of stay of this disease without operation, complications or other diseases, with an operation or additional diseases and with an operation without complications. The frequency distribution between these three types differs a lot, which may be something to take into account during our research.

Marazzi et al. [1998], adequacy of the Lognormal-, Weibull- and Gamma Distribution are being assessed with respect to describing the length of stay. They conclude that LoS distributions can be described with the same model through years. Diagnosis-Related Groups, in their work, had to be described with different models for different countries.

4.3 Modelling of Bed Planning

There are various papers on the modelling of bed planning for hospitals. A widely used paper is Jun et al. [1999] where the application of simulation in health care is being reviewed. In their paper, papers on applying simulation in health care are being discussed. This study is devided into several topics, where our relevant topic is 'Allocation of resources'. Dumas [1984] focusses on interrelationships with wards when a patient cannot be allocated at a ward with the preferred specialism. Cohen et al. [1980] use a model for bed planning where patients are moved between units when there is a change of their condition. These papers are relevant within our research because we need to make certain assumptions on our model and such papers can give better insight on where the focus in such a model has to be.

In De Bruin et al. [2010] bed allocation is being modelled with use of an Erlang loss model, which is a queueing model. In van Oostrum [2009], they use computer simulation with two years of operating room data within the Erasmus University Medical Center to construct two sets of schedules for surgery. They construct different scenarios to look at the full service level agreement at the operating rooms. In this paper, they measure the effect of a full service guarantee by utilization, number of late finishing ORs, and cancellation rates of emergency and elective patients, which is something we could look at as well.

5 Datatools

At the Erasmus University Medical Center, there are several tools to obtain data. Elpado is the commonly used electronic patient record system, in which all data on patients is being stored. Everything that has to be recorded can be put in here. Data regarding patientlogistics are put together in SAP Business Objects, a Business Intellegence tool to create reports and analyse data. Financial data is stored in the Oracle Business Intellegence Enterprise Edition (OBIEE) in a same sort of way. Both SAP BI and OBIEE are BI tools, which are an architecture for transforming raw data into usefull information. Another way to assess the data is within ORACLE SQL designer. Because the data is organised in a certain way, with use of SQL designer, obtaining different reports is less limited than with the architecture of both BI tools.

6 Length of Stay

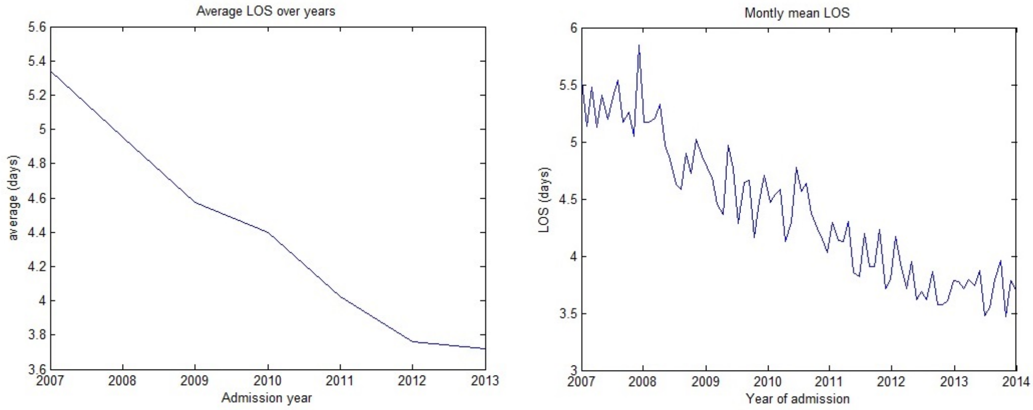
For this question, a large set of data is collected from the Erasmus University Medical Center. We collected the available data from 2004 until 2013, but since there is no data on DTC diagnosis until 2007 we use data from 2007 until June 2014. For Surgery and Internal Medicine we have over 30.000 records regarding admissions in the hospital. For Pediatrics we have over 6.000 records. In our dataset we have the admission date and time and discharge date and time. Also, the day of admission and discharge is available. We have information on the way of admission, so, emergency or through an outdoor department, on the admission type, which can be daytreatment, clinical or others. Because we want to create a general view, we will analyse all data and we will not differentiate in admission types.

6.1 Data

6.1.1 General data

To create a general view on the length of stay at the Erasmus University Medical Center, we will first analyse the general data.

Figure 3: Average LOS for 2007 until 2014 for the whole hospital



In the left figure of Figure 3 we see the average LoS per year for this period of time, where in the figure on the right side the average LoS per month is shown. We see that there is a decline over the years from an average length of stay of 5.3 days in the year 2007 to an average length of stay of 3.7 in 2013. Because there are lots of different specialisms with different average length of stay, we will analyse the three specialisms Surgery, Internal Medicine and Pediatrics in the next Subsection.

6.1.2 Data per specialism

In Table 1 we see the average Length of Stay over the years for our three specialisms.

Year	2007	2008	2009	2010	2011	2012	2013
CHI	8.71	7.45	6.71	6.70	6.89	6.47	6.08
INW	6.40	6.39	5.88	5.72	5.28	4.42	4.24
KGA	7.95	6.89	8.48	8.64	6.43	5.55	5.59

Table 1: Average LOS per year

Figure 4: Average LoS for 2007 until 2014 for the Pediatrics (KGA) per month

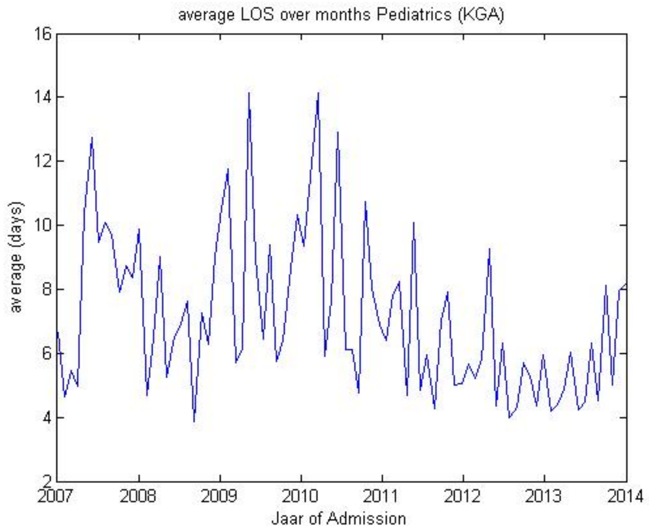
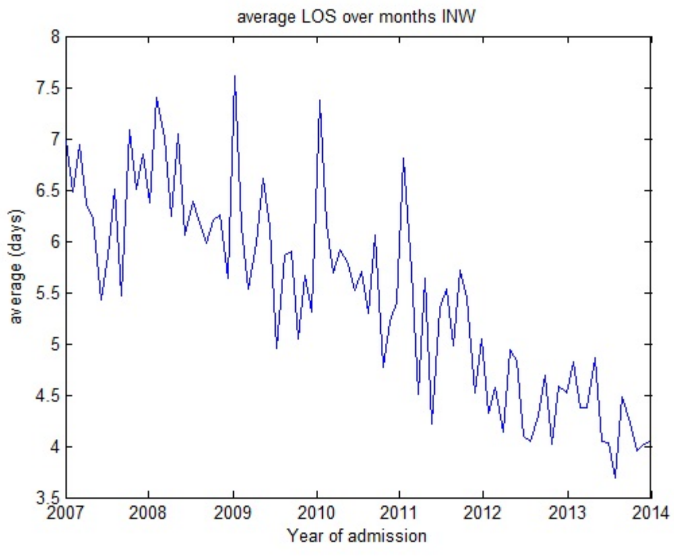
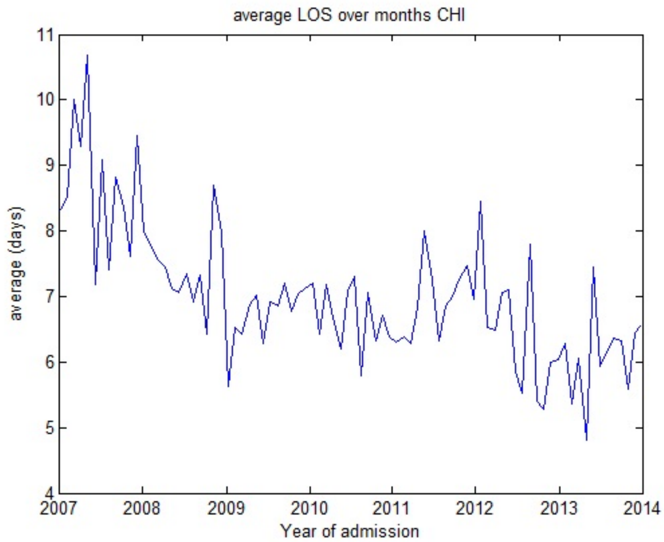


Figure 5: Average LOS for 2007 until 2014 for the Internal Medicine (INW) per month



When we look at Table 1 and Figures 4 until 6 we see that for Surgery (CHI) and Internal Medicine (INW) there is a decline in length of stay over the years. For Pediatrics a decline starts at 2011, but there is a high average yearly LoS in 2009 and 2010. Also, the standard deviation is high in those years in contrast to the standard deviation in the other years. Because the length of stay varies a lot over different DTC diagnoses, we have looked at the ten most frequent DTC diagnose codes per specialism for further analysis, where we do not include

Figure 6: Average LOS for 2007 until 2014 for the Surgery (CHI) per month



admissions where no DTC Diagnose is available.

6.2 Methods

In this research we distinguish ten DTC diagnose codes per specialism to analyse for patterns or regularities. We analyse descriptive statistics for the years 2012 up to now, to have the most recent data. We will look at the mean, median, standard deviation and outliers. An outlier will be found with means of a Boxplot. In Figure 7 a psuedo-random sample from the uniform distribution on the interval [0,10] is drawn and added with two outliers. An observation is an extreme outlier, if it is $3\times$ the Inter Quartile Range (IQR) from the box, which runs from the 1^{st} until the 3^{rd} quartile. The IQR is the difference between the 3^{rd} and 1^{st} quartile as shown in Figure 7. A weak outlier is an observation that lies $1.5\times$IQR from the box. We define an outlier as the *extreme* outlier. Because the smallest outlier does not change over the years, we will only calculate the outlier once, before applying the models.

For our forecast, we will create different models and categorize the data in different ways to answer our research question. We will use the following models:

- Simple mean and median, which are the mean and median respectively over the past two years. So for an admission in 2013, we will use the mean or median over 2010 and 2011
- Previous observation, where the expected length of stay of the current admission is equal to the previous admission of the same type

Figure 7: Average LOS for 2007 until 2014 for the Internal Medicine (INW) per month

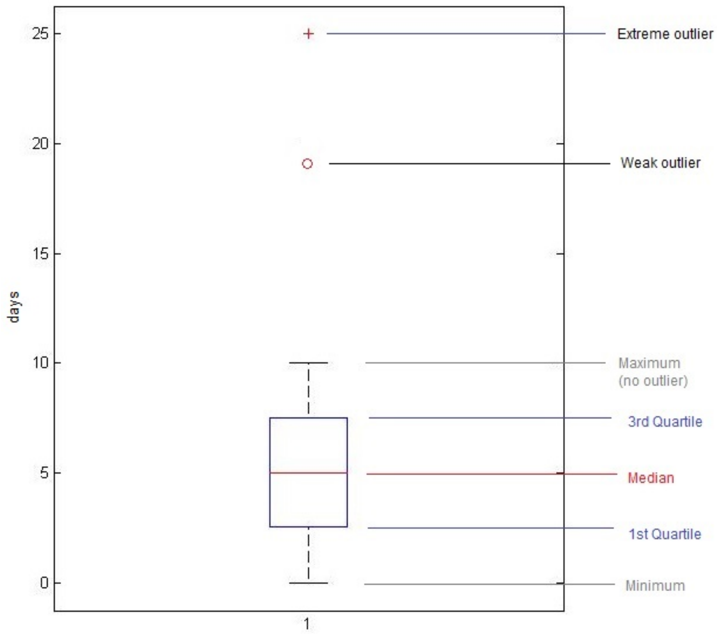


Figure 8: Example-figure for determining outliers

- Moving average models with a horizon of 2 years, 1 year, 50 past observations, 20 past observations, 10 past observations and 5 past observations
- Moving median where, instead of the mean we take the median of the past z observations, with z the horizon equal to the horizons for the moving average

As a performance measure we will use the Mean Absolute Deviation (MAD), which is defined as follows:

$$MAD = \frac{\sum_{j=1}^{N} |x_j - \hat{x_j}|}{N} \tag{1}$$

Where x_j represents the observed LoS and $\hat{x_j}$ represents the predicted LoS. We will use the top ten most common DTC Diagnose Codes from 2012, because it is more useful to analyse Diagnoses that are common recently. For the forecasts, we will use data from 2009 until 2011, to predict the length of stay from January 2012 through June 2014. We will not exclude the detected outliers as these length of stays will occur in reality, which we have to take into account.

6.3 Results

The first question we would like to answer is the following:

In what way is it possible to forecast length of stay?

We will investigate this question for three specific specialisms and hope to find a way to forecast all specialisms in the same sort of way. The three specialisms we distinguish in this research are Surgery (CHI), Pediatrics (KGA) and Internal Medicine (INW). At first, we chose Psychiatry instead of Pediatrics, but due to the closed facility we cannot retrieve all data on these patients. We also decided that it is of lower importance to analyse Psychiatry, because the waiting list is long and the psychiatric institution is always full. As soon as there is a release, a new patient will be admitted. We chose the other specialisms because we now have one surgical specialism (CHI), one non-surgical specialism (INW) and one specialism that is different from all specialisms (KGA). If we find the same method for forecasting for all three specialisms we might conclude this approach may work very well for all specialisms.
We will present our results into three sections and will compare results in Section 6.4.

In Table 4, 7 and 10 with the forecast results, MAD_{best} represents the Mean Absolute Deviation of the best performing method, where the methods are presented in Table 25 in Appendix A. The MAD_{med} represents the MAD of the simple median, so Method 2 and the MAD_{mean} represents the MAD of the simple mean, Method 1. Δ_{med} and Δ_{mean} are their differences, respectively. A '-' is stated if there were no observations for the training period or the testing period for that DTC.
Method 1 and 4 through 9 are methods including the mean, Method 2 and 10 through 15 are methods regarding the median and Method 3 uses the previous observation as forecast.

6.3.1 Surgery (CHI)

Table 2 shows the top ten DTC diagnoses for Surgery (CHI), with the frequency with which they are available in our sample from 2012. In almost 45% of all observations no DTC code is registered. These observations can contain all different types of diagnoses, so we expect the standard deviation in this set to be very high. When we look at the amount of observations for the rest of the codes, we observe that this only contains 2% of the data.

No.	DTC code	DTC description	# observations	% of total
0	-	No DTC Code available	5008	44.88
1	349,5	maligne neoplasma lever secundair	253	2.26
2	418,1	Fontaine II claudicatio intermittens(fem,pop,c	253	2.26
3	318,0	maligne neoplasma mamma	233	2.08
4	352,0	maligne neoplasma weke delen	232	2.08
5	335,0	maligne neoplasma rectum	223	2.00
6	558,0	Niertransplantatie donor	198	1.77
7	179,0	Overige algemene diagnosen	194	1.74
8	319,0	Maligne neoplasma oesofagus—cardia	170	1.52
9	349,2	maligne neoplasma lever primair	148	1.32
10	332,12	Maligne pancreas / periampullaire tumor	118	1.06
-	-	Remaining observations	4146	37.10

Table 2: Top 10 DTC Diagnoses for Surgery

In Table 3 descriptive statistics are presented. As we expected, the standard deviation of the observations without a DTC code registered is high for both observations with operation and without operation. We also observe that the mean en median deviate. For admission without an operation the length of stay is shorter than for admissions with an operation. The extreme values, or outliers, are high. For all other DTC codes the length of stay is much longer for admissions with an operation. Standard deviations are often lower when there has been no operation. The smallest extreme values in our dataset, in Table 3 marked as outliers, are in almost all cases much larger than the median or mean.
With such high standard deviations it may be hard to forecast the expected length of stay.

No.	Type	Median	Mean	Std. Dev.	Outlier	Fraction
0	Operation	7	10.70	16.48	28	32.39
	No Operation	4	7.65	9.85	21	67.61
1	Operation	7	8.63	6.02	16	62.69
	No Operation	2	3.45	4.08	8	37.31
2	Operation	5.5	7.38	7.11	17	30.57
	No Operation	3	2.64	1.62	15	69.43
3	Operation	3	3.03	1.97	12	94.08
	No Operation	2	5.22	5.89	-	5.92
4	Operation	3	4.77	4.54	15	90.97
	No Operation	1	3.15	4.06	-	9.03
5	Operation	9	10.61	7.35	30	64.46
	No Operation	2	3.73	4.64	16	35.54
6	Operation	5	5.61	1.52	12	95.9
	No Operation	2	4.00	4.66	15	4.10
7	Operation	9	12.18	11.53	49	39.88
	No Operation	5	8.49	11.87	31	60.12
8	Operation	15	17.94	10.70	48	55.75
	No Operation	2	3.50	3.62	20	44.25
9	Operation	9.5	14.13	9.79	27	35.38
	No Operation	3	3.88	5.54	10	64.62
10	Operation	12	20.86	36.26	26	61.76
	No Operation	3	4.28	3.44	17	38.24

Table 3: Descriptive statistics Surgery (CHI), with the fraction of the total observation with and without an operation

In Table 4 the results for the top ten DTC's are presented. We see that the lowest MAD's, so the 'best performing methods', are still high. Also, the best method does not differ very much in most cases from the simple median. In a few cases the MAD of the simple mean does differ a lot from the best performing method. Remarkableis that for only one set of data, the best forecast includes the mean, all other methods include the median.

No.	MAD_{best}	$method$	MAD_{med}	MAD_{mean}	Δ_{med}	Δ_{mean}
0	4.18	15	9.21	13.68	5.04	9.50
	2.83	11	4.28	4.52	1.44	1.69
1	3.93	15	5.29	5.9	1.36	1.98
	2.5	13	2.61	2.54	0.11	0.04
2	4.05	15	4.68	5.76	0.63	1.71
	2.39	2	2.39	2.4	0	0.02
3	3.9	15	3.96	3.96	0.06	0.06
	2.39	2	2.39	2.46	0	0.07
4	3.84	10	3.93	4.24	0.09	0.40
	2.46	4	3.17	2.53	0.70	0.07
5	4.06	15	7.50	9.03	3.44	4.97
	2.52	1	3.17	2.52	0.64	0
6	-	-	-	-	-	-
	-	-	-	-	-	-
7	4.18	14	5.61	14.03	1.43	9.85
	2.61	2	2.61	3.72	0	1.11
8	-	-	-	-	-	-
	-	-	-	-	-	-
9	4.07	15	6.68	9.98	2.61	5.91
	2.39	11	2.61	2.50	0.22	0.11
10	4.07	15	10.07	14.11	6	10.04
	2.39	2	2.39	3.38	0	0.99

Table 4: Forecast results (CHI)

6.3.2 Internal Medicine (INW)

Table 5 represents the top 10 DTC's for Internal Medicine from 2012 until June 2014. In this table, we observe that a lot of DTC's are very general. Number 2, 6 and 8, for example, are all remaining DTC's of a certain type. Number 4 has DTC code 'Unknown'. With these codes in our top 10, it may be hard to forecast, because within one code, there may be several different diagnoses.

No.	DTC code	DTC description	# observations	% of total
0	-	No DTC Code available	5701	45.39
1	076	Begeleiding niertransplantatie ontvanger	360	2.87
2	399	overige nierziekten nno	292	2.32
3	493	primaire immuundeficientie nno	269	2.14
4	ONB	onbekend	231	1.84
5	283	adipositas (obesitas) met complicaties	221	1.76
6	979	overige maligniteiten tractus digestivus	208	1.66
7	701	ijzergebreksanemie nno	181	1.44
8	299	Overige endocriene en metabole aandoeningen	168	1.34
9	431	bacteriaemie — sepsis	160	1.27
10	526	systemische vasculitis	152	1.21
-	-	Remaining observations	4617	36.76

Table 5: Top 10 DTC codes for Internal Medicine from 2012

In Table 6 we see the descriptive statistics for Internal Medicine. We observe that the median does only exceed 4 days for two cases. The mean for our codes is somewhat higher than the median. The standard deviation varies from 0.46 for Adipositas a form of obesity, to 25.31 for Hypercotisolism. For three diagnoses, there are no outliers in the data, for the rest of the DTCs, they all exceed eleven days.

No.	Median	Mean	Std. Dev.	Outlier
0	4	6.56	8.77	21
1	4	6.39	7.43	2
2	3	5.84	9.23	12
3	2	4.70	6.43	15
4	7	12.38	19.93	22
5	2	2.25	0.46	-
6	3	4.17	3.46	12
7	2	4.69	6.87	-
8	2	3.84	3.32	15
9	7	11.56	14.97	38
10	2	6.50	10.16	-

Table 6: Descriptive statistics Internal Medicine (INW)

Table 7 represents the forecast methods with results. Here, $\Delta_m ed$ is always smaller than one, which implies that the best performing method does not outperform the median over 2 years much. The mean over the past 2 years performs worse than the median. Furthermore, the forecastmodels do not perform very well for DTC codes with high standard deviations. Again, on all DTC codes except 'Adipositas' the best performing method includes the median.

No.	MAD_{best}	$method$	MAD_{med}	MAD_{mean}	Δ_{med}	Δ_{mean}
0	4.21	10	4.99	9.59	0.77	5.37
1	-	-	-	-	-	-
2	3.91	10	3.95	5.16	0.04	1.25
3	2.88	14	2.89	3.68	0.01	0.80
4	9.15	13	9.83	9.26	0.67	0.11
5	0.25	3	0.75	0.55	0.50	0.30
6	1.68	2	1.68	3.21	0	1.53
7	2.67	10	2.69	3.87	0.02	1.20
8	-	-	-	-	-	-
9	7.60	10	7.69	9.62	0.10	2.02
10	-	-	-	-	-	-

Table 7: Forecast results (INW)

6.3.3 Pediatrics (KGA)

As for Internal Medicine in Section 6.3.2, several DTC codes are a remainder of a certain type of code at Pediatrics as well. Here, 'Unknown' is the most common DTC code from 2012. In Table 10 we observe that standard deviations are high anad mean and median deviate. As for Internal Medicine, the median for all diagnoses is not very high. Although, standard deviations are this high, there are four DTC codes without any outliers.

No.	DBC code	DBC description	# observations	% of total
0	-	No DTC code available	1069	43.88
1	ONB	onbekend	183	7.51
2	9902	basiszorg pasgeborene—kind	61	2.50
3	7799	overige IC-indicaties	54	2.22
4	3328	voedingsproblemen — -fouten	45	1.85
5	3208	onderste luchtweginfectie	41	1.68
6	3327	voedingsallergie	37	1.52
7	3299	overige onderste luchtwegproblematiek	36	1.48
8	7406	vasculaire afwijkingen	33	1.35
9	3202	astma — BHR (behalve allergisch, zie 3109)	31	1.27
10	3499	overige cardiologische aandoeningen	31	1.27
-	-	Remaining observations	815	33.46

Table 8: Top 10 DTC codes Pediatrics from 2012

No.	Median	Mean	Std. Dev.	Outlier
0	3	7.48	12.94	15
1	2	3.39	5.76	14
2	3	10.96	15.69	14
3	2	6.19	7.39	-
4	8	19.63	39.00	29
5	5.5	9.86	14.71	18
6	1	3.80	6.26	-
7	3	5.06	5.61	12
8	2	3.57	7.30	35
9	3	3.86	2.20	-
10	2	3.22	2.86	12

Table 9: Descriptive statistics Pediatrics (KGA)

When we analyse the results of the forecast presented in Table 10, we observe that the best methods perform slightly better than the median. Again, only for one DTC code, the best forecasting method does not include the median.

No.	MAD_{best}	$method$	MAD_{med}	MAD_{mean}	Δ_{med}	Δ_{mean}
0	5.45	10	5.62	8.23	0.17	2.78
1	1.40	2	1.40	2.47	0	1.07
2	9.08	10	10.53	16.11	1.45	7.03
3	4.19	2	4.19	7.20	0	3.01
4	16.47	2	16.47	19.65	0	3.18
5	6.47	13	6.58	7.73	0.11	1.26
6	3.80	6	5.20	5.20	1.40	1.40
7	3.13	11	3.87	19.28	0.74	16.15
8	2.24	10	2.86	3.40	0.62	1.16
9	1.57	10	1.76	1.91	0.19	0.34
10	1.33	14	1.63	7.33	0.30	6.00

Table 10: Forecast results (KGA)

6.4 Conclusion and Advice

After analysing descriptives and forecasts of all three specialisms, we have seen that deviations are high and the mean often is higher than the median. For Surgery, admissions with operations, mostly, have higher length of stay than the same diagnosis without surgery. For some diagnoses with operation the standard deviation is higher, for others it is lower. Also the fraction of admissions with an operation differs for each diagnosis. Outliers are almost for all DTC codes greater 10 days. The best performing forecast methods are almost for every DTC slighlty lower than the simple median. Only in a few cases it exceeds one day on average. Because the median performs this well, for simplicity we do not exclude outliers in our observations, since the median is not affected much by these outliers, as is the mean. One important main observation is that almost in all cases, the best performing method includes the mean. Since this method does not outperform the median over the past 2 years, our advice for the Health

Information System is to implement the median of the past two years as default length of stay for each DTC. For Surgery-types of specialisms, we would advise to distinguish in admission with and without operations, since the median does differ for these types.

7 Bed planning

For the second problem mentioned in this research, a simulation model will be created to get a better insight in bed planning.
The research question we would like to answer is the following:

Is it desirable to set up another workflow for the admission of emergency patients?

For studying this research question, we will try to model the current situation as accurate as possible to obtain an insight in the current process. We will compare this scenario with two other scenarios that may be implemented in the future. Difference between those scenarios will be presented in Section 7.2.
When great differences will come forward between different scenarios, we might advise to adjust the current workflow.

In this Section, we will first describe data required for this research in Section 7.1, following with our methods and decision rules in Section 7.2. Results will be presented in 7.3, where we will conclude this problem in Section 7.4.

7.1 Data

To create a model for admissions from the emergency department, we need to obtain data on which departments we will take into account and how many beds there are available. For this research we will study the Cardiology department, because this is a specialism where there are often admissions from the emergency department. When the Cardiology department does not have capacity to admit their patients, we are able to expand to Thoracic surgery. We will not expand from Thoracic surgery to Cardiology, because Thoracic patients are more complex patients on average and nurses from Cardiology are not trained to handle these types of patients as they are trained for Cardiac patients only.
A specialism has several wards to place patients, but since patients arrive at the emergency department with a specialism and not a ward, we will combine all wards for this specialism to one department with the total number of beds.
For each patient we obtain the following items:

1. Admissionnumber
2. Admissionpart number
3. Date of admission
4. Time of admission
5. Date of discharge
6. Time of discharge
7. Specialism
8. Emergency indicator

Because our model will not be on minute-level, we will divide the time of admission and discharge in three intervals as presented in Table 11. The reason

Number	Name	Time Interval
1	Morning	07.00 a.m. - 00.59 p.m.
2	Afternoon	01.00 p.m. - 05.59 p.m.
3	Night	06.00 p.m. - 06.59 a.m.

Table 11: Distribution of time

for this deviation is because, in practice, elective patients are planned in the morning and afternoon (because these are at the 'normal' working hours). Patients are on average discharged in the afternoon. In this way, the night is the emergency-daypart, as elective patients are not planned on this part of the day. At an emergency admission, the emergency indicator is not always completed and since its default value is "No" the amount of emergencies may be under-registrated. With interviews, we will investigate the extent at which the emergency admissions are under-registrated by comparing our numbers with numbers of the (head-)nurses.

7.1.1 Data description

To retrieve the right data for our simulation model, we first studied all departments in the hospital. We found seven departments at which were mostly patients of Cardiology and Thoracic surgery. These seven departments were easy to divide under Cardiology and Thoracic surgery as is shown in Table 12.

Department Code	Specialism	# Admissions	% Admissions
08TH	CAR	180	5.6
	THC	3000	94.0
	Others	10	0.3
	Total	3190	100
12CD	CAR	1466	99.9
	THC	0	0.0
	Others	2	0.1
	Total	1468	100
12HT	CAR	970	98.9
	THC	9	0.9
	Others	2	0.2
	Total	981	100
16CD	CAR	6517	99.4
	THC	5	0.1
	Others	34	0.5
	Total	6556	100
16TH	CAR	59	1.8
	THC	3188	94.8
	Others	116	3.5
	Total	3363	100
MCCL	CAR	5654	100.0
	THC	0	0.0
	Others	1	0.0
	Total	5655	100
MCEF	CAR	4726	99.9
	THC	2	0.0
	Others	1	0.0
	Total	4729	100

Table 12: Departments with Cardiology and Thoracic surgery patients with their amount from 01/07/2009 until 31/12/2013.

From Table 12 we can ascertain that there are two departments for Thoracic surgery and five departments for Cardiology, namely 08TH, 16TH and 12CD, 12HT, 16CD, MCCL and MCEF respectively. In Table 26 in Appendix B descriptions of these departments are provided.

Because of the default value of the emergency-indicator and the fact that this is not a mandatory field, only 13% of the admissions at Cardiology was registered as an emergency admission. In consultation with specialists, we assumed that the fraction of emergency admissions at both Cardiology and Thoracic surgery were approximately 60%. The difference between 60% and 13% may look high, but this can be explained: In the current situation the emergency indicator has the default value ‘No’. To maintain a fast transition from emergency department into an admission ward, this default value is not changed in their administration, what leads to this underregistration of emergency patients. With the use of an algorithm, patients which were originally not admitted as emergency patients, are now assigned as emergency patients.. The dataset with which we will perform our simulation has the statistics as shown in Table 13. In this table, we see that 80% of the patients are Cardiology patients, where 52.11% of the 80% is an emergency patient. This is approximately 65%, against 60% patients for Thoracic surgery.

Specialism	Emergency	# Admissions	% Admissions
CAR	Y	16034	52.11
	N	8630	28.04
	Total	24664	80.15
THC	Y	3650	11.86
	N	2458	7.99
	Total	6108	19.85
Total		30772	100.00

Table 13: Departments with Cardiology and Thoracic surgery patients with their calculated amounts from 01/07/2009 until 31/12/2013

Table 14 describes the length of stay for the admissions for the time period in the simulation model. In this table, we observe that the mean and median for Cardiology are much lower than for Thoracic surgery, which might imply the higher complexity of patients for Thoracic surgery. Standard deviations are high and when we combine our observations in Table 14 with Figure 9 until 12, we observe that for Cardiology the median might describe our data somewhat better. For Thoracic surgery, we observe that there are two values with high amount of admissions, which are 1 and 7.

Specialism	Emergency	Mean	Standard Deviation	Median	Maximum	Minimum
CAR	Y	3.55	7.39	1.00	368	1
	N	3.05	5.57	1.00	80	1
	All	3.37	6.81	1.00	368	1
THC	Y	7.48	8.12	7.00	137	1
	N	7.15	7.10	7.00	92	1
	Total	7.35	7.73	7.00	137	1

Table 14: Statistics of length of stay from 01/07/2009 until 31/12/2013

Figure 9: Histogram 95% of the length of stay for Cardiology patients from 01/07/2009 until 31/12/2013

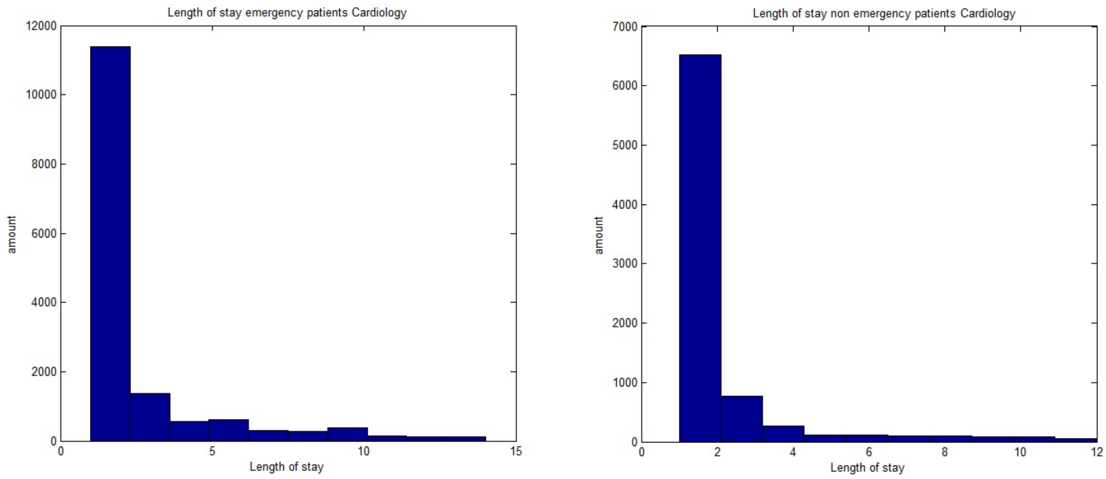


Figure 10: Histogram 95% of the length of stay for Cardiology patients from 01/07/2009 until 31/12/2013

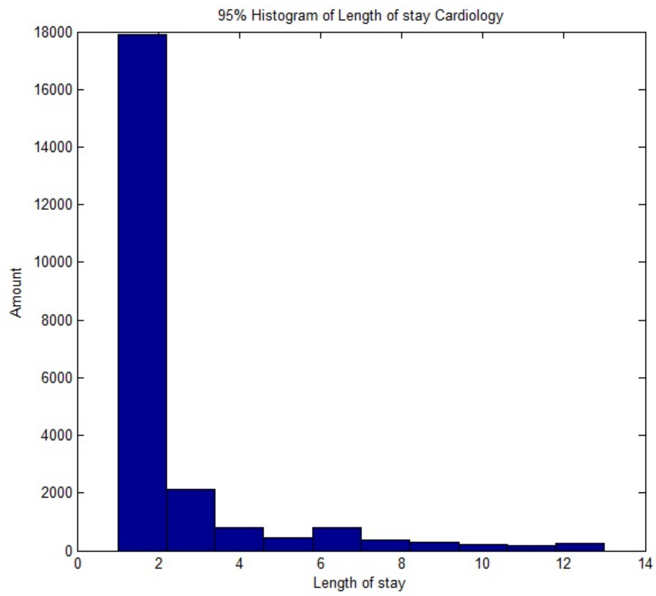


Figure 11: Histogram 95% of the length of stay for Thoracic patients from 01/07/2009 until 31/12/2013

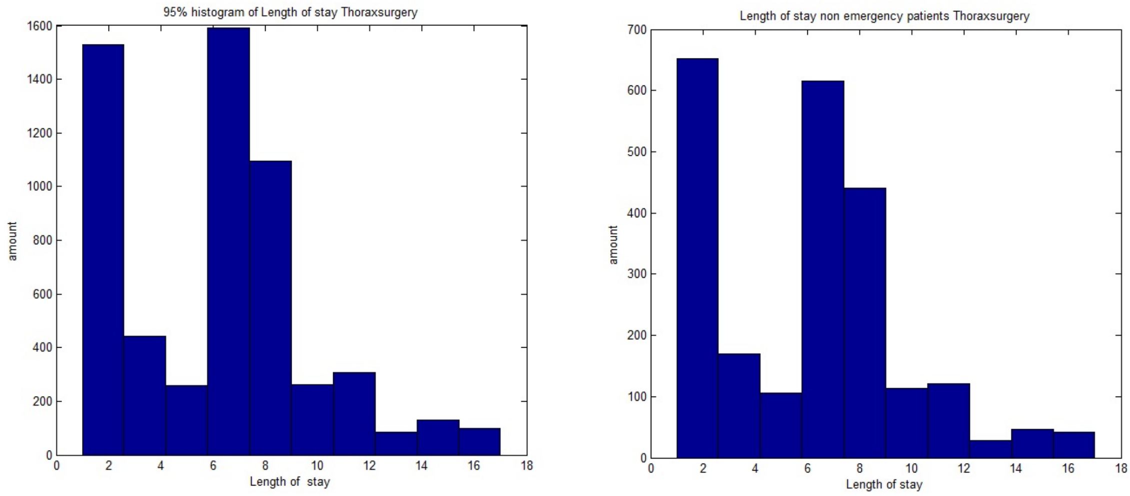
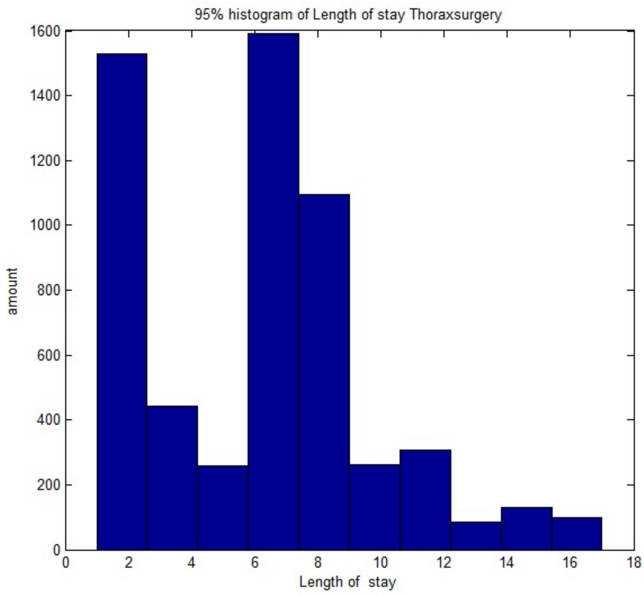


Figure 12: Histogram 95% of the length of stay for Thoracic patients from 01/07/2009 until 31/12/2013



7.2 Methods

For the second problem mentioned in this research, a simulation model will be created to get a better insight in bed planning.

The research question we would like to answer is the following:

Is it desirable to set up another workflow for the admission of emergency patients?

In the following sections we will discuss the three scenarios with their decision rules and assumptions made in our model.

7.2.1 General assumptions and calculations

For creating this simulation model, several assumptions are necessary. We will use historical data to perform our simulation and create the simulation model based on decision rules, set from information obtained from employees. We will calculate the following statistics during our simulation:

- Not admitted emergency patients
- Elective patients that have to be cancelled as a result of admitted emergency patients
- Amount of times the planning had to be changed to admit both emergency patients and elective patients
- Patients that are admitted on the 'wrong' department. So for Cardiology patients, they are admitted at the Thoracic-department

For the different scenarios, other calculations are added, which are discussed in their specific chapters.
We will calculate the statistics below for a specialism in the following way.

$$Bed\ occupancy = \frac{average\ number\ of\ occupied\ beds}{total\ operational\ beds} \tag{2}$$

$$Transfer\ rate = \frac{not\ admitted\ patients}{total\ arrivals} \tag{3}$$

$$Ward\ availability = \frac{admitted\ patients}{total\ arrivals} \tag{4}$$

$$Cancelled\ Electives = \frac{cancelled\ elective\ patients}{total\ elective\ arrivals} \tag{5}$$

$$Not\ Admitted\ Emergency = \frac{not\ admitted\ emergency\ patients}{total\ emergency\ arrivals} \tag{6}$$

$$Changed\ Planning = \frac{patient\ on\ planning\ changed}{total\ planned\ patients} \tag{7}$$

A bed will be chosen randomly with equal probability when more beds are available for one patient. Elective patients are planned a week in advance.
After performing the simulation, we will evaluate the results of the models and give an advice.
We will study three scenarios, discussed in the following sections.

7.2.2 The algorithm

The algorithm used in this simulation model, will generally be the same for the three scenarios, with additions and subtractions for the different cases.

As is presented in Algorithm 1, each iteration is a part of the day (morning, afternoon or night) from 01/06/2009 until 31/12/2013. Because the first week starts on wednesday, patients are planned on capacity from wednesday until sunday. All patients that are on the waitinglist are retrieved from the dataset and planned on capacity (*planCapacity*). In all other weeks, patients are being planned on capacity on each friday (***if*** *isFriday*). After this, on every morning ($DayPart = 1$), a bed is assigned to each patient that is planned for the whole day for both Cardiology and Thoracic surgery (*PlanElectivePatients*).

For emergency patients in Algorithm 2, every part of the day the model checks whether there is enough capacity for the first 24 hours of their length of stay. If there is, there will be investigated whether there is enough capacity for the whole LoS of the patient. When there is more than one elective patient which has to be cancelled, we will look if the emergency patient can be admitted to the Thoracic department, otherwise the patient is not admitted. When there is one elective patient that has to be cancelled, the patient will be cancelled and planned for the next week. Patients are cancelled for their whole admission. We will not cancell patients that are already admitted to the hospital. After this, the emergency patient can be admitted to the department. When there is no elective patient to be cancelled, which means that there is enough capacity, it may occur that there is enough capacity, but not on one bed for the patients length of stay. In this case, patients will be replaced between beds until the emergency patient can be admitted to the department. When there are more beds available for one patient, beds are assigned randomly. Also patients are pulled randomly from the emergency waiting list.

Algorithm 1: Main

```
Input: CARdepartment,THCdepartment, Admissions
Output: CARdepartment, THCdepartment, Counters
Initialize Counters
DayPart ← 1
StartDate ← 01/06/2009
for j ∈ iterationDays do
    PlanCapacityTHC, PlanCapacityCAR
    if DayPart = 1 then
        for i ∈ j,j+2 do
            GetPatientsToPlanTHC, GetPatientsToPlanCAR
            PlanElectivePatientsTHC
            PlanElectivePatientsCAR
    planEmergencyPatient
    if isFriday then
        PlanCapacityTHC, PlanCapacityCAR
    if DayPart < 3 then
        DayPart=DayPart+1
    else
        DayPart=1
```

In this basic algorithm, we distinguish three situations, where there are deviations from the basic algorithm for each situation, discussed in chapter 7.2.3, 7.2.4 and 7.2.5.

Algorithm 2: planEmergency

```
Input: CARdepartment,THCdepartment, emergencyList, Counters,
       Capacity, currentDate
Output: CARdepartment, THCdepartment, Counters, Capacity
i ← currentDate
while emergencyList is not empty do
    j ← random number between 1 and length(emergencyList)
    currentPatient=emergencyList(j)
    if currentPatient.specialism = "CAR" then
        if no bed empty on CARdep on i, i+1, i+2 then
            if available bed on THC then
                place patient on THC
                update Counters
            else
                do not admit patient, update Counters
                delete patient j from emergencyList, Next Patient
        else
            patientRemoved=length(removePatient)
        if patientRemoved >1 elective patient have to be removed then
            if available bed on THC then
                place patient on THC
                update Counters
            else
                do not admit patient, update Counters
                delete patient j from emergencyList, Next Patient
        else
            remove 1 elective patient from planning
        if no bed available for whole LOS of currentPatient then
            replacePatients
    else if currentPatient.specialism = "THC" then
        if no bed empty on THCdep on i, i+1, i+2 then
            do not admit patient, update Counters
            delete patient j from emergencyList, Next Patient
        else if  no bed available for whole LOS of currentPatient then
            patientRemoved=length(removePatient)
        if patientRemoved > 1 elective patient have to be removed then
            update Counters
            delete patient j from emergencyList, Next Patient
        else
            remove 1 elective patient from planning
    choose department (THC or CAR)
    chosenBed = rand(length(availableBeds))
    place patient on bed
    upate Capacity
    delete patient from emergencyList
```

7.2.3 The current situation: The nurses decide

In the current situation, the nurses decide whether emergency patients will be admitted at a ward or not. There are several reasons for emergency patients to be rejected to a ward.

1. There are 'difficult' patients admitted, such as patients with allergies, snoring patients, when this is the case, beds will be blocked.
2. There are 'complex' patients admitted, which means that with the same capacity, more nurses are needed to admit new emergency patients. Nurses are not able to provide enough care when admitting new patients, which leads to the emergency patient not being admitted.

Because of the fact that there is no data on these matters, but only knowledge by nurses we were not able to exactly researching this subject. Therefore, we translated this into the model as (1) an equal possibiliy of the need to block 0, 1 or 2 beds at a certain day and (2) the a possibility of 50% to reject a patient while there are beds available, physically. The latter case will only happen when two or less beds are available on the ward.

7.2.4 Admission coordinator is in charge of the admissions

In this scenario, the admission coordinator has an overview on the whole department and decides whether patients will be admitted or not. The reason behind this, is that when nurses decide, every nurse can have another perception of 'complex' patients. Some nurses will never block beds and other nurses will block beds more frequently. In the scenario of an admission coordinator, one person will be responsible for admitting patients. In this scenario, we will assume that beds will not be blocked and when there are beds available, physically, they can and will be used. The acute admission coordinator will, thus, not take into account the 'complexity' or other situations discussed in Section 7.2.3.

So in this scenario, at least one bed has to be available for the first 24 hours to admit a patient (as is a requirement in all situations), but no beds will be blocked and when there are beds physically available, patients will be placed on that department.

7.2.5 Acute Admission Ward

In this scenario, the same decision rules hold as for the first scenario. We now add an acute admission ward, where emergency patients with a length of stay of less than 72 hours can stay. In this way the nurses can still decide whether there is undercapacity of staff and is it not necessary to send these patients to another hospital.

7.3 Results

With our simulation model, three situations have been modelled and results have been obtained.
For providing the hospital a sound advice, several statistics were obtained and

will be discussed in this section.

Our simulation model, described in Section 7.2 was performed 100 times, to prevent our results from being influenced by our pseudo-random numbers. Our pseudo-random numbers in these scenarios were

- The order of patients admitted. Historical patient admission is used and patients are divided into groups for each day (morning, afternoon, night). From these groups, the order of patient admission is drawn with equal probability for all patients. This for both elective patients as emergency patients. As a result, for every simulation, other emergency patients can be rejected with other LoS which could influence results.
- The number of blocked beds per day.
- The possibility of an emergency patient being rejected due to admitted 'complex' patients.

Statistics of the results for the three scenarios are shown in Sections 7.3.1, 7.3.2 and 7.3.3. Statistics we will discuss with their abbreviations are shortly represented in Table 7.3.

Code	Description
Bed Occupancy	Bed Occupancy
Cancelled Elect	Cancelled Elective Patients
Not Admitted Emerg	Not Admitted Emergency Patients
Changed Planning	Changed Planning due to an Emergency Patient
wrong Spcm	Patient on 'wrong' specialism
AAWadm	Acute Admission Ward Admission (only in scenario 3)
Blocked Beds	Blocked Beds due to undercapacity of staff (not in scenario 2)

Table 15: This table contains abbreviations of our results, represented in Section 7.3.1, 7.3.2 and 7.3.3
.

7.3.1 Results: The current situation

In the current situation, when emergency patients for Cardiology arrive and cannot be admitted here and there are available beds at Thoracic surgery, they can be put at this department. This will not be the case vice versa, because of the complexity of Thoracic patients and the high workload at Cardiology, generally. Beds will not be blocked at Thoracic surgery, due to the lower capacity of this department.

When we study Table 16 and 17, we observe that the bed occupancy is above 75% for both departments, which is higher than the bed occupancy in the whole hospital, which is 65%. The standard deviation of the bed occupancy is nearly zero, which means that over all 100 simulations, the bed occupancy is almost equal for all cases. There are almost no elective patients that have to be cancelled due to undercapacity, which can be caused by the 'replacePatients' algorithm, which is performed 198 times, with a maximum of 248 times. There are on average 2371 patients of Cardiology that are put on Thoracic surgery and 4784 bed blocked over the period of approximately 3,5 years. Standard deviations of all statistics except bed occupancy annd cancelled electives are high on 100 runs, but do not affect the bed occupancy on both departments. The amount of emergency Thoracic patients is low compared to Cardiology, but when we observe the number of Cardiology patients that are admitted to the Thoracic department, these refused Thoracic patients might not have been necessary.

Statistic	Mean	Standard Deviation	Median	Minimum	Maximum
Bed Occupancy (%)	80.34	0.00	80.36	79.89	80.65
Cancelled Elect	3	1.73	3	0	9
Not Admitted Emerg	489	15.91	488	449	541
Changed Planning	198	20.38	201	136	248
Wrong Spcm	2371	54.96	2384	2199	2476
Blocked Beds	4784	93.21	4782	4575	5016

Table 16: Results of the simulation model of patients for the Cardiology specialism.

Statistic	Mean	Standard Deviation	Median	Minimum	Maximum
Bed Occupancy (%)	76.53	0.00	76.53	76.01	76.9876.01
Cancelled Elect	1	1.09	1	0	4
Not Admitted Emerg	161	8.33	161	140	183
Changed Planning	27	5.42	28	14	46

Table 17: Results of the simulation model of patients for the Thoracic surgery specialism.

In Table 18 we see that almost 15% of all Cardiology emergency patients has to be placed on Thoracic surgery. As a result, the transfer rate of 2.64% of not admitted patients of Thoracic surgery itself may not be necessary to refuse. The low percentage of patients which are not admitted on both departments might be a result of the 'replacePatients' algorithm. This algorithm is not being used at the departments, which may cause inefficient planning. In practice, nurses plan in an Excel document, which might not be updated as much as is needed to admit more emergency patients.

Specialism	Statistic	% of total patients
CAR	Cancelled Elect	0.03
	Transfer rate	3.05
	Changed Planning	2.29
	Wrong Spcm	14.79
	Ward availablity	96.95
THC	Cancelled Elect	0.04
	Transfer rate	4.41
	Changed Planning	1.10
	Ward availablity	95.96

Table 18: Results of the simulation model of patients for the Thoracic surgery specialism.

7.3.2 Results: An Admission coordinator

In the second scenario, an admission coordinator has been assigned, that has a more overall view on the departments. When we study the results on this scenario, we see that bed occupancy of Cardiology is somewhat higher than without the admission coordinator. There are over 18% less emergency patients that are not admitted to the hospital compared to the first scenario and there is a decline of almost 17% of patients that are put on the wrong department, compared to scenario 1. Although standard deviations of Cancelled Elect, Not Admitted Emerg, Changed Planning and Wrong specialism are lower than in the current situation, they are still high. But again, these deviation do not affect the standard deviation of the bed occupancy. When we look at the 'Changed Planning', we see that this counter is over 300% higher for Cardiology relative to this counter in the first scenario, which is high, but since this does not affect the admission of emergency or elective patients in a negative way and is simply an administrative task, this might not lead too much problems on these departments.

For Thoracic surgery bed occupancy is somewhat lower, but less patients that are not admitted. This can be the cause of the Cardiology department having a higher capacity, which means the lower bed occupancy might be positive in this scenario. In both scenarios, the amount of cancelled elective is still low as is the amount of times the planning is changed for Thoracic surgery.

Statistic	Mean	Standard Deviation	Median	Minimum	Maximum
Bed Occupancy (%)	82.41	0.00	82.42	82.60	82.18
Cancelled Elect	7	2.28	7	2	12
Not Admitted Emerg	398	13.51	399	364	430
Changed Planning	671	26.54	671	610	733
Wrong Spcm	1969	35.30	1969	2185	2075

Table 19: Results of the simulation model of patients for the Cardiology specialism for Scenario 2

Statistic	Mean	Standard Deviation	Median	Minimum	Maximum
Bed Occupancy (%)	75.09	0.00	75.51	75.50	74.67
Cancelled Elect	2	1.07	2	0	5
Not Admitted Emerg	126	6.40	127	110	139
Changed Planning	23	5.16	22	12	38

Table 20: Results of the simulation model of patients for the Thoracic surgery specialism.

When we look at Table 21, again, we see a lower fraction of patients that are placed at a wrong specialism, a higher percentage of times the planning is changed for Cardiology and a lower value of patients that are not admitted (transfer rate) to the hospital. Based on these results, we might conclude that this scenario performs better than the scenario in Section 7.3.1.

Specialism	Statistic	% of total patients
CAR	Cancelled Elect	0.08
	Transfer rate	2.48
	Changed Planning	7.78
	Wrong Spcm	12.28
	Ward availability	97.52
THC	Cancelled Elect	0.08
	Transfer rate	3.45
	Changed Planning	0.94
	Ward availability	96.55

Table 21: Results of the simulation model of patients for the Thoracic surgery specialism.

7.3.3 Results: Acute Admission Ward

In this scenario, an Acute Admission Ward is added for emergency patients that cannot be admitted at that moment and have an expected length of stay of less than 72 hours. This ward is for every specialism and contains 10 beds. Since Cardiology is one of the specialisms which is going to need this ward most, we did not add a maximum number of beds available for only Cardiology or Thoracic surgery, which means that the total capacity is the capacity for both Cardiology- and Thoracicpatients. When we study the results, we see that there are only 415 patients admitted to this ward at most. The bed occupancy at Cardiology is equal to that of the current situation. Also the patients that are admitted to the wrong specialism as a result of undercapacity and the amount of blocked beds are almost equal, as is the amount of times the planning needed to change to admit an emergency patient. Striking is the amount of patients that are not admitted to Cardiology, which is 80% lower compared to scenario 1 and for scenario 2 this counter is lower as well. The amount of Thoracic surgery patients that could not be admitted is lower than both other scenarios while the other results are comparable with scenario. Standard deviations are high in this scenario as well, but, again, do not affect the standard deviation of the bed occupancy. Compared to the total amount of admissions, these deviations do not affect results..

Statistic	Mean	Standard Deviation	Median	Minimum	Maximum
Bed Occupancy (%)	80.34	0.00	80.35	80.75	79.87
Cancelled Elect	3	1.68	3	0	7
Not Admitted Emerg	95	6.39	95	80	112
Changed Planning	198	20.09	200	149	255
Wrong Spcm	2366	55.55	2371	2228	2486
Blocked Beds	4766	108.35	4757	4482	5082
AAWward	379	15.57	373	336	415

Table 22: Results of the simulation model of patients for the Cardiology specialism.

Statistic	Mean	Standard Deviation	Median	Minimum	Maximum
Bed Occupancy (%)	76.51	0.00	76.50	77.00	76.04
Cancelled Elect	1	1.22	1	0	6
Not Admitted Emerg	99	6.45	101	87	113
Changed Planning	27	5.43	26	14	38
AAWward	39	4.82	39	30	50

Table 23: Results of the simulation model of patients for the Thoracic surgery specialism.

looking at Table 24, again, we see a high fraction of Cardiology emergency patients that are put on the Thoracic surgery department. The fraction of emergency patients that is not admitted to the hospital (transfer rate), however, is very low. This indicates the AAW is a positive addition to the hospital.

Specialism	Statistic	% of total patients
CAR	Cancelled Elect	0.03
	Transfer rate	0.59
	Changed Planning	2.29
	Wrong Spcm	14.76
	Ward availability	99.41
	AAWward	2.36
THC	Cancelled Elect	0.04
	Transfer rate	1.10
	Changed Planning	2.71
	Ward availability	98.90
	AAWward	1.07

Table 24: Results of the simulation model of patients for the Thoracic surgery specialism.

7.4 Conclusion and Advice

In this research, we were focussing on the research question:

Is it desirable to set up one workflow for the hospitalization of emergency patients?

To answer this question, we studied three scenarios, where one workflow will be used in scenario 2. The three scenarios we considered were the following:

1. The current situation: Nurses decide whether there is enough capacity to admit an emergency patient. Beds can be blocked and patients can be refused as a result of complex patients or undercapacity of staff.

2. An admission coordinator: In this situation, there is an admission coordinator (one workflow) that decides whether emergency patients can be admitted or not. We will assume that in this way, no beds will be blocked and no patients will be refused when there are beds pysically available.

3. Acute Admission Ward: This scenario has the same decision rules as scenario 1, but now there is an Acute Admission Ward, to admit emergency patients, when they cannot be admitted on the department of their specialism. Patients that can be admitted at an AAW have an expected length of stay of a maximum of 72 hours.

When we compare the results of Scenario 1 with the results of Scenario 2 and 3, we observe that in Scenario 2, the bed occupancy is highest for Cardiology, but the Transfer rate is lower than for Scenario 3. Since our goal is to reduce the amount of patients that cannot be admitted, Scenario 3 scores best at this point for Cardiology. Also for Thoracic surgery, there are the least patients not admitted in Scenario 3. Of course, in Scenario 3 we added capacity, which could be the main reason for this result. When we observed the amount of patients that were put on the wrong department, Scenario 2 scores significantly better than the other two scenarios. When patients are put on another department, this may lead to difficulties on the wards and patient might have to be transferred during their stay. As a results, workingpressure may rise at both department, which leads to more beds blocked and less emergency patients admitted.

Based on the results of our model for Cardiology, we would advice to set up an Acute Admission Ward. At this ward, not only Cardiology patients can be admitted, patients from other specialisms can be admitted here as well. Creating such a department costs money, space, time and requires nurses to be widely trained, so they can handle patients from different specialisms, which is not the case right now. Before starting an Acute Admission Ward, we would recommend studying whether this has the same effect for other departments. When other department do not benefit of an AAW as Cardiology does, it may be more efficient to enlarge the Cardiology department or hire the admission coordinator from Scenario 2. With the addition of an admission coordinator, the number of refused patients declines and less patients will have to be placed at another department.

For this research, we have seen that an Acute Admission Ward reduces the amount of refused patients from the emergency room to the Cardiology. Based on only this simulation model and data research, we will therefore, advice to set up such an appartment. Before setting up such a department, we do, however, strongly advice to perform more research on this matter, which we will represent in the discussion in Section 7.5.

7.5 Discussion

As a result of this research, an advice is provided to start an Acute Admission Ward at the hospital. There are, however, a few matters that have to be discussed before this can be realised.

First, data on the exact amount of emergency patients in the hospital, was not fully available. In the administrative process of admitting patients, this checkbox had a default value what caused the emergency indicator to not being fully correct. Discussing this with nurses, we concluded that the emergency value of only 13% was too low. We upgraded this to 60%, because we did not have any exact numbers at all. We did, however, perform our simulation with a percentage of emergency patients of 50%, but this did not affect our results very much. Before following our advice, we will strongly recommend to investigate what the amount of emergency patient is at the hospital, as it is how many emergency patients arrive at the emergency room in the hospital. According to research, which was performed manually, over 800 Cardiology patients were transferred to another hospital without being admitted at our hospital for one year. These 800 patients could not be found exactly in the overall system, which do have to be investigated.

In our research, we tried to design our model as well as possible. In discussions with employees, we found that the workflow is very different in each department, which may cause our model to be not as exact as we would have wanted.
We did not take into account the availability and planning of staff and complexity of patients in a specific way. In our research, we assumed that when there was little capacity, beds would be blocked with an equal probability for 0, 1 or 2 beds blocked and patients could be rejected for that same reason.

Creating an Acute Admission Ward may cost a lot of money, time and space. Nurses need to be widely trained to nurse all different patients and doctors need to go to the Acute Admission Ward, when a patient is placed there. This will cost time they have to schedule and could be at the expense of other patients. For this reason, an Acute Admission Ward has to have impact on other departments as well. When this is not the case, we could investigate whether it might be a better solution to expand the Cardiology department if possible.

Our final point of discussion is the fact that we planned the patients that were historically actually admitted with an algorithm. When there was capacity, but no empty beds, we rearranged our planning to create a more efficient planning, what may have caused the bed occupancy to be higher than in reality. A planning tool may be a solution for this problem.

Without these point of research we already contributed a lot to this problem. We did not only point out research points, but we have seen that there is a relative difference between the different scenarios. As a result, we did see that an Acute Admission Ward, would create a higher fraction of admitted emergency patients.

A Used Methods

Number	Method
1	Mean
2	Median
3	Previous observation
4	Moving average 2 yrs
5	Moving average 1 yr
6	Moving average 50 obs
7	Moving average 20 obs
8	Moving average 10 obs
9	Moving average 5 obs
10	Moving median 2 yrs
11	Moving median 1 yr
12	Moving median 50 obs
13	Moving median 20 obs
14	Moving median 10 obs
15	Moving median 5 obs

Table 25: Methods and numbers

B Bed planning wards

Department Code	Department description
08TH	Clinic Medium Care & High Care Thoracic surgery
12HT	Clinic Hearttransplant
12CD	Clinic Medium Care Cardiology
16CD	Clinic Intensive Cardiac Care Unit
16TH	Clinic Intensive Care Thoracic surgery
DCAD	Clinic Thoracic Cardiologic operations Day Care
MCCL	Clinic Medium Care Cardiology
MCEF	Clinic Medium Care Elektrofysiology

Table 26: Cardiology & Thoracic departments

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