

MASTER

Optimizing hospital bed capacity at the department of hematology, UMCN

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Award date:
2012

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Eindhoven, May 2012

**Optimizing Hospital Bed Capacity at
the Department of Hematology,
UMCN**

by

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Student identity number 0574084

in partial fulfilment of the requirements for the degree of

Master of Science

in Operations Management and Logistics

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Series Master Theses Operations Management and Logistics

Subject headings: Bed capacity, healthcare, resource allocation, simulation

I. Acknowledgements

I would like to thank dr.ir. Nico Dellaert for being my first supervisor during the thesis project. I am very grateful for his personal approach and support.

I also would like to thank my second supervisor prof. dr. ir. Uzay Kaymak. His remarks played an important role in building up and writing the report.

From UMC st. Radboud, I would to thank ir. Leo Berrevoets and dr. Nicole Blijlevens for the opportunity and freedom to conduct the research in a way which suited me.

Furthermore, I want to thank my family for their support and faith in me. Especially I want to thank Ruud for his help with the corrections of my English in this thesis.

Jeroen den Hollander

Nijmegen, the Netherlands

May, 2012

II. Preface

This is a report on my final master thesis project on bed capacity at a nursing ward. The research was conducted at the department of hematology at the University Medical Center Nijmegen (UMCN), St. Radboud in Nijmegen, the Netherlands. UMCN is one of the leading academic hospitals in the Netherlands for patient care, education and research.

This report provides an operational research on determining the bed capacity. The main goal of the thesis is to research allocation rules and determining the number of beds to optimize the bed capacity of the hematology department. The research was conducted by adopting operations management techniques to optimize the healthcare process. Furthermore, research was done to quantify the number of isolation and non-isolation beds at the hematology ward in conformity with a redesign of the current situation and a growth scenario.

The research was preceded by a literature review (Den Hollander, 2010). It provided a review of operational research on planning of scarce resources. The literature review was used to identify and review the following subjects: identification of patients, process mining, planning, scheduling, performance measurement, capacity and resources, queueing theory and simulation.

In the first chapter general background information of the UMC St. Radboud and the hematology department will be described. In the second chapter, the contextual problem setting at the hematology department will be explored. In the third chapter the underlying research problems and used methodology will be explained of this project. In the fourth chapter a data analysis will be performed. In the fifth chapter queueing theory will be used to determine the total number of beds. In chapter six a simulation model will be used to answer the research questions. In the last chapter a conclusion and managerial implications will be given.

III. Summary

The research was conducted at the hematology nursing ward (E00) at the University Medical Center, St. Radboud in Nijmegen, the Netherlands. The challenge of the hematology department is to reduce costs and improve the financial aspects, while maintaining the commitment to offer the best care for the patients. The hematology department wants to admit more patients to suppress the fixed costs. This will result among others in an extension of the bed capacity.

The patients at E00 are diagnosed and treated for severe malignant hematological disorders. At E00, patients can be treated with a range of therapies. All the treatments at E00 are conducted in isolation rooms. The reason for having the isolation rooms is that most of the patients have a reduced immune system which makes them susceptible for infection, molds and/or specific bacteria.

This report provides an operational research on planning of bed resources. The main goal of the thesis is to determine the number of beds to optimize the bed capacity of the hematology department and a research on allocation rules. Research was done to quantify the number of isolation and non-isolation beds at the hematology ward in conformity with a redesign of the current situation and a growth scenario.

There are described multiple problems concerning the bed capacity of E00. The focus will be that there is unnecessary use of isolation bed capacity at E00. There are treatments where it is not necessary to treat a patient in an isolation room and there are treatments which a patient must be in an isolation room.

A simulation model is built for the redesign situation and for the future prognosis situation. The redesign situation is the differentiation between isolation beds and non-isolation beds. In the current situation there are only isolation beds. In the future prognosis situation the management of hematology wants to treat more patients, therefore a simulation model is made to determine the number of isolation beds and non-isolation beds.

To compare the simulation outcomes of different scenarios, different key performance indicators (KPIs) and performance indicators (PIs) are defined to choose the best outcome. The best outcome is when the waiting time for emergency patients is less than one day (24 hours) in combination of a minimum of the total number of beds. Therefore the main KPI is the average waiting time for the emergency patients.

A simulation model is built in the software program Arena to determine the number of hospital beds according to the future growth scenario. The simulation model contains three main blocks.

The first block is the arrival of emergency patients and the arrival of elective patients. The interarrival times pattern of emergency patients have a goodness-of-fit index with a Beta distribution. The goodness-of-fit index test is done with a Chi-square test according to a p-value. The p-value indicates how well the specific distribution fits to the data. The data is in this case the interarrival times of emergency patients.

The interarrival times of elective patients have a bad fit index with different distributions. Because of the bad fit, another arrival pattern is made, namely the 'schedule' pattern. The schedule pattern is based on the average arrival rate per hour per specific day according to the real sampled data.

The second block is the decision if patients will be assigned to the isolation beds or non-isolation beds. According to the HRS data and a meeting with the hematologists 55% of the patients can be treated in an isolation bed and 45% can be treated in a non-isolation bed.

The third block is the Length of Stay (LoS) of isolation beds and non-isolation beds. The LoS histogram has not a good fit with different distributions. Therefore a scenario will be made with the original empirical LoS data for simulation.

The input aspects of the simulation model are the number of isolation beds, non-isolation beds and the number of reservations of isolation beds. The ranges of the number of isolation beds are 18 till 28 and for non-isolation beds are 0 till 22 with an interval of two beds. The number of reservations of isolation beds was a range of 0, 2 and 4. The end result is to determine the best variable combination which yields a waiting time less than 24 hours for emergency patients and has a minimum total number of beds. There are four scenarios made for the redesign situation and four scenarios for the future prognosis.

The conclusion of the simulation results for the redesign is that the combination of 22 isolation beds, 10 non-isolation beds and a reservation of four isolation beds is the best combination. The best combination is based on the waiting time that is less than one day for emergency patients and the lowest number of total beds. The average waiting time in this combination for emergency patients is 21 hours. The total number of beds is therefore 32. Because the expansion of these extra beds results in extra costs the redesign is not a good choice. And therefore it is preferable to maintain the 28 isolation beds in the current situation.

The conclusion of the simulation results for the future prognosis for the best combination is 24 isolation beds, 12 extra non-isolation beds and an allocation rule with four reservations of isolation beds for patients. The average waiting time for emergency patients is 19 hours. The total number of beds will be 36.

When the management of the hematology department wants to maintain the 28 isolation beds, 10 extra non-isolation beds will be sufficient to maintain the future growth scenario for 2015 with a reservation of four isolation beds. The total number of beds will be then 38 beds; this is the same number of beds from the queueing model G/G/m with correction. The correction is based on the difference between the queueing model and the historical data of the current situation.

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1 Introduction

The project has been performed at the inpatient department of hematology at the University Medical Center Nijmegen (UMCN), St. Radboud in Nijmegen, the Netherlands. In the first paragraph general information will be given about the UMC st. Radboud. In the second paragraph the hematology department and the inpatient ward will be explained. In the last paragraph the initial research problem will be given.

1.1 The UMC St. Radboud Nijmegen

The UMC St. Radboud is one of the eight university hospitals in the Netherlands and exists since 1956. The UMC St. Radboud is a center for patient care, education and research in cooperation with the Radboud University Nijmegen. The UMC St. Radboud is a leading academic centre with expertise in medical science and healthcare. The UMC St. Radboud is committed to excellence in patient care, science and research.

Patient Care	Number	Employees	Number
Visits to the outpatient clinic	146.389	Employees	9.973
Inpatient Admissions	29.080	Full Time Employee (FTE)	6.901
Day Treatments	45.326		
Visits at the emergency department	27.487	Education & Research	Number
Surgeries (elective)	19.379	Students in medical science	3.159
Nursing days	196.306	Diploma's	441
Beds	953	Dissertations	135
Bed Occupancy	63%	Scientific Publications	2.624
Average Length of Stay (days)	6.75		

Table 1 Statistical data of the UMC St. Radboud in 2010

To have an insight into the size of the hospital some statistical data is given according to the annual report of the UMC St Radboud hospital of 2010, see Table 1. The hospital has 146.389 patient visits at the outpatients' clinics, while 29.080 patients got admitted into hospitalization with an average length of stay (LoS) of 6.75 days. The average bed occupancy was 63%. In 2010 the UMCN has almost 10.000 employees. The employees are scientists, medical doctors, specialists, nurses, teachers, and supporting personnel. The number of students in the medical science is about 3000.

There are around fifty departments at the St. Radboud, among others oncology, internal diseases, surgery, intensive care, pediatric, and cardiology. The focus of the research will be at the inpatients ward of the hematology department. In the next paragraph further details of the hematology department will be described.

1.2 The hematology department

The research is focused on the inpatients ward of the hematology department; this is a sub specialism of the internal diseases department. The internal disease departments are located in the E-building and have nine specialisms, these are: general internal diseases, endocrine diseases, hematology, gastroenterology, nephrology, rheumatology, oncology, palliative care and nuclear medicine.

The department of hematology concentrates on the diagnosis and treatment of patients with blood diseases. The hematology department contains day-care facilities like the outpatient clinic, the

hemapheresis department and the haemophilia treatment center. The hematology department contains a hematology inpatients ward of 28 isolation beds (E00), see Figure 1.

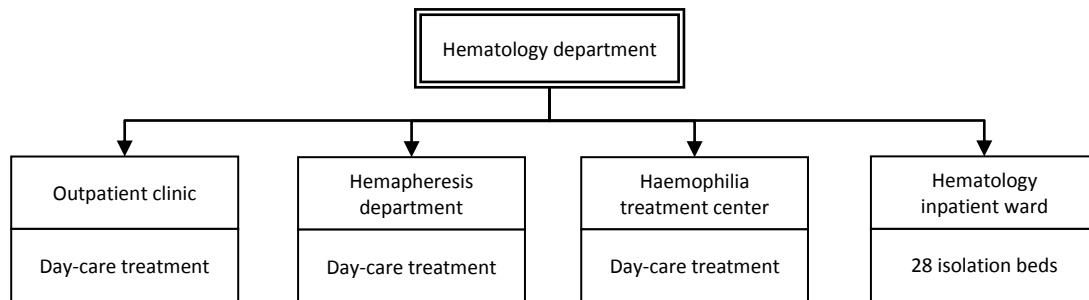


Figure 1 Organization of the hematology department

The first unit of the hematology department is the outpatient clinic, this clinic provides day-care treatments and polyclinic cares for hematology patients. The second unit is the hemapheresis department. This day-care treatment department will collect cell- or plasma components from the blood from patients and donors. The third unit is the haemophilia treatment center; this is a diagnosis and treatment center for haemophilia patients. This center cooperates also with the Pediatric department. The last unit is the hematology inpatients ward with 28 isolation beds. In this research, we will focus on the hematology inpatients ward where a more detailed explanation will be described in the next paragraph.

1.2.1 The hematology inpatients ward

The hematology inpatients wards contains 28 isolation beds which are intensive care beds, because most of the time the patients need a high intensive care during the treatments. Most employees are specifically educated to treat hematology patients. The hematology ward has 28 beds on E00 to hospitalize patients in special isolation rooms. There are 12 isolated rooms with one bed and there are 8 isolated rooms with two beds. The reason for having the isolation rooms is that most of the patients have a reduced immune system which makes them susceptible for infection, moulds and/or specific bacteria. The isolation rooms have positive-pressure ventilation and the air flow is cleaned with high-efficiency particulate air (HEPA) filters to prevent infection for the susceptible patients. The isolation beds are therefore more costly than standard hospital beds.

The patients at E00 are diagnosed and treated for severe malignant hematological disorders such as leukaemia, myelo-dysplastic syndrome, multiple myeloma, lymphoma, Hodgkin and non-Hodgkin. At E00, patients can be treated with a range of therapies such as chemotherapy, autologous stem cell transplantation (SCT) using a patient's own stem cells and allogeneic SCT using stem cells from a donor.

The hematology department of the St. Radboud hospital plays an important role in the region of south east Netherlands for treating hematology patients in cooperation with other hospitals. Not all hospitals in the Netherlands have a permit to perform stem cell transplantations. The main difference between the hospitals is that there are 'level A' and 'level B' hospitals (see Figure 2).

1. [UMCG](#)
[Level A]
2. [UMCN St Radboud](#)
[Level A]
3. [MST Enschede](#)
[Level B]
4. [AZ Maastricht](#)
[Level A]
5. [Erasmus MC](#)
[Level A]
6. [LUMC](#)
[Level A]
7. [Haga Ziekenhuis](#)
(Locatie Leyweg)
[Level B]
8. [UMCU](#)
[Level A]
9. [AMC](#)
[Level A]
10. [VUmc](#)
[Level A]



Figure 2 Overview of the cooperation of 'level A' and 'level B' hospitals that have a permit to perform specific SCT's (source: HOVON.nl)

A 'level A' means that the hematology department have a permit to perform an autologous stem cell transplantation (autologous SCT), and an allogeneic stem cell transplantation (allogeneic SCT). There are in total eight 'level A' hospitals in the Netherlands, these hospitals are all the academic hospitals in the Netherlands. 'Level B' means that the hospital only has a permit for autologous SCT, these are two hospitals in the Netherlands. These are the MST Enschede hospital and the Haga hospital in The Hague. The other dots on Figure 2 are other hospitals were the 'level A' and 'level B' cooperate with.

1.3 Initial research problems

The first impression at the hematology inpatient ward is that there are periods of time in which the demand of patients exceeds the capacity of the ward, which is governed by its maximum bed capacity. As a consequence, the admission of patients will be postponed or patients are refused and need to go to another department or hospital. According to the data 'Bed Monitoring System' the utilization of E00 beds in 2008 and 2009 was the highest of all other UMCN inpatient care departments.

The management of the hematology department wants to improve their financial situation. The hematology management and the board of the UMCN have conducted a report to improve the financial aspects. One of the conclusions was that the hematology department wants to admit more patients to suppress the fixed cost of the department.

On the one hand, the management indicated that the bed utilization at E00 is considerably high in the current situation. And on the other hand, the management of hematology wants to improve their financial aspects to admit more patients in the future to suppress the fixed costs. It is challenging to admit more patients when the bed utilization is already considerably high. The initial research problems are:

- Which factors are influencing the bed capacity of E00?
- Which factor has the most impact on the bed capacity of E00?
- Which method(s) can be used to determine the bed capacity?

With above initial research problems, the problem analysis is described by focusing on the current situation of the E00 bed capacity. The results of the problem analysis are presented in the next chapter.

2 Problem analysis at the hematology inpatient ward

In the past decades, there has been considerable pressure by the government and health insurance companies to reduce costs in the healthcare sector. As a reaction, researchers and healthcare professionals started investigating new ways to improve efficiency and to reduce healthcare costs (Jun et al., 1999).

The management of the hematology department has also been faced with the pressure to reduce costs and improve the financial aspects, while maintaining the commitment to offer the best care for the patients. As mentioned before the management of the hematology department wants to admit more patients, to suppress the fixed costs. Conversely the bed utilization of E00 is already considerable high. The medical resources of the hematology department are scarce and expensive. Therefore, an expansion of these resources, such as extra isolation beds or medical staff, is costly. Additionally, it is a challenge to meet the demand for hematology services with a sufficient internal bed capacity. The first step in the problem analysis is to discover which factors are influencing the bed capacity at E00. The second is to discover which factor has the most impact at the bed capacity of E00. The last step is indentifying a method that can be used to calculate the extension of beds when there will be more patients admitted in the future. To have a better insight of the hematology department, the patient flows will be discussed.

2.1 Hematology patient flows

This paragraph will describe the patient flows that go through the bed capacity of the hematology inpatient ward. This is done to have a better insight in the interactions between the hematology inpatient ward and other departments. There are three phases, namely the inflow, stay and outflow of patients, see Figure 4. First the inflow phase will be explained. There are in general two different inflows of patients, namely emergency patients and the elective patients.

The emergency patients arrive 24 hours during the day and are spread during the week. They are mainly arrived from the emergency department and must be served as soon as possible. Emergency patients have a higher priority than elective patients. Two beds are reserved for emergency patients to be sure that the emergency patient can be admitted. When an emergency patient arrives on the same day as an elective patient, the admittance of the elective patient will be postponed.

The elective patients can be planned by the doctor or planner and arrive mostly during daytime and on weekdays. When the admission for an elective patient has arrived and there are no beds available, the doctors and nurses will discuss if another patient can be discharged or sent to another department. If this is not possible, the patient that arrives will be placed at another department depending on the type of treatment the patient needs. When this is also not possible, the admission of the elective patient will be postponed.

The second phase according to the patient flows and Figure 4 is the stay phase. When a hematology patient is admitted at the inpatient ward E00 the patients will be treated. The current allocation rule is that all hematology patients will be admitted at the isolation beds of E00. The patients can leave the E00 department temporarily for a medical test or for a specific treatment that cannot be performed at the hematology inpatient ward. For example the patient can go temporarily to the MRI scan for a medical test or can go to a radiation treatment at the radiotherapy department. A

hematology patient can also be admitted at another department when this is possible. When the patient is critical the patient can be temporally referred to the intensive care.

The last phase is the outflow phase in which the patients are discharged. The patient can go home, can go to a rehabilitation center, or can be referred to another department. The most common reason that the patient will be referred to another department is that all beds are occupied at E00.

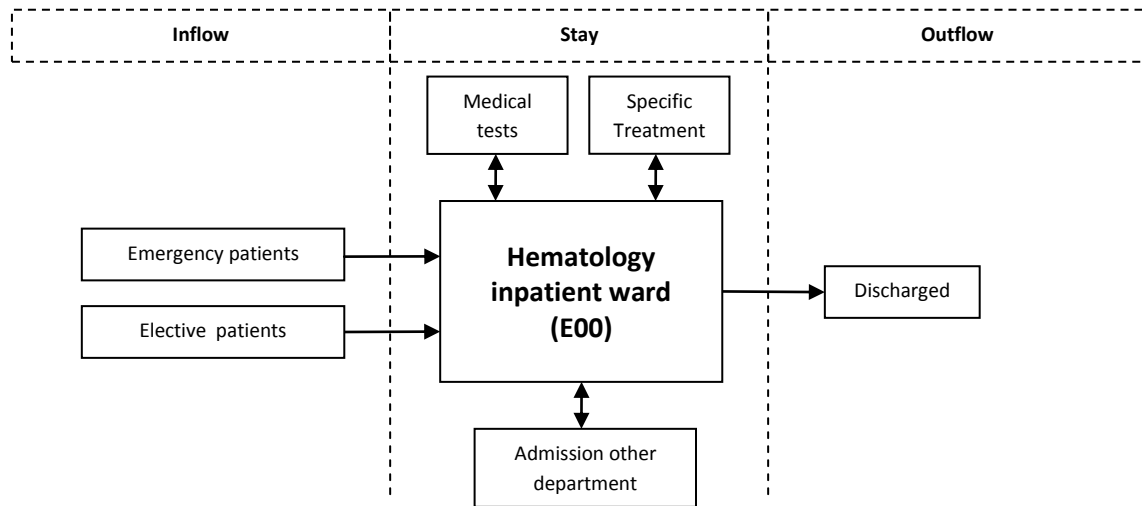


Figure 3 Patient flow at the hematology inpatient ward

The conclusion is that the hematology inpatient ward is generally an autonomous department; this means that the department is treating only hematology patients on strategy level, with limited interdisciplinary treatments with other departments. On operational level sometimes other patients than hematology patients will be admitted, this will occur when there are available beds at E00 for a longer period.

2.2 Current situation at the hematology inpatient ward

In the current situation, there are multiple defined factors that are influencing the bed capacity of E00. These factors came to light when conducting the interviews and are summarized in Figure 4. The intention is to describe the factors general and broad. It is namely unknown which factors are influencing the bed capacity of E00. The next step is when all the factors are summarized the factor will be identified that are influencing the bed capacity of E00 the most.

To have a better insight about the bed capacity of E00 and the factors that are influencing the bed capacity the current situation will be explained according to Figure 4.

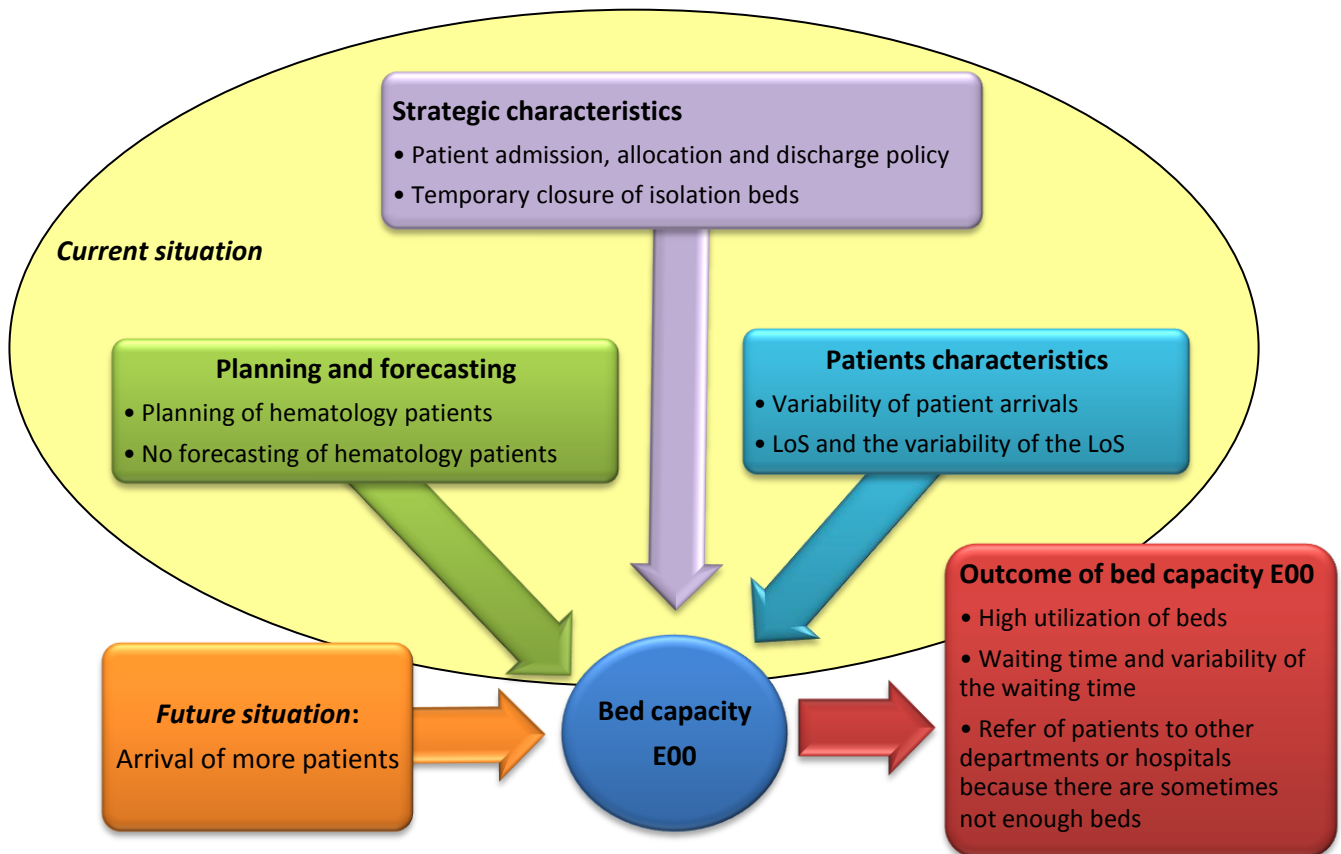


Figure 4 Factors that are influencing the bed capacity of E00

Figure 4 is divided in the current situation (the big oval) and the future situation (figure lower left). The goal of this figure is to show how the factors are related with bed capacity. The current situation is also divided into three parts, 1) strategic characteristics, 2) planning and forecasting, and 3) patient characteristics. Each problem is classified in these divisions. Some problems can be found from the available data. The search into the data is to 'validate' the outcome of the interviews. However, in the thesis the data will be explored to a greater extent. First the strategic characteristics in the current situation will be discussed.

2.2.1 Strategic characteristics

The first part of Figure 4 is the strategic characteristics; this paragraph will describe the factors associated with policy and execution of this policy by the management. In this paragraph the patient admission, allocation and discharge policy will be described. After this the temporary closure of isolation beds will be explained.

2.2.1.1 Patient admission, allocation and discharge policy

There are two operational admission rules in the current situation; the first rule is that all hematology patients entering the inpatient ward will be admitted at E00. The only exception to this rule is that there will be no patients admitted when all beds are occupied for a longer period. Therefore, there is an uncertainty of admission whether a patient can be admitted at E00. The second admission rule is that there is a distinction between non-emergency and emergency patients.

Generally, the process of the operational admission for patients at E00 is as follows. When a patient arrives at the outpatient department or emergency departments and the doctor wants to admit this

patient at E00, the doctor will fill in the preferred date of admission on a form. For emergency patients the admission must be as soon as possible, the prefer date will be the same as the date the doctor fill in the form. The reception office of E00 will subsequently enter the date into the computer system. When the preferred date of admission has arrived and there are no beds available, the doctors and nurses will discuss if another patient can be discharged or sent to another department or hospital. If this is not possible, the admission of the patient will be postponed or will be referred to another department. In general, two beds are reserved at E00 for the admission of emergency patients, in case all beds are occupied. In that way, the admission of emergency patients does not have to be postponed.

The current allocation rule is that all hematology patients will be allocated to the isolation beds of E00. There is no decision for example if a hematology patient can also be treated in a non-isolation bed. There are some hematology patients that are unnecessarily using the isolation rooms. There are treatments where it is not necessary to treat patient in an isolation room and there are treatments that patient must be in an isolation room. In the first case, the patient can be moved to another department right at the beginning of the admission, and stay there until the doctor(s) discharge the patient. In the second case the patient can change during a treatment between an isolation room and a non-isolation room. For example, a patient has to initially be treated in an isolation room due to a weakened immune system but when his immune system becomes increasingly stronger the patient can be transferred to a non-isolation room.

There is no discharge policy of patients; the discharge moment of a patient is decided on a daily basis when the team of medical experts agrees on this.

The conclusion is that there are ad-hoc decisions on an operational level, with limited strategic decision of patient admission, allocation and discharge policy.

2.2.1.2 Temporary closure of isolation beds

Sometimes an isolation bed will be temporarily closed at the hematology inpatient ward. The most common reason in 2009 for a bed closure (the bed is then becoming unavailable for patients) is when a bed is reserved for a planned admission of a hematology patient (see Figure 5). The second most common reason is that five out of the 28 beds are not available during ‘summer periods’ of six weeks because of lack of personnel. In 2011 the management of hematology decide that they will not close beds anymore during the summer periods and solve the problem of the absence of personnel.

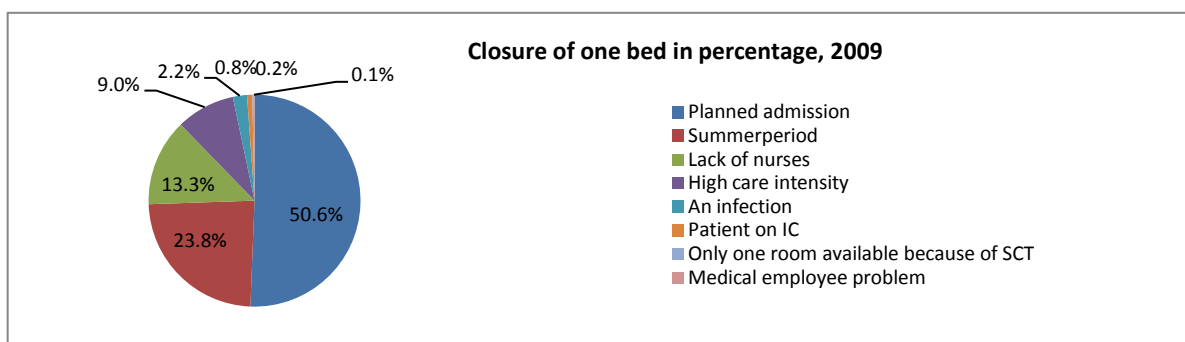


Figure 5 Reasons of closure of one bed for 24 hours, 2009 (source: reception data)

Another reason to close a bed could be that when there are not enough nurses, one or more beds will be closed. When, in this case, the bed would still be open, there is a chance that the quality of care will decrease because of the lack of nurses. 'High care intensity' means that the care for patients is high during a period. In order to achieve the same high quality of care, some beds will be closed if there are not enough extra nurses. 'An infection' means that a patient has an infection in a room of two beds, therefore a second patient in the room is not possible because of the infection of the other patient in the same room, this occurs when there are no available beds in a single person room. 'Patient on the IC' means when a patient is transferred from E00 to the intensive care (IC) an E00 bed will be reserved for 24 hours in case the patient comes back from the IC.

2.2.2 Planning and forecasting

The second part of Figure 4 is the planning of hematology patients. This is only conducted on operational level; at this level the scheduling of individual hematology patients will be done. There is no planning of strategic (long term) or tactical (medium term) level. There is no forecasting about the Length of Stay (LoS) of individual patients or possible revisits; this will be further explained in the paragraph forecasting.

2.2.2.1 Planning of hematology patients

The planner makes a schedule for the patients that have an SCT in the treatment path. It is a treatment path because different other treatments can be performed before or after a specific SCT, for example chemotherapy can be planned before a specific SCT. The planning strategy is only focused on the SCT treatment. This is one autologous- and one allogeneic SCT per week. The planning is done this way during the year, because when the planner will exceed the admission of more than two SCT's per week this will result in a high work pressure for the employees of E00 and for other departments that are related with hematology department for example the laboratory and radiology departments. Therefore, the maximum number of both autologous SCTs and allogeneic SCTs is 52 per year; the total is then 104 SCTs per year. When patients have no SCT treatment in the treatment path this will not be scheduled by the planner.

2.2.2.2 Forecasting of hematology patients

At the hematology department the doctors are not using forecasting information for planning purposes. For example, sometimes the doctors know beforehand that some patients will have a longer LoS than other patients. However, this valuable information will not be used for planning purposes. In addition, data from the history about possible planned or unplanned revisits of patients are also not used for planning purposes. For some specific treatments, the planner knows in advance that the patient will revisit E00. This will be taken into account when the planning is made. With most of the other treatments, there is a chance that the patient will revisit E00 but this will not be included in the planning.

2.2.3 Patients characteristics

In the third part of Figure 4 the patient characteristics will be shortly describe. This is the variability of patient arrivals and the LoS of patients according to the DBC data. The DBC data will be explored in more depth during the data analysis.

2.2.3.1 Variability of patient arrivals

According to the interviews and the DBC data of 2009, there is a considerable variability of patient arrivals. The average number of arrivals per week is 11.5 arrivals per week; this is 1.64 arrivals per

day. The standard deviation is 1.41 arrivals per day. The unit is arrivals and not patients per week, because it is possible for example that a patient will arrive in the beginning of the week and will be discharged and that the patient will arrive again at the end of the same week.

2.2.3.2 LoS and the variability of the LoS

The LoS is defined as the period of time between hospital admission and discharge at E00. The average LoS for 2009 was 11 days, with a standard deviation of 13 days according to the DBC data. Therefore, the variation is extremely high. Among other things, this is due to the outliers; the longest LoS was 110 days, see Figure 6 . This particular patient can be identified as a ‘bed-blocker’ (Harper, 2002). It is clear that high LoS has a negative impact on the bed capacity of E00. The LoS per different treatments will be also further discussed in the chapter data analysis.

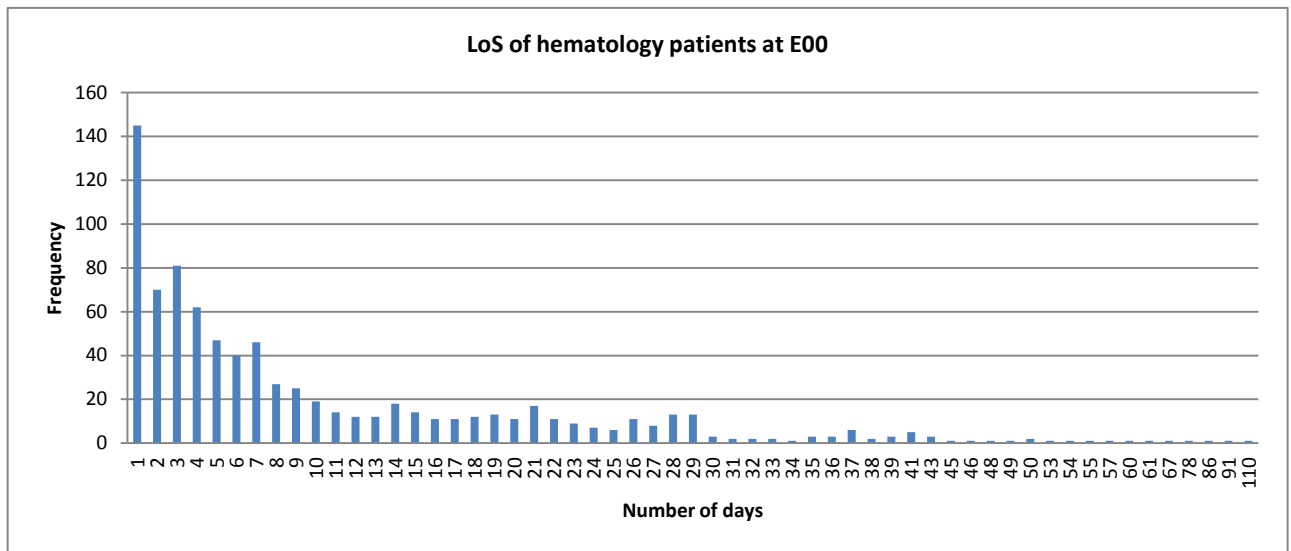


Figure 6. Length of stay for Hematology patients, 2009, Source: DBC

2.3 Future prognosis situation

The conclusion of the internal policy report by the hematology management that was sent to the board of directors at the UMCN was that the hematology management advises the board to expand the bed capacity of E00.

The management of hematology wants the department to grow, because they expect that more patients will arrive for treatments in the future. The management made a

Future prognosis: arrival of more patients. The reason that there are more treatments is that the region of care will be expanding to a huger area; this will lead to more competition between hospitals. The management of the hematology wants to know how many extra beds should be made available to fulfill the future demand of the patients.

2.4 Outcome of the bed capacity at E00

Changes in demand will influence the availability of bed resources. Later in this document the calculated future demand prognosis of the patients can be found. In this paragraph, the outcome of the calculation is based on the current situation.

2.4.1 High utilization of beds

The average bed utilization was 85% according to the data from the Bed Monitoring System. As mentioned before the utilization of E00 beds in 2008 and 2009 was the highest of all UMCN inpatient care departments. In the literature there is no general rule of an optimal utilization rate. A high utilization will enlarge the referral of patients (Cardoen et al., 2010). According to Houdenhoven et al. (2007), it is unlikely to have a healthcare process with 100% utilization, because of the inherent variability. A low utilization is costly because of expensive resources such as the isolation rooms not being used. According to the literature study by Hollander (2010), a trade-off between over-utilization and under-utilization is preferable. When the hospital only accepts a low risk with a complex mix of patients, this will result in a low utilization rate. When the accepted risk is higher and the patient mix is less complex, a high utilization rate can be reached (Houdenhoven et al. ,2007). According to Houdenhoven et al. (2007), a high utilization rate brings the risk of overtime, but also the risk that a bed is occupied. The dilemma faced by many hospital units is that they are financially forced to have high utilization and must increasingly reject then new patient admissions. McManus et al. (2004) shows that during periods of high demand, external requests for transfer are diverted to other institutions. Some patient admissions were refused and diverted to another department within the hospital, because a bed was unavailable in the primary unit and were considered “rejected” or “turn-aways”.

McManus et al. (2004) illustrate that there is a trade-off between the utilization and turn-away rate as the number of available beds varies. The trade-off is at a utilization of 85%. Utilization under an average of 85% produces lower rejection rates, and higher utilization above an average of 85% produces higher rejection rates. Also the number of beds are influencing the utilization rate, when there are a high number of beds, and a high utilization rate this situation has more flexibility in relation with the bed capacity than a situation with a low number of beds with the same high utilization rate. Both in practice and in simulation, turn-away rates increased exponentially when utilization exceeded 80-85%. Therefore, when utilization is maintained at high levels, there is an increasing probability that patients will be rejected from the system.

2.4.2 Waiting time and the variability of the waiting time

One of the outcomes of the interviews was that there is a high variability in the waiting times for patients, according to the data from the reception at E00, the average waiting time is 4 days with indeed a high variability, the standard deviation being 6.60 days. The definition of the waiting time

according to the management of hematology is when a patient arrives at the outpatient department or emergency department and the doctor wants to admit this patient at E00, the doctor will fill in the preferred date of admission on a form. The difference of the preferred date and the actual admission date is the waiting time. When the actual date is earlier than the preferred date, the waiting time will be zero. Some patients have to wait long before they were admitted; it is unknown why these patients were not referred to another department or hospital. However, most of the time patients do not have to wait (see Figure 7). The longest waiting period in 2009 was 38 days. It is unknown whether these patients in Figure 7 were elective patients or emergency patients. According to the DBC data in 2009, 37% were emergency patients and 63% were non emergency patients.

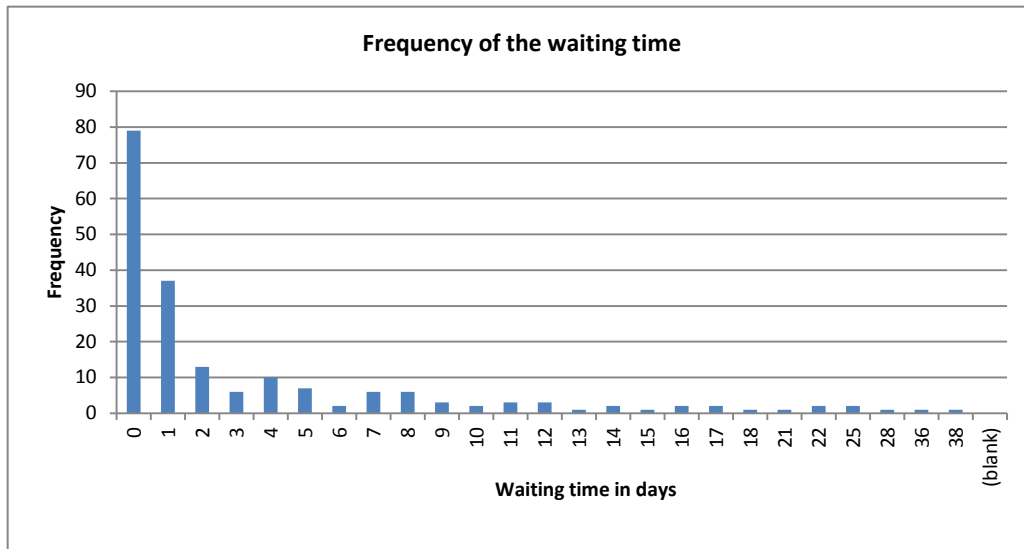


Figure 7 Frequency of the waiting time in 2009 at E00 (source: reception of E00)

The reception registered 187 waiting times in 2009, while there were 554 arrivals of patients at E00 in 2009. The different of 367 patients that are not registered at the reception is huge; the reason of this difference is unknown. The assumption is that the data of the reception is reliable, because of the limited number of registrations of the waiting time. There is no alternative registration data of the waiting time at E00.

2.4.3 Referral of patients

The reason that patients are referred to another department or to another hospital is because sometimes there are no available beds at E00. In the period of 2009 there was on average 0.85 bed continuously occupied by a hematology patient in another department in the UMCN hospital than E00. In 2009 from the 599 arrivals at E00 there were 12 hematology patients referred to another hospital.

2.5 Bed capacity determination method

The third initial problem question is to identify a method to determine the bed capacity. In the literature there are different methods to determine the bed capacity. According to Asaduzzaman et al. (2009) queueing theory and simulation are among the most popular and suitable healthcare modeling techniques to determine for example the bed capacity. The reason of this is because the care process is considered as heavily stochastic.

Queueing theory is a mathematical approach and is originated in the engineering industry for analysis and modeling of processes that involve waiting lines. Queueing analysis is dependent on accurate measurement of three variables: arrival rate, service time, and the number of servers in the system, in this case this will be the number of beds. The reason that queueing theory is used to determine the bed capacity is that most of the time queueing theory has accessible calculation.

Simulation is also useful to forecast the outcome of a strategy change or predict and evaluate an implementation of an alternative policy. Jun et al. (1999) summarizes more than 100 simulation papers that were applied in the healthcare. In general, simulation implies that rules and policies can help to balance the tradeoff between resource utilization and patient waiting times. Simulation can provide to evaluate 'what if' scenarios for example when deciding the number of beds that are needed to meet the demand and maintain the profitability of the hospital.

The article of Mustafee (2010) reports four simulation techniques these are, discrete-event simulation (DES), Monte Carlo simulation (MCS), system dynamics (SD) and agent-based simulation (ABS). Combinations of the different simulation techniques will be not considered in this report.

The first technique is DES, here the behavior of a model and therefore the system state, varies in time. DES is widely used to model queueing systems, planning of healthcare services like scheduling health staff–patient admissions appointments–ambulances, bed and equipment capacity (Katsaliaki and Mustafee, 2011).

The second technique is the MCS. This is a statistical technique, which uses a sequence of random numbers to generate values from a known probability distribution associated with a source of uncertainty. The MCS technique is formed by a class of computational algorithms that rely on repeated random sampling to compute a result. The MCS is in generally used when it is difficult to compute an exact result using fixed values or deterministic algorithms.

The third technique is SD, this is a modeling approach with the main focus on the analysis of the behavior of complex systems over time. SD engage feedback loops and time delays that affect the behavior of the entire system. SD enables to adopt a holistic systems perspective and uses stocks, flows, feedback loops to study and understand the structure of dynamic complex systems (Sterman, 2000). According to Katsaliaki and Mustafee (2011), SD is most used to evaluate public health policy and economic models like harm reduction policies, long-term health impact, disease population dynamics, treating strategies, reconfiguration of health services, health insurance strategies.

The fourth technique is the ABS, it has a bottom-up approach to model the behavior of the instrument that simulate the real-world system. The overall system behavior emerges a result of the actions and interact. ABS is particularly applicable for modeling scenarios where the consequences are not clear (Mustafee, 2010).

In this case to determine the bed capacity the simulation technique DES has the best overlap. In the sample review of the DES technique the simulation software Arena is the most popular, followed by the programming language Borland Delphi and COTS package Simul8 (Katsaliaki and Mustafee, 2011). The simulation program Arena will be therefore chosen to determine the bed capacity. The simulation program Enterprise Dynamics (ED) was also considered, although Arena was more user friendly than ED.

The possibilities for simulation model is unlimited, the model can be made as complex as the builder wants. According to Sinreich and Marmor (2004) it is therefore important to simplify simulation processes as much as possible. It is preferable that the simulation tool has the following principles (Sinreich and Marmor, 2004); it is desirable that the simulation tool can be used in general and is flexible enough to model different possible hospital settings. The tool has to be insightful, transparent. With these principles the hospital managers, engineers and other nonprofessional simulation modelers are able to use the simulation models with little effort. And the last element is that some default values for the system parameters are applicable in the simulation tool.

The conclusion is that simulation is the proper method to determine the bed capacity, because queueing theory cannot divide emergency and non emergency patients in the same model in combination that emergency patients has a higher priority in the waiting line than non emergency patients

2.6 Conclusion of the problem analysis

The problem analysis is broadly described, the reason for this is because it was unknown which factors are influencing the bed capacity of E00. According to Figure 4 there are now many identified factors that are related bed capacity of E00. The bed utilization of E00 is in the current situation already considerable high and in the future when there will be arrive more patients the utilization will be higher. An approximation by the medical experts is that 50 percent of the hematology patients can be also treated in a non-isolation bed. Therefore the factor that is influencing the bed utilization the most is the unnecessary use of isolation beds at E00.

The current allocation rule is that all hematology patients will be allocated to the isolation beds of E00. In the current situation some hematology patients are unnecessarily using the isolation rooms. There are treatments where it is not necessary to treat a patient in an isolation room and there are treatments which a patient must be in an isolation room.

There are different methods to determine the bed capacity. The most used methods to determine the bed capacity is queueing theory and simulation. These methods will be used to determine the bed capacity.

3 Research problem

The conclusion of the problem analysis was that the factor that is influencing the bed capacity the most was the unnecessary use of isolation beds by hematology patients. Therefore the next step is to determine which treatments should be carried out in non-isolated rooms and which treatments into an isolation room. The main focus is to determine the number of isolation beds and non-isolation at the hematology department for the redesign situation and the future prognosis situation. The difference between the current situation and the redesign situation is the differentiation between isolation beds and non-isolation beds. In the current situation there are only isolation beds.

The management of hematology has drawn up a policy report 'Hematologie in balans' for the middle and long term admissions. The future growth scenario has been established for the year 2011 to 2015. In this report, the management established a growth scenario to increase the number of treatments which results in an extension of the bed capacity of E00. The main problem the hematology management is facing is what the extension of isolation beds and non-isolation beds should be to satisfy the number of treatments that are described in the future growth scenario 2011-2015. In the current situation all hematology patients are treated in an isolation room, in the future situation some hematology patients could also be treated in a non-isolation bed.

According to the previous literature study of Hollander (2010), there is a lack of literature in different research areas. The areas with an overlap in the defined problems of the hematology departments are:

1. Patient's allocation rules to optimize bed capacity.
2. There are limited simulation models that have been developed to analyze arrivals at multi-departments, like an isolation room department and a non-isolation room department. The literature is mainly focused on the internal improvement of the facility utilization per department. There is limited literature on simulation models that can depict the interaction of different departments and the information that can be gained from analyzing the system as a whole.

The research problem contains an interesting input for enhancing the practical applications of research.

3.1 Research questions

Following from the research problem above, the central explorative research is formulated as follows:

"How many beds are necessary to fulfill the redesign scenario and the future prognosis scenario?"

The research question can be divided into four sub research questions, namely:

1. How should allocation rules be formulated to determine if a patient must be treated in an isolation bed or a non-isolation bed?
2. How many isolation beds and non-isolation beds are necessary to fulfill the redesign scenario?
3. How many isolation beds and non-isolation beds are necessary to fulfill the future growth scenario?

4. How many isolation beds need to be reserved to have an adequate waiting time for patients?

The research questions are now formulated, the research objectives that are related with the question can be determined.

3.2 Research objectives

The vision of the UMCN is to offer a high quality healthcare in order to be able to help patients as quickly, friendly, efficiently and effectively as possible. The outcome of this project should be relevant to the UMCN by helping the hospital with allocation rules for patients that enhance an efficient use of the isolation beds. Moreover, the design of a simulation model can be used for healthcare processes in general, which a positive contribution to science in the field of healthcare operation planning.

The practical objective of this project is to provide recommendations to the board of the hematology department, on how more treatments can be performed by an effective use of the isolation rooms and non-isolation rooms. With the following additional objectives:

1. Define allocation rules to determine which treatments should be carried out in non-isolated rooms and which treatments into an isolation room.
2. Determine the number of isolation and non-isolation beds that are needed in the redesign situation.
3. Determine the required bed capacity to fulfill the growth scenario according to the policy report "Hematologie in balans" growth scenario 2011-2015. The required bed capacity represents the number of beds required for the satisfaction of future patient demand. The required bed capacity will be the number of isolation beds and non-isolation beds for the hematology inpatient department (E00).
4. The number of reservations of isolation beds which yields an adequate waiting time for patients. The current adequate waiting time for emergency patients is to admit the patient as soon as possible. An adequate waiting time will be determined during the interviews with the medical experts.

3.3 Scope of the research

There is the following scope on the research:

- Research will be conducted on the bed capacity for the hematology inpatients ward.
- The LoS of patients will be not reduced.
- The research will mainly focus on bed resources. The bed resources are divided in non-isolation bed and isolation room beds. In the current situation there are single patient isolation room and a double patient isolation room. The delimitation is that in the simulation the isolation rooms are not divided in single patient isolation room and a double patient isolation room. The main reason is that the available data was not easy to extract if a patient must be treated into a single patient isolation room or a double patient isolation room. The data was available, but the information must be collected per patient, and a doctor must identify per patient if the patient can be treated into a single patient isolation room or a double patient isolation room. Because of this costly process, it was chosen to simulate only

based on isolation beds with no differentiation on single patient isolation room and double patient isolation room.

- The focus will not be on employee resources, other departments or other resources.

3.4 Methodology

To answer the research questions a methodology will be used with the following three steps.

The first step is a data analysis to have a better insight in the current bed utilization, the most executed treatments at the E00 inpatient ward and the current LoS of patients. Process mining will be used as a methodology in the data analysis to determine the main patient paths. These paths can be used as input for the simulation model. Process mining can be a technique to obtain meaningful knowledge about care flows or clinical pathways (Mans et al., 2004). Process mining can provide new insights related to care paths that are followed by particular groups (Mans et al., 2004). When the patients groups are known, the arrival and arrival pattern of these groups will be determined in the current situation. According to the hematology management report there is an estimation made of the number of patients that will arrived in the future prognosis situation. The last paragraph in the data analysis will be the forecasting by random picking of patients in the future arrivals. This will be used as input for the queueing model and simulation model.

The second step in the methodology is to use queueing theory. Queueing theory is applicable to calculate the number of beds when the norm is known for the average waiting time. On the one hand the total number of beds can be determined; on the other hand distinction between different beds is not possible. Therefore queueing theory will be used to answer the general question of “how many beds are necessary to fulfill the future prognosis scenario?”. Before this question can be answered, the outcome of the queueing model will be compared the current situation, with of course the input of the historical data of the current situation. The outcome of the queueing theory will be compared the outcome of the simulation.

The third step is to make a simulation model. Simulation can make a distinction between isolation beds and non-isolation beds. In addition, simulation is also able to evaluate different reservation of isolation beds to find the adequate waiting time for patients. Therefore a simulation model will be used to determine the number of isolation and non-isolation beds for the redesign situation and the future situation.

In the conclusion the research question will be answered with the results of the queueing model and simulation model.

As described in the methodology the first step is the data analysis, this will explained in the next chapter.

4 Data analysis

This chapter emphasizes data collection, a data analysis about the bed utilization and LoS in the current situation. After this the most used patient frequent paths will be identified with the data mining program ProM. When the patient groups are identified, the arrival of these patients will be determined. The data that will be used for the queueing model and simulation model will be explained. In the last paragraph in this chapter there will be a forecast about the future prognosis situation with the arrival of more patients.

4.1 Data collection

First the data collection will be described, the main question is where the data for the data analysis comes from. Different data sources were used to perform this research. The data sources were used as input for the data analysis, process mining, queueing theory and the building of the simulation model. Four different data sources were used; 1) the DBC data, this is in Dutch the “Diagnose Behandeling Combinatie”, 2) the HRS data, this is the data from the Hematology Registration System, 3) the Bed Monitoring System, this is an application that is following the bed occupancy rate and 4) the data from the reception of the hematology department.

The DBC data is used as the main data. There was among others information about the arrival of patient, discharge of the patients and if a patient was labeled as an emergency patient. The HRS data was used to determine if a patient must be treated in an isolation bed or a non-isolation bed. The Bed Monitoring System is used to extract data regarding the occupied beds during the hospitalization of hematology patients. The hematology reception data was used to calculate the bed utilization and to determine the waiting times of hematology patients. The waiting time is defined as the difference between the time the doctor wants to admit the patient at the hematology inpatient ward and the actual time the patient is admitted.

4.2 Data input for the queueing – and simulation model

In this paragraph the data input will be described for the queueing – and simulation model. The main data is as mentioned before from the DBC data. Another data base is the Hematology Registration System (HRS). The DBC and HRS data are coming from a dataset with execution data spanning period from January 2009 to December 2009.

The following useful information is available from the DBC data; the date and time of arrival of a patient, if the patient is classified as an emergency patient and the date and time of discharge of a patient. With the date and time of the arrival and discharge of the patient the LoS of the patient is then also available.

The HRS data is used to identify the patient that can be treated in an isolation bed or a non- isolation bed, depending on which treatment is needed. The differentiation is done using the treatment list that is made as a result from a meeting with all the twelve hematologists at the hematology department. See the result in appendix B. One treatment is labeled in the appendix as ‘combination’; this means that the patients are sometimes treated in an isolation bed and sometimes in a non-isolation bed. There is a lack of information if the patient can be treated in an isolation bed or a non-isolation bed; therefore the assumption is that all the treatments will be treated in an isolation bed, because this is the safest situation for a hematology patient that possibly has a weakened immune

system. The current situation is that all treatments are done in an isolation bed. The redesign is that some treatments can also be performed in a non-isolation bed.

A part of the HRS data of the treatments was classified as “others” and “unknown”. “Others” means that there was another treatment than the regular treatments on the treatment list, see appendix B. The class “others” is 13 percent of all the treatments in 2009. Some treatments were identified as unknown; this is because there are patients that are treated according to the DBC data that were not on the HRS data, this was 28 percent of all the treatments in 2009. The patients classes “others” and “unknown” cannot be identified if these patients must be treated in an isolation bed or a non-isolation bed, therefore the percentage of the isolation bed and non-isolation bed that are known are used to classified the patients classes “others” and “unknown”. The result of the data that was known is that 45% of all patients are treated in an isolation bed and 55% is treated in a non-isolation bed. Therefore the assumption is that for the unknown data the same proportion is used in comparison with the data that was known. Therefore the end result is that 55% of the patients can be treated in an isolation bed and 45% in a non-isolation bed.

Several assumptions are made during the data analysis.

- Patients that are discharged and are admitted again at the hematology department are seen as new arrivals. One patient can have multiple arrivals.
- The treatment classes “others” and “unknown” have the same differentiation percentage for isolation beds and non-isolation beds as the treatment classes that are known.

The data plays an important role for the input of the queueing- and simulation model. To secure that the DBC data is reliable and valid, an interview with the reception (that is responsible for the input of the data) is performed. Also an analysis of the patient arrivals revealed that the reception registers the patient directly during the admission of the patients. There were no bulk arrivals of patients in the same time frame. The DBC data registered the arrival date and time of the patients, and the discharge date and time. The validity of the DBC data was checked if the number of patients that are admitted at E00 was exceeding the number of 28 isolation beds at E00. The number of beds was not exceeding the maximum in the DBC data. The DBC data and the HRS data were compared to each other. There was a difference between the numbers of patient arrivals. The HRS data registered only 360 patient arrivals in 2009, the DBC registered 599 patient arrivals in 2009, the difference is 239. The DBC data registered also hematology patients that are admitted elsewhere then E00; this was 45 patients in 2009. The difference is then still 194 patients. During interviews the reason for these differences were asked to the reception and to the medical specialists but the reason for this difference was unknown. The patient arrivals and discharge dates that were registered in HRS were to a large extent the same as in the DBC data. From an interview with the reception it was clear that DBC data had more realistic number of patients per week then the HRS data. The assumption is that the validity of the DBC data is mainly not at risk. Nevertheless the conclusion is that it was very hard to discover en reveal reliable basic data about the arrival of hematology patients and their LoS.

4.3 Bed utilization of hematology

The average bed utilization was 85% according to the data from the Bed Monitoring System and according to the 'reception data' the average bed utilization was 92% in 2009, see Figure 8. There is a difference between the bed utilization lines in Figure 8. However the utilization lines are following each other quit well. The difference/trend between the 'reception data' and the Bed Monitoring System is nearly constant. According to the reception of E00, which keeps daily registration, the average bed utilization (before 8 o'clock in the morning) is 92%. The difference in percentage might be explained by the number of registrations moments during the day. The Bed Monitoring System has a constant registrations and the reception has registration points on a daily basis.

According to Figure 8 there is also a variation in the utilization during the year. In the beginning of 2009 and in October of 2009, there was a low utilization in comparison to the rest of the period. However, during the summer period (from July 20th to Augustus 30th), there was a utilization of more than 100%. This can occur when during the summer period beds which are not made available are used for the benefit of capacity. The utilization of E00 had the highest utilization rate in 2009 of all inpatients departments at the UMCN.

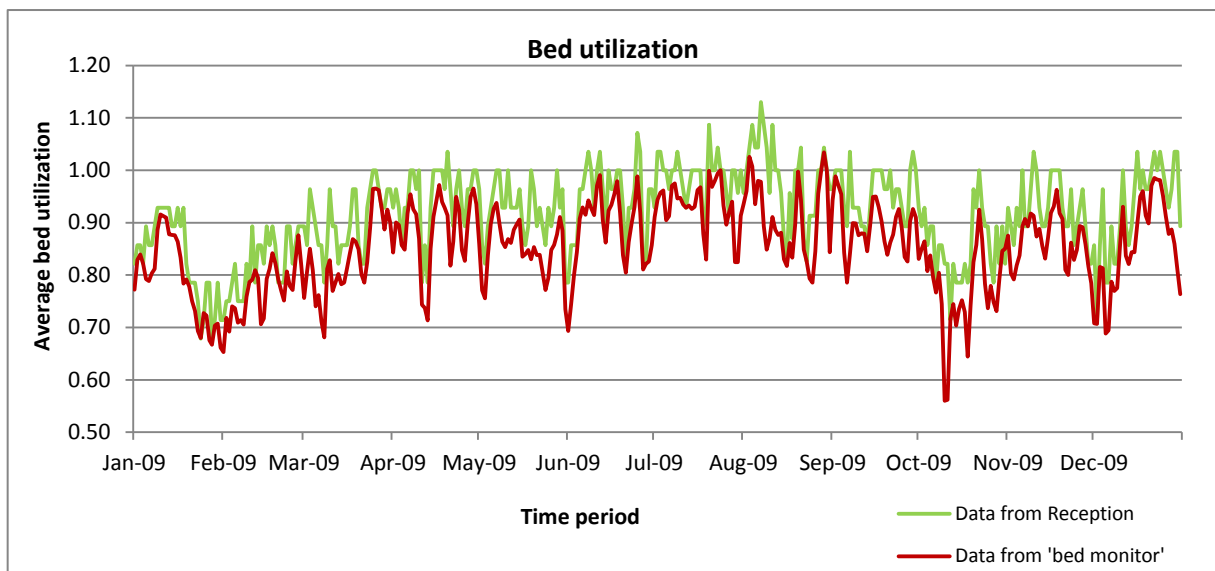


Figure 8 Average bed utilization in 2009 at E00

4.4 Length of Stay

In the problem analysis the average and the standard deviation was given about the LoS. In this paragraph a deeper data analysis will be given. There are different treatments performed at the hematology inpatient ward. In 2009, around 550 hematology patients were treated (source: DBC system) in different treatment groups (Figure 9). The total length of stay (LoS) is shown in Figure 9 as a percentage per treatment. Figure 9 shows the sum of the LoS of hematology patients per treatment group, divided by the sum of all the LoS of all hematology patients at E00 in 2009. The data in Figure 9 is from the hematology registration system (HRS). The LoS is defined as the time between the date of admission and date of discharge of the patient at E00.

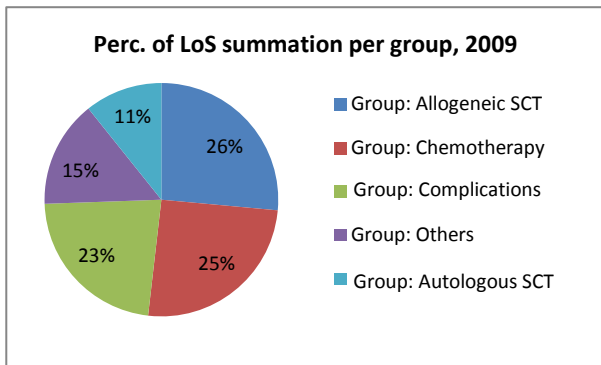


Figure 9 LoS summation of all treatment per treatment group in percentage at Hematology, 2009.

Source: HRS data, dr. P. Donnelly

In Figure 9 there is also a patient group that has complications after a treatment. This can occur after a specific treatment and sometimes the doctors know before the treatments which complication can occur.

Treatments that are not included in Figure 9 are: the day admissions, the donor admissions, diagnosis and the 'empty' fields. The reason for the exclusion is that there were only 17 day admissions (17 patients with a total of 17 days in 2009) and only seven donor admissions (seven patients with a total of 11 days in 2009). The diagnosis registrations are not included because they contain a lot of errors; a possible reason could be that the status of the patient in the computer will not change in time. The sort of treatment is unknown when the treatment is labeled as an 'empty' field and therefore no information can be found on what a possible admission reason would be. The group 'others' is a treatment group that has another treatment than the regular treatments that are summarized in appendix B.

From Figure 9 it is concluded that the 'Group: Allogeneic SCT' has the largest bed capacity impact on E00. Now with the program process mining will be used to identify patient groups.

4.5 Process mining

In a complex environment like the hospital it is important to characterize individual patients into patient groups. The reason is that it is hard for planning, scheduling and simulation reason to focus on individual patients. The process mining framework contains patient classification techniques to identify patient groups. According to Harper (2002) patient groups can be used to develop simulation models. The main question to be answered with process mining is to discover the most frequent patient paths. When this is known a simulation model can be made with the most used frequent patient paths.

The hematology treatment process is a complicated care process with different care flows. A possible technique to obtain meaningful knowledge about care flows or clinical pathways is process mining (Mans et al., 2004). Process mining can provide new insights related to care flows like; the identification of care paths followed by particular groups of patients or collaboration between departments (Mans et al., 2004). The idea of process mining is to discover, monitor and improve real processes with no assumption beforehand of the process. This is done by extracting knowledge from event logs, which are registration points during the process that is accessible in data of the process (Mans et al., 2004). The software ProM framework is used to analyze and describe the care flows.

The first step in a process mining is the collection and formatting of the data needed to perform the analyses. The data that is used is in Dutch and from the Hematology Registration System (HRS) and is used with real execution data, coming from a dataset with execution data spanning period from January 2008 to March 2010. The following relevant information is available: Event logs of the date of arrival of a specific patient, the date of discharge of a patient and the sort of treatments of the patients. Every patient has a unique identification number, therefore the revisits of the patients at the hematology department are then also known. The input of the HRS data is from the reception of the hematology department in cooperation with the sort of treatment that is filled in by the medical specialist.

The input of the ProM framework needs to be in a MXML format, this stands for Mining eXtensible Markup Language. This is performed with the “User manual for converting data from a Microsoft Access Database to the ProM MXML format” (Mans, 2009). The data preparation of process mining is not the primary focus of this research, only the results of this process will be shortly discussed.

The input of the HRS data is based on Microsoft Excel format, the data is reconstructed to Microsoft Access with the underlying database structures that is formatted conform the manual according to Mans (2009). By reordering and pre-processing the data in this format and then converting it with the ProM Import framework, the MXML format event-log was realized. The final product of the MXML format contains only the relevant attributes that were needed for data mining purposes.

Key Data from ProM	Number
Cases	298
Event types	2
Events	1346
Event classes	34

Table 2 Key data from the data mining program ProM

Now the data is formatted in the program Prom, the key data is available. The practical meaning of the key data of ProM is as follows (see Table 2), the cases are the number of unique patients, there were in this log 298 unique patients. In the time frame of January 2008 to March 2010 there were a total 673 arrivals, but there were 298 unique individual patients, therefore some patients were revisiting the department several times. In this log there are two time stamps per treatment, this is the ‘start’ timestamp when the treatments is started and the ‘complete’ timestamp when the treatment is finished. The number of events are the total number of events, these are 1346 events this is include the ‘start’ and the ‘complete’ timestamp of a specific admissions. This means that there were 1346 divided by two (‘start’ and the ‘completed’ timestamps) 673 admissions of patients for different treatments. This means that there were more admissions than patient. With other words some patient were admitted for several times at the inpatient ward. There were 34 event classes, this means that there were 17 different treatment types; this is also divided by two because of the two different timestamps.

The first technique is the heuristic mining algorithm, according to Weijters and van der Aalst (2003) this technique can deal with noise and exceptions, filtering out non-relevant details and thereby focusing on the main process in the process log. The end result of the heuristic algorithm (see appendix A1) is a spaghetti model (Mans, et al. 2004). To make the model easier to read, the frequency paths of less than 5 percent of the total will be deleted in the model, see appendix A2. The conclusion of the model in appendix A2 is that the main frequent path is the path “others” (in

appendix A2 this is in Dutch “overige”). This means that it is still unknown which treatments “others” means, the only thing is known that it is not the treatments that are summated in appendix B.

The process is visualized in Appendix A1 with the program ProM. From interviews there is also a treatment process visualized see appendix A3. The process of appendix A1 and A3 are different, because appendix A1 is mainly focused on the treatments, and appendix A3 from interviews is linked with the diseases and the treatments.

The conclusion is that the hematology treatment process is a complicated process that will be difficult to simulate based on the process mining outcome, therefore a simplification must be made to simulate the hematology treatment process.

4.6 Arrival of patients

The conclusion of the previous paragraph was that the most frequent patient path are the patient path with the treatments “others”. This means that it is still unclear to classify the arrival of patients in specific patient group.

The deviation of patients is chosen according to Jun et al. (1999) this is that the demand for clinic beds can be decomposed into both emergency (unscheduled) and elective (scheduled) arrival. The reason is that this is the most logical distinction about the arrival of patients, because of the “natural” unexpected arrival pattern of emergency patients and the “unnatural” expected arrival of elective patients. Emergency patients can arrive 24 hours during the day. Elective patients are arrived according the schedule that is made by the planner. Therefore for the simulation model the patients will be divided into the arrival of emergency and elective patient. The arrival of patients can be divided into emergency patients and elective patients. According to the DBC data there were a total of 599 patients arrived at the hematology inpatient ward in 2009, 222 emergency patients this is 37 percent and 377 elective patients this is 63 percent. Therefore there are more arrivals of elective patients than emergency patients.

There are made two graphs to have a better insight about the patient arrival pattern for emergency and elective patients in 2009. The first graph is the arrivals of patients that are during the day per hour. The second graph is the arrival of patient per day in the week.

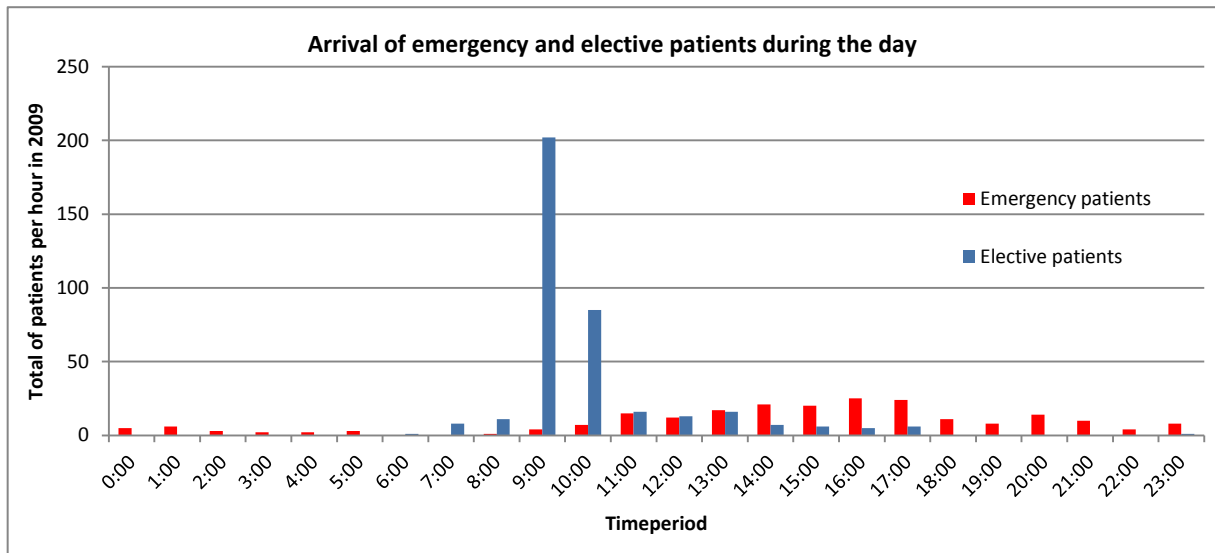


Figure 10 Arrival of patients during the day in 2009

The horizontal axis of Figure 10 is the time period during the specific time; this means for example the time period 8:00 means the arrival patients during the time frame of 8:00 and 8:59. The first thing that can be noticed is the different of the arrival pattern of emergency patients and elective patients. The main difference is that emergency patients are mainly spread during the day and elective patients arrived during daytime. This is also logical because the elective patients are patients that are planned during daytime. The second thing that can be noticed is that there is a peak of the arrival of elective patients in the time period of 9:00 till 9:59 o'clock, see Figure 10. During this time period there is an arrival of 202 elective patients, compared with four emergency patients. A possible reason is that the elective patients are admitted before 10 o'clock is that the doctors are visiting the patients at 10 o'clock to evaluate the medical condition of the patients. The emergency patients are arrived also more during daytime then in the night, a possible reason is that most emergency patients arrive from the outpatient's clinic that is open during daytime.

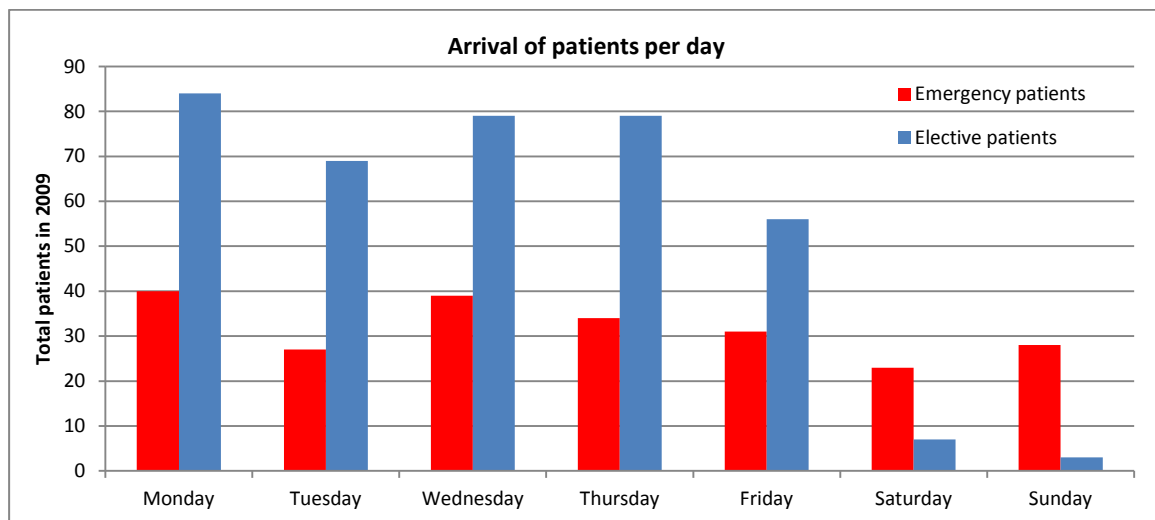


Figure 11 Arrival of patients per day in 2009

As mentioned before there are more arrivals of elective patients then emergency patients, this is also visible at Figure 10 and Figure 11. The arrival of emergency patients per day is nearly constant, see

Figure 11. The arrival of elective patients per day is also almost constant, except on Saturday and Sunday. Generally there are no admissions of planned patients in the weekend; the reason for these arrivals in the weekend is unknown. A possible reason could be that these arrivals were emergency arrivals instead of elective patient arrivals.

Some patients arrive for the first time at the hematology inpatient ward and some patients have a revisit. A revisit is a visit of a hematology patient to the E00 department after a previous treatment at E00. 63 percent of all E00 patients will visit E00 two or more times. The other 37% will only visit the E00 department once (see Figure 12). The expectation of patients revisiting more than once has a great impact on the capacity E00, this is approximately 50% on the bed capacity (Figure 12, source HRS, period Sept. 2005 to Dec. 2009). The most general reason that a patient will revisit the department is because the patients must treat several times.

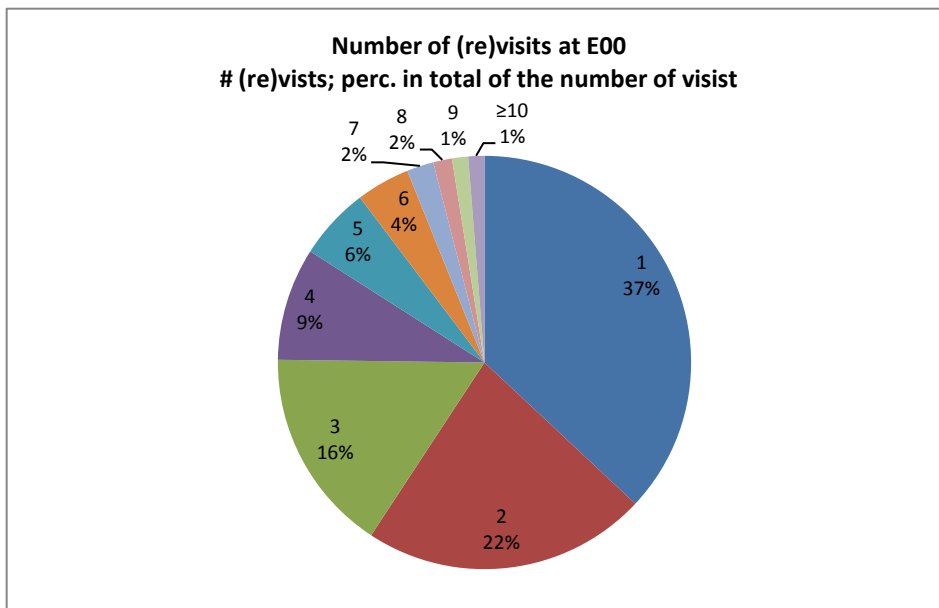


Figure 12 Number of revisits of hematology patients at E00 in percentage (source: HRS, period sept-2005 till dec-2009)

The conclusion of the arrival during the day (see Figure 10) is that there a huge difference between the arrivals of emergency and elective patients. The arrival of emergency patients is general constant during the day, and the arrival of elective patients is concentrated at 9 and 10 o'clock in the morning. The conclusion of the arrival of patients per day (see Figure 11) is that elective patients are mainly not arrived in the weekend. Most of the time when a patient arrived at the hematology inpatients ward the patient will revisit the department several times. Combination of these findings in the literature and in the data it is a proper choice to divide the patient arrival into the arrival of emergency patients and elective patients for simulation purposes. Now the distinction is known about the arrival of emergency and elective patients, the future prognosis of the arrival of more patients will be calculated.

4.7 Future prognosis: arrival of more patients

To answer the research question about the number of beds that are needed to fulfill the future growth scenario, the future prognosis must be calculated. The management of hematology expects that there will be arrive more patients in the future. These are the future prognosis or the future growth scenario and this will be the input for the queueing- and simulation model. The queueing and simulation model will be used to calculate the number of beds. Therefore an approximation must be made for the future growth scenario to determine among others the arrival of patients in the future.

The input of the approximation of the future growth scenario is according to the policy report “Hematologie in balans” for the middle and long term admissions. The future growth scenario has been established for the year 2011 till 2015; see Table 3 for the SCT’s treatment. The growth scenario is based on more SCT’s per year. Not all patients at E00 have an SCT treatment (allogeneic or autologous SCT) in their individual patient paths. According to the DBC data 56 % of the patients in 2009 have not a SCT treatment in there patient path. The assumption from the hematology policy report is that in 2015 this percentage of the patients that have none SCT in their treatment path will be the same as in 2009. The management of hematology established a growth scenario to increase the number of SCT treatments which results in an extension of the arrival of patients and the bed capacity of E00. The year 2009 is used as input for the queueing model and for the simulation model. The data of 2009 is used to determine the arrival pattern and the LoS. The year 2009 is chosen because from the outcome of the interviews it was clear that 2009 was a representative year for the queueing model and simulation. The year 2010 was namely not a representative year, because the target of 95 SCT’s for 2010 was not reached that year. The future prognosis is used for the year 2015, in this year the management of hematology wants to see more patients treated. The year 2015 is used because the expectation is that in this year the most SCT’s will be performed. Therefore the expectation is that in the year 2015 the maximum number of beds will be occupied.

SCT’s	2009	2010	2011	2012	2013	2014	2015	Different of 2009 and 2015
Allogeneic SCT	56	60	65	70	80	80	90	+34
Autologous SCT	61	35	45	58	60	60	60	-1
Total of SCT’s	117	95	110	128	140	140	150	+33

Table 3 The year 2009 till 2012 and the prognosis of the number of SCT’s per year

Most of the time patients have more treatments than one and will revisit the hematology department (see Figure 12), these are the individual patient paths. This is also the case for the SCT treatments. An SCT treatment is most of the time not one treatment that stands alone. Most of the time a SCT treatment has another treatment before and/or after. For example the individual patient paths begins with a chemotherapy, the patients will be temporary discharge at the inpatient ward, then the patient will be admitted again and the SCT treatment will be performed. In this case the patient will arrive two times, while there is only one SCT treatment. Therefore there will be more arrivals than only the SCT treatment. In the queueing and simulation model, revisits will be seen has new arrivals. Therefore it is not possible to only increase the arrival rates with for example 34 more arrivals for allogeneic SCT’s, because the allogeneic SCT treatment stands not alone. Therefore there will be a random picking of the individual patient paths.

In 2015 there are more SCT treatments then 2009, to determine the arrival pattern and the LoS in the future prognosis of 2015 is based on a random picking of individual patient paths of 2009. Based on this fact there are 34 allogeneic SCT (see Table 3) individual patient paths randomly allocated

from the DBC data of 2009, this is the extension or the different of 2009 and 2015 for allogeneic SCT's. For the autologous SCT, there is one individual patient path based on a random allocation reduced for the prognosis in 2015, see Table 3. There are 34 allogeneic SCT individual patient paths copied from the DBC data of 2009 to forecast the growth scenario. In the future prognosis file there are now 34 identical allogeneic SCT individual patient paths. And one autologous SCT individual patient paths is reduced, see Table 3.

For the simulation input there are now double identical allogeneic SCT's individual patient paths, there is a modification of the double arrivals. The arrival date and the discharge date is delayed with two weeks of all the random picked treatments, the identification number of the patients is also changed, all the other information of the patients will be the same, this is the LoS, the labeling if the patient is an emergency patient or an elective patient, and the sort of treatments in the patients paths.

As input for the queueing – and simulation model the future prognosis in 2015 there are now a total of 150 SCT's treatments (see Table 3). As mentioned before the SCT treatments are not standing alone, but have different individual patient paths, copied from 2009. Therefore there are 66 more arrivals and not 33 (see Table 3). The expected total arrivals are then 665 (66 plus 599) for 2015. The conclusion is that for the queueing- and simulation model the arrival for 2015 will be 665 arrivals. Now the total number of arrivals is known in the future scenario a queueing model can be chosen and a simulation model can be made to determine the number of beds that are needed to fulfill the future demand of hematology patients.

5 Queueing theory

5.1 Introduction

Queueing theory can be used to determine the total number of beds in the future scenario. According to the literature queueing theory is originated in the engineering industry for analysis and modeling of processes that involve waiting lines. This theory enables managers to calculate the optimal supply of fixed resources necessary to meet a variable demand. A partial classification of queueing systems is given by Kendall's notation, which characterizes a queueing station by means of four parameters (Hopp and Spearman, 2008). The notation is $A/B/m/b$ where A describes the distribution of the interarrival times, B describes the distribution of process or service time (in this case the LoS), m the number of servers (number of beds) in the system and b is the maximum number of jobs (number of patients) that can be in the system. Typical distributions for A (arrival) and B (service time), along with their interpretation are; D for constant (deterministic) distribution, M for exponential (Markovian) distribution, G for completely general distribution. There are more distributions although these values are the most common distributions in queueing theory. m the number of beds and will be in this case variable, for example m will be 28 beds for the current situation. In our case the queue size is not restricted and the Kendall's notation will be then $A/B/m$.

For example the queueing model of Liyanage et al. (1995) assumes that daily admission rates (arrivals) follow a Poisson distribution and that durations of stay (service times) are either constant or follow an exponential distribution. The authors observed the monthly admission rates, available beds, and stay durations as inputs, monthly utilizations and rejection probabilities for the critical care resources for a period of two years at the ICU. These observations were used as an input for the queueing model. The patient arrivals rates were found to be random, and this randomness permitted successful application of a standard stochastic model, that assumes a Poisson distribution. The chosen queueing model in the article is denoted as $M/M/m/b$, which means that the inter arrival times follow a Markovian distribution, which are modeled as a Poisson process, Markovian service times, m servers, and b patient spaces in the system.

Kim et al. (1999) looked at the arrival and service-time data and attempted to determine whether the data followed the Poisson and exponential patterns. In the LoS data, there were outliers. The authors excluded all the outliers from the analysis and thereby reduced the total ICU beds with one bed, assuming that the outliers are covering one ICU bed during time.

5.2 Selection of the queueing model

The input for the queueing model is gathered from the DBC data based on real execution data, coming from a dataset with execution data spanning period from January 2009 to December 2009.

The main question will be to choose a proper queueing model for the hematology case for the situation in 2009 and the future prognosis situation in 2015. With a queueing model it is for instance possible to determine the total number of beds with a norm of the average waiting time for patients.

There are two distinctions made between patients for the queueing model. The first distinction is the hematology patients that are admitted at E00, this will be noted as "E00 patients". The second distinction is the hematology patients that are admitted at E00 and other departments, a notation for this situation will be "all hematology patients".

The arrival date and time of the patients in the DBC data of 2009 is used to calculate the interarrival times of the patients. This is done by first sorting the arrival data in a chronological order and then subtracts the arrival date and time of the first patient from the second patient, and the second patient from the third patient etc. The interarrival time for all the four situations has a high standard deviation; the standard deviation per situation is higher than the average per situation. Therefore the interarrival time does not follow a constant (deterministic) distribution.

The second distribution to compare the arrival rate with is the exponential (Poisson) distribution. In the healthcare queuing theory is broadly the most used arrival rate (Brahimi and Worthington, 1991, Green 2005, Green and Nguyen 2001, Gorunescu et al. 2002, Kim et al. 1999, Liyanage et al., 1995, McManus et al. 2004, Milne and Whitty, 1995 and Worthington, 1987). When the interarrival times are known a histogram is made to test the goodness-of-fit an exponential distribution on the hand of the Chi-square test, see Figure 13. The chi-square test will be used as methodology to quantify the goodness-of-fit test with a distribution and a sample test.

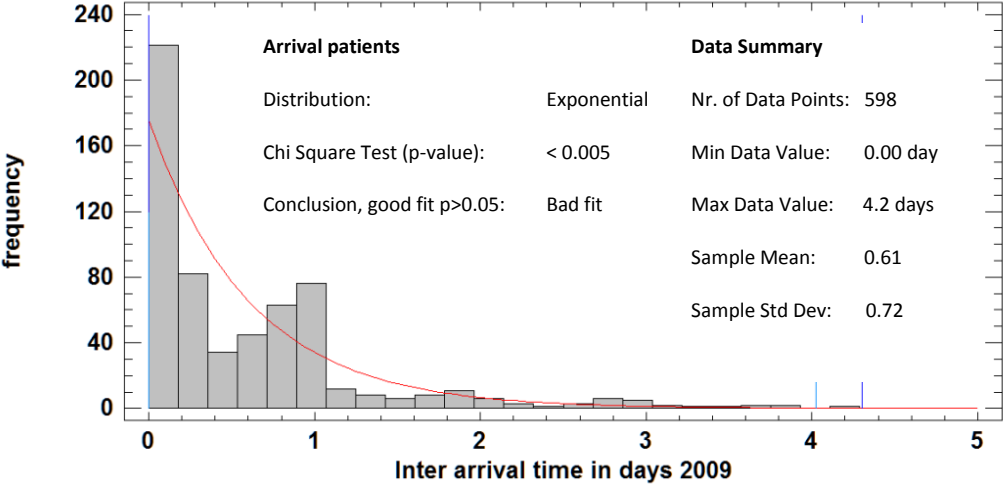


Figure 13 Histogram showing the frequency of the interarrival times of all hematology patients in 2009

The Chi-square test is the most widely used test for goodness-of-fit of a distribution to a sample test (Altiok and Melamed, 2007). The p-value indicates how well the specific distribution fits to the data. The norm of the p-value will be 0.05 according to Altiok and Melamed (2007) and Kim et al. (1998). When the p-value is smaller than 0.05, it can be assumed that the dataset does not fit from the selected distribution with 95% confidence. When the p-value is larger than 0.05 it can be assumed that the data follows the specific distribution. In general; how higher the p-value, how better the fit.

According to Statgraphics Centurion there is a bad fit index for the interarrival time of 2009 for hematology patients, because the outcome of the smallest p-value amongst the tests performed is less than 0.05. Statgraphics reject therefore the idea that Interarrival time 2009 for hematology patients comes from an Exponential distribution with 95% confidence.

The same method is used for the other three situations which are the E00 patients in the current situation, the hematology patients in the future prognosis and the E00 patients in the future prognosis. The p-values are also less than 0.05. Therefore these situations are also not according to

an Exponential distribution with 95% confidence. The three different histograms are not visualized in figures.

The last distribution to compare with is the G for completely general distribution, this is also the distribution to choose when the interarrival times are not constant or nonexponential (Hopp and Spearman, 2008). Therefore the assumption of the interarrival time is chosen is according to the G for completely general distribution.

Now the Kendall's notation for the arrival rate is known, the distribution of the LoS will be determined also for the four situations. The LoS is not distributed according to a constant (deterministic) distribution, because the four situations have a large standard deviation.

The other distribution to compare with is the Exponential distribution. This distribution is used by Green (2005) and Green and Nguyen (2001). For the four situations the p-values are less than 0.05. Therefore the four situations are also not according to an Exponential distribution with 95% confidence. For the first situation, this is the LoS of 2009 for all the hematology patients, a histogram is visualized in Figure 14.

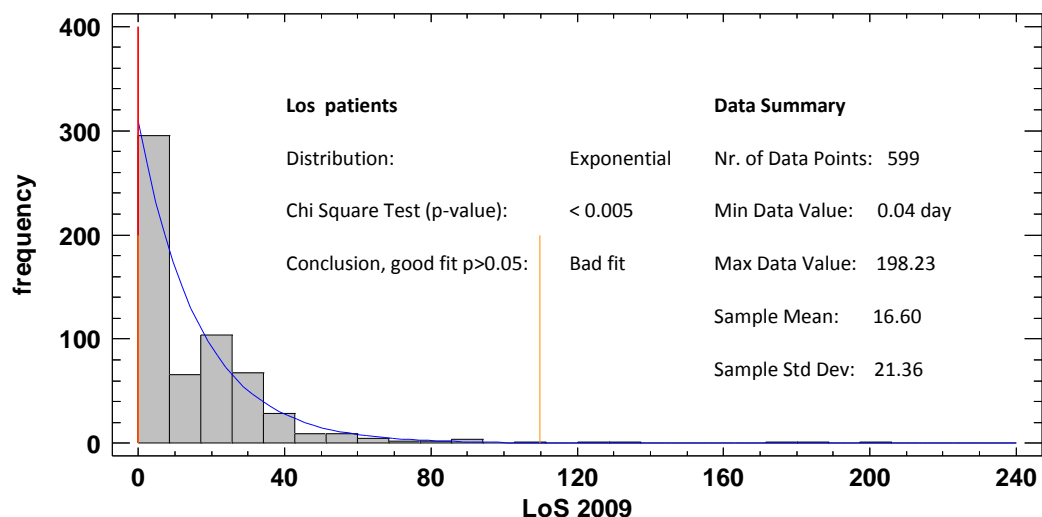


Figure 14 Histogram showing the frequency of the LoS of all hematology patients conform an Exponential distribution in 2009

The LoS data is not constant and have a non exponential distribution therefore the assumption of the LoS chosen is according to the G for completely general distribution. Now the queueing model is known, this is the G/G/m model. This model is also chosen according to Bruin et al. (2010) in their healthcare queueing model.

5.2.1 Queueing model (G/G/m)

With the G/G/m queueing model it is among others possible to calculate the average waiting time per patient with a formula and to determine the total number of beds. In the model all patients are the same and are waiting in a single queue with no bulk arrivals according to the priority rule FCFS (first come first served). The beds are identical of each other with the same LoS. This priority rule is a limitation of the model because in reality the emergency patients will have more priority than the elective patients; this will be further explained in the next chapter. The m is the number of beds and will be the variable in the queueing model from $m = 27 \dots 50$ beds.

$$CT_q (G / G / m) = \left(\frac{c_a^2 + c_e^2}{2} \right) \left(\frac{u \sqrt{2(m+1)-1}}{m(1-u)} \right) t_e$$

Hopp and Spearman, (2008)

Where:

CT_q = average queue time for a patient

c_a = coefficient of variation of the time between arrivals to a station

c_e = coefficient of variation of effective process time (LoS) at a station

u = utilization with the formula $u = \frac{r_a t_e}{m}$

r_a = rate of arrivals in patients per unit time

t_e = mean effective process time (average LoS)

m = number of beds

Now all the variables are known the total beds can be calculated with the different waiting times for the patients.

5.3 Results of the queueing theory

The average waiting time for E00 patients of the queueing model in 2009 is 13 days for 28 beds, see Table 4. The reason that there are empty fields in Table 4 is that there are of course only data of the current situation that has 28 beds. According to the data of the reception in 2009 the average waiting time for E00 patients is 4 days with a standard deviation of 6.60 days. As mentioned before the definition according to the hematology department of the waiting time is when a patient arrives at the outpatient department or emergency department and the doctor wants to admit this patient at E00, the doctor will fill in the preferred date of admission on a form. The difference of the preferred date and the actual admission date is the waiting time. When the actual date is earlier than the preferred date, the waiting time will be zero. This definition general fits with the definition of the waiting time according to the queueing theory. The definition according to the queueing theory is the time between a patient arrive at the hematology department and the patient is being treated.

Number of beds (m)	Average waiting time queueing model In days	Historical data (reception) Average waiting time in days
27	59	
28	13	4
29	6	
30	3	

Table 4 Average waiting time for E00 patients 2009 according to the queueing model G/G/m, range m = 27 ..30

The different between the model and the current situation is still 2 beds extra for the queueing model (30 beds minus 28 beds). In the queueing model the average waiting time of three days at 30 beds is general the same in the current situation of four days. Therefore the assumption is that a correction of two extra beds at the queueing model is a proper enough for validation based on the historical data.

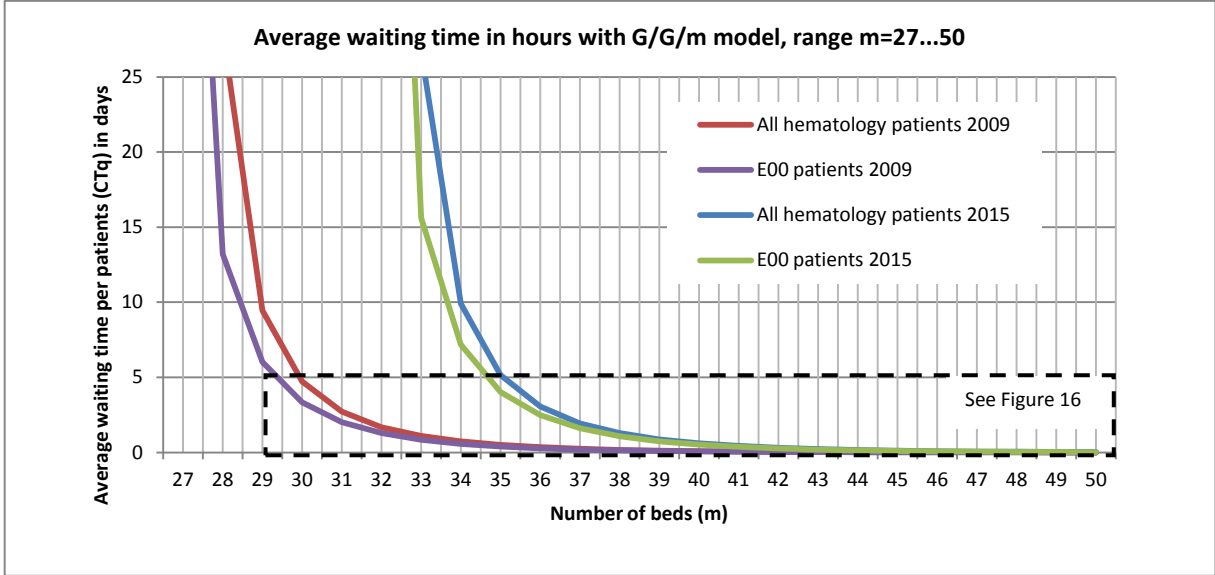


Figure 15 Outcome of the average waiting time per patient in days according to the queueing model G/G/m, range m = 27...50

In general, the higher the variance in either interarrival times or LoS, the longer the average waiting time. According to Figure 15 when the number of beds increases, the average waiting time will decrease exponentially.

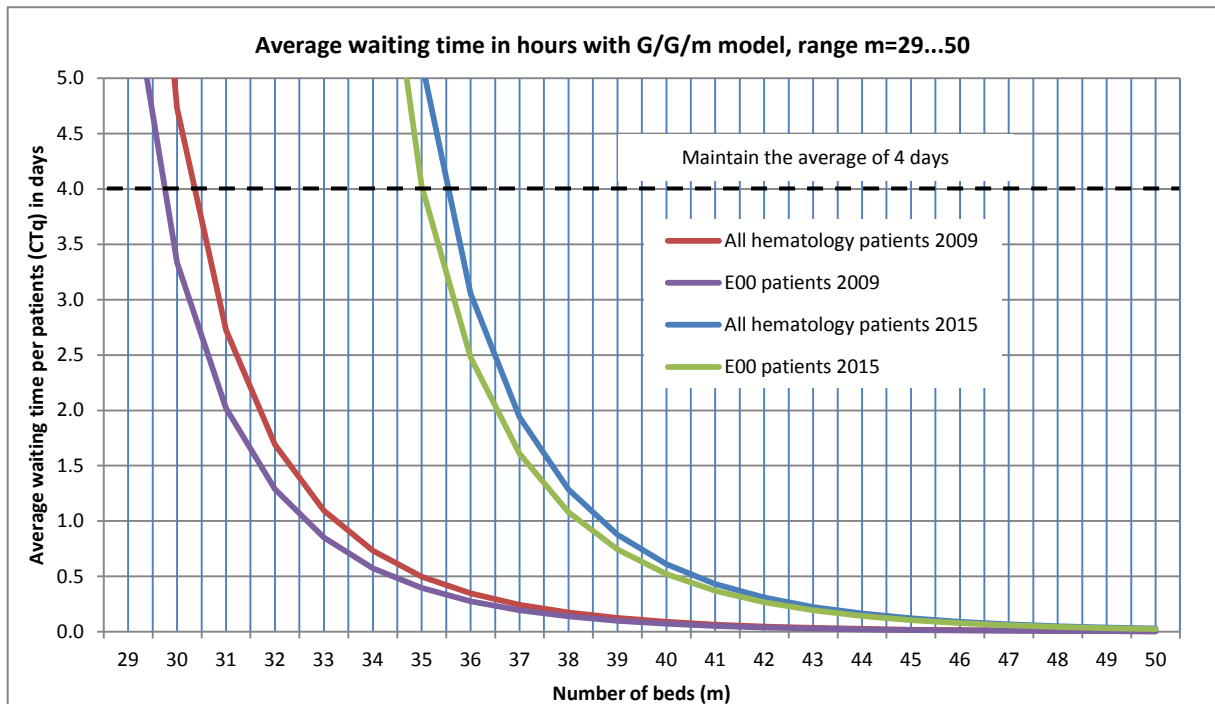


Figure 16 Outcome of the average waiting time per patient in days according to the queueing model G/G/m, range m = 29...50

It is difficult to determine an average norm for hematology patients for the waiting time. In the arrival of patient there are some patients that are emergency patients and some patients that are elective patients. To have an approximation for the future prognosis the average of 4 days of 2009 will be chosen to determine the number of beds. For the future prognosis if all the hematology patients will be admitted, a minimum bed capacity of 36 beds will be appropriate enough to fulfill the future demand. With a correction of two extra beds this will be 38 beds. To admit the E00 patients, a minimum bed capacity of 35 beds will be enough to fulfill the future grow. With the same correction of two beds this will be 37 beds.

According to McManus et al. (2004) most proposed queueing models have unfortunately a lacked real-world validation. The queueing model has also some limitations. The limitations are:

- The queueing model is not able to interact with different resources for example isolation beds and non-isolation beds.
- It is not possible to have another priority rule then FCFS for example that emergency patients have a higher priority than elective patients.
- Reservation of resources for example beds for emergency patients is not possible.

The G/G/m model is a general model when the arrival rate and the service time don't fit with a distribution. Therefore a simulation model will be made to handle these limitations. Nevertheless the outcome gives a good approximation of the total number of beds.

6 Simulation

6.1 Introduction

According to Asaduzzaman et al. (2009) simulation and queueing theory are among the most popular and suitable healthcare modeling techniques because the care process is considered as heavily stochastic. There were several limitations for the queueing model that was described in the previous chapter; therefore a simulation model is made to handle these limitations.

In this chapter a simulation model will be described that will be used to simulate the redesign scenario and the future prognosis scenario with different variables. The simulation model is made to evaluate different scenarios. The simulation model is built with the Arena program from Rockwell Automation.

Simulation is broadly applied in the healthcare for example Jun et al. (1999) summarizes more than 100 simulation papers that were applied in the healthcare.

According to Mustafee (2010) simulation is valuable in providing evidence and insights to deal with stochastic systems. Simulation is also useful to forecast the outcome of a strategy change or predict and evaluate an implementation of an alternative policy.

6.2 Design of the simulation model

The design of the simulation model is visualized in Figure 17. The simulation model is a simplification of the real hematology treatment process; the reason is that the 'real' treatment process is too complex for simulation, see appendix A1. This appendix is the outcome of the heuristic mining algorithm based on the process mining tool. The input of the process mining was the HRS data, the conclusion of the HRS data was that these data was not realistic, this is based on interviews. The outcome from these interviews was that the DBC data was more realistic based on the number of arrivals of hematology patients. The simulation model is built into three main blocks.

The first block is the arrivals of the emergency patients and the arrival of the elective patients. There are three different scenarios for the patient arrivals; this will be further explained in paragraph 6.3.1. After the patient arrival, the emergency patients will be labeled as a high priority; this means that the emergency patients have always the first priority into the waiting queue in comparison with the elective patients.

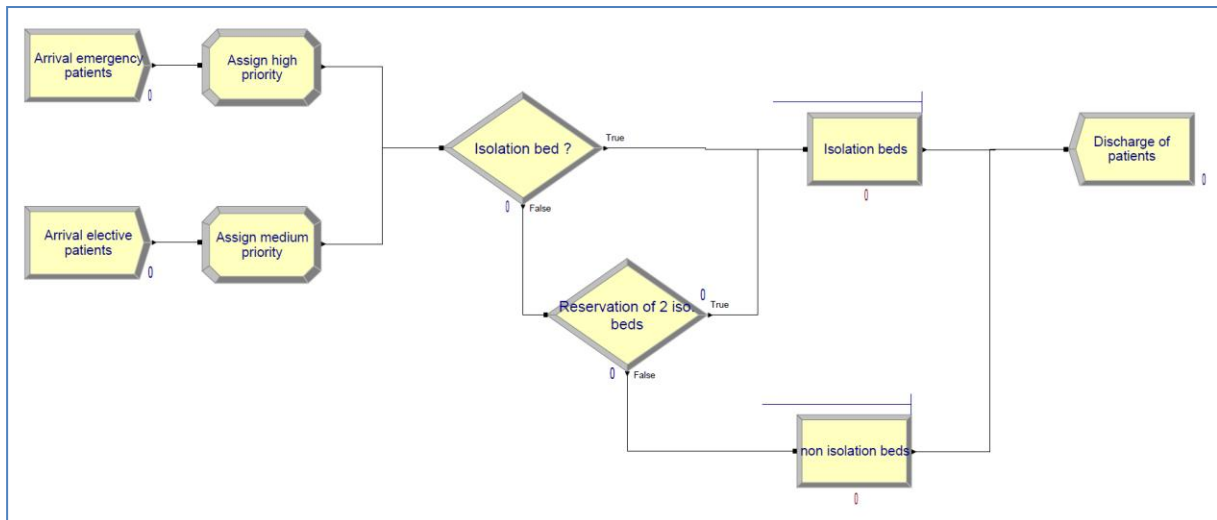


Figure 17 Simulation model built in the application Arena

The second block is the decision if the emergency patients or the elective patients will be assigned to an isolation bed or a non-isolation bed, this is named as “Isolation bed?”. Based on the history of the HRS data of 2009, and the list on appendix B is that 45% of all the hematology patients must be treated in an isolation bed. The second decision element is the number of reservations of the isolation beds, the reservation variable is described in paragraph 6.3.3. When patients are assigned to a non-isolation bed in the first decision element, it is still possible that the patient will be assigned to an isolation bed; this is for example when the variable is made on four reservations of isolation beds. This means when there are more than four available isolation beds, a non-isolation bed patient based on the first decision element will be assigned to an isolation bed based on the second decision element. The patient could be an emergency patient or an elective patient. The reservation is done in order to secure that the isolation beds will be occupied, because of the fact that the isolation beds are expensive resources. And therefore a low utility of the isolation beds is not preferable.

The third block in the simulation model is the simulation of the LoS of isolation patients and non-isolation patients. The LoS is based on the DBC data of 2009. The assumption is that the patient flow has no interaction with isolation beds and non-isolation beds, after the treatment. There is namely no line between the isolation beds and non-isolation beds see Figure 17. The simulation model is made when for example a patient will be discharged at the isolation bed and will be admitted to a non-isolation bed will simulated as a new arrival.

The last element is the discharge of patients; the patients will leave the simulation model. Possible revisits of patients will be simulated as new arrivals.

6.2.1 Simulation runs and warming up period

The length of a simulation run was one year. There were 20 simulation runs to encounter the reliability of the output of the simulation. A long run will encounter for a steady state behavior of the system. The total time of simulation for one combination was therefore 20 years. The warming up length was determined with the average utilization of the bed capacity for isolation beds and non-isolation beds. This was done by the following steps, when the average utilization of the beds was reached 90% for the first time, the simulation run was stopped and the execution time was written up. This was done by all the 30 combination of 2009 (see appendix C) for the first scenario in 2009.

The average warming up length was 35 days. For all the other simulation runs 35 days was taken for the warm up period. The reason to determine a proper warm up period is that at the beginning of a simulation run the model is empty, and therefore this will influence the output of the simulation. Therefore the registration of the output will be done after the warming up period of the model.

6.3 Input aspects

The simulation model has different input aspects. These are; different arrival patterns of patients, the resources (isolation beds and non-isolation beds) and the number of reservations for the isolation beds. The future prognosis is also an important aspect..

6.3.1 Different arrival pattern of patients

The arrival date and time of the patients is used to calculate the inter arrival times of the patients. This is done by the same method that was described in the previous chapter to calculate the inter arrival times for the queueing model. As previously mentioned, in the period of 2009 there was on average 0.85 bed continuously occupied by a hematology patient in another department in the UMCN hospital than E00. These patient arrivals are also included into the total arrival pattern of patients. The main distinction is the arrival of emergency patients and the elective patients. The first intention is to simulate the patient arrival conform a specific distribution. The program Arena has a tool "Input Analyzer" which compares the data to different distribution functions. There are ten different distributions made in this tool these are Beta, Empirical, Erlang, Exponential, Gamma, Lognormal, Normal, Triangular, Uniform, Weibull distributions. The tool will compare the data with the distribution with a best fit index according to the lowest squared error parameter.

According to the "input analyzer" tool, the inter arrival times of the emergency patients in 2009 are following a Beta distribution, because from all the ten distributions the Beta distribution has the lowest square error of 0.002448.

Now the best fit is known from the ten different distributions using the square error, the tool "Input Analyzer" will give also the p-value of the Chi-square test. As mentioned before the Chi-square tests are the most widely used tests for goodness-of-fit of a distribution to a sample test (Altiok and Melamed, 2007). The p-value indicates how well the specific distribution fits to the data. The norm of the p-value will be 0.05 according to Altiok and Melamed (2007) and Kim et. al. (1999). When the p-value is smaller than 0.05, it can be assumed that the dataset does not fit from the selected distribution with 95% confidence. When the p-value is larger than 0.05 it can be assumed that the data follows the specific distribution. The emergency patient arrival has a p-value of 0.199, this is a good fit, see Figure 19.

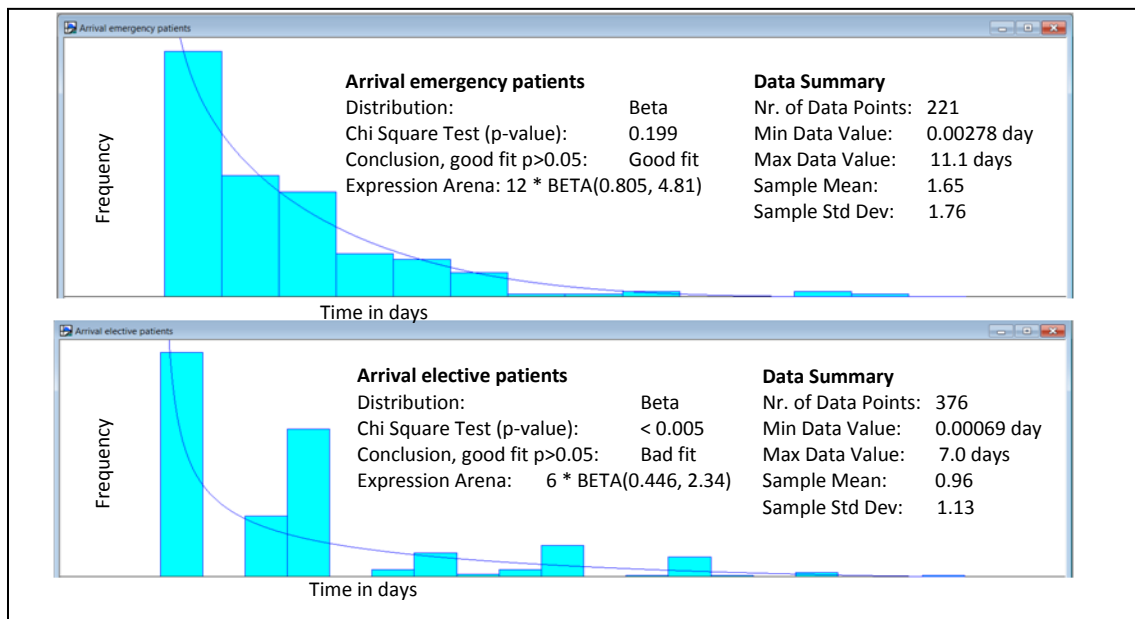


Figure 18 Histogram showing the frequency of the interarrival times of patients of the **current situation** for emergency patients and elective patient conform a Beta distribution

The histogram of the arrival of elective patients, see Figure 19 has some empty fields, this are “artificial gaps”. These artificial gaps occur because there is almost no arrival in the weekend and in the evening periods. For example when the last patient is admitted at Friday it will take two days (Saturday and Sunday) when the next patients will be admitted on Monday. The reason is that there will be no admission of elective patients during these periods, because elective patients are scheduled according to the planner and there is no admission in general in the evening or weekend. Emergency patients will always be admitted irrespective of the time or specific day. It was also possible in the simulation to delete the artificial gaps for the arrival pattern of elective patients. This will encounter a more natural arrival pattern for elective patients, compared to the natural arrival of emergency patients. The drawback was that then the arrival of patients was much more than the arrival pattern with the artificial gaps. That results in substantial more number of beds and a difficulty to calculate the number of beds based with the arrival patterns with the evening and weekend gaps. Therefore it is chosen to simulate an arrival pattern with the artificial gaps.

The elective patients are following also a Beta distribution, however this has a bad goodness of fit index because the p-value is under the norm of 0.05, see Figure 19. A reason that the elective patient arrival has a bad goodness of fit index can be that these patients are scheduled according to the planner. Because of the bad fit, another arrival pattern is made, namely the ‘schedule’ pattern. Therefore the second combination is that the emergency patients arrivals follow a specific distribution and that the elective patients are simulated with a scheduled pattern. This is done to calculate the arrival per hour of patients with the real arrival pattern data, in other words, the average arrival of patients per day and per hour in 2009. An example of the pattern is visualized in Figure 19.

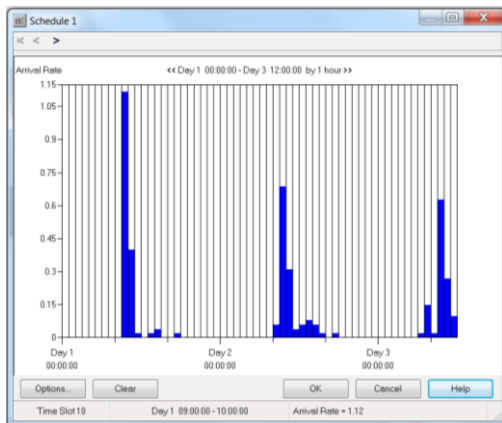


Figure 19 Example of a schedule arrival pattern for elective patients of the current situation

The third combination is that the emergency- and elective patient arrivals are simulated both according to a scheduled pattern. The fourth possible combination, this is when the emergency patients are scheduled and the elective patients are according a specific distribution is not simulated, because there was a bad goodness of fit index of the elective patients.

The future situation is also visualized in Figure 21, the future prognosis has also three combinations of patient arrivals.

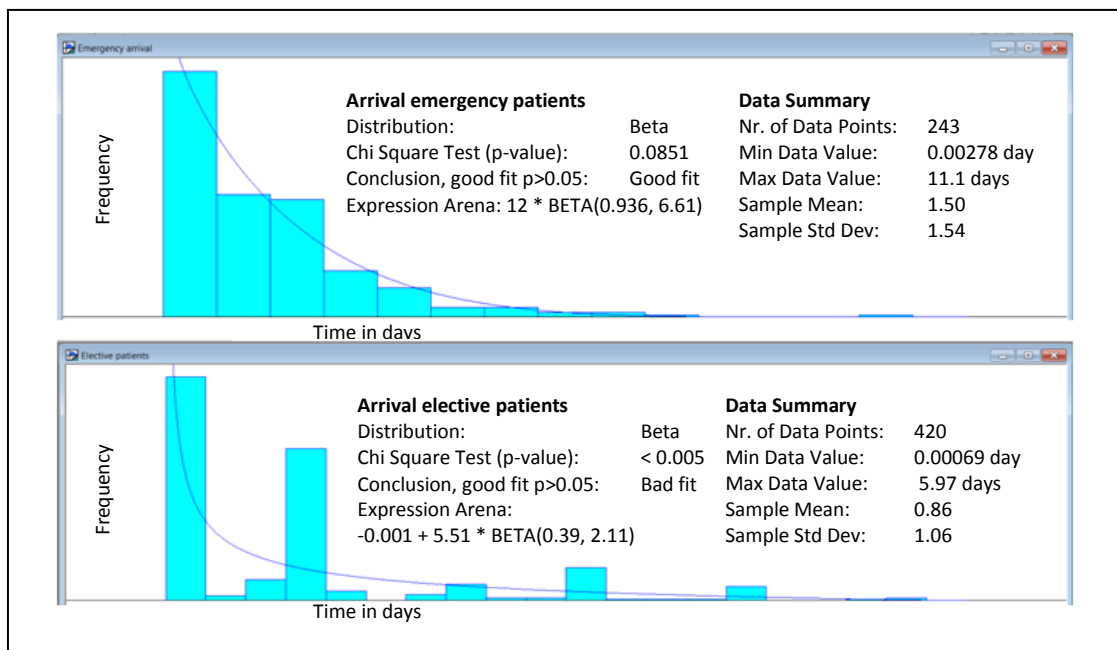


Figure 20 Histogram showing the frequency of the interarrival times of patients of the future situation for emergency patients and elective patient conform a Beta distribution

Now the different arrival patterns are described the next block of the simulation model will be described, this is the resources.

6.3.2 The resources; isolation beds and non-isolation beds

In the redesign of the current situation is that not all hematology treatments must be treated in isolation beds, since it is also possible to treat a hematology patient in a non-isolation bed. Therefore the main question during the simulation of the redesign situation is to determine the number of isolation beds and non-isolation beds. In the simulation model there are two resource groups, namely the group isolation beds and the group non-isolation beds. A group contains a specific number of isolation beds or non-isolation beds. Per simulation run, the number of isolation beds and/or non-isolation beds will change to calculate the waiting time that is according the norm for emergency patients. The borders are 18 till 28 isolation beds with an interval of two beds. And the borders for the non-isolation beds are from zero till 22 beds. The combinations of these two types of beds are summarized in appendix C.

The LoS that patients are admitted in E00 are from the DBC data in 2009, the LoS data is divided into the LoS for isolation beds and the non-isolation beds. The LoS is also compared with a specific distribution, with the same method to determine the arrival pattern in the previous paragraph. The conclusion is that the LoS for isolation beds in the current situation are following a Weibull distribution with a p-value that is under the norm of 0.05, the data has therefore a bad fit with a Weibull distribution. See Figure 22.

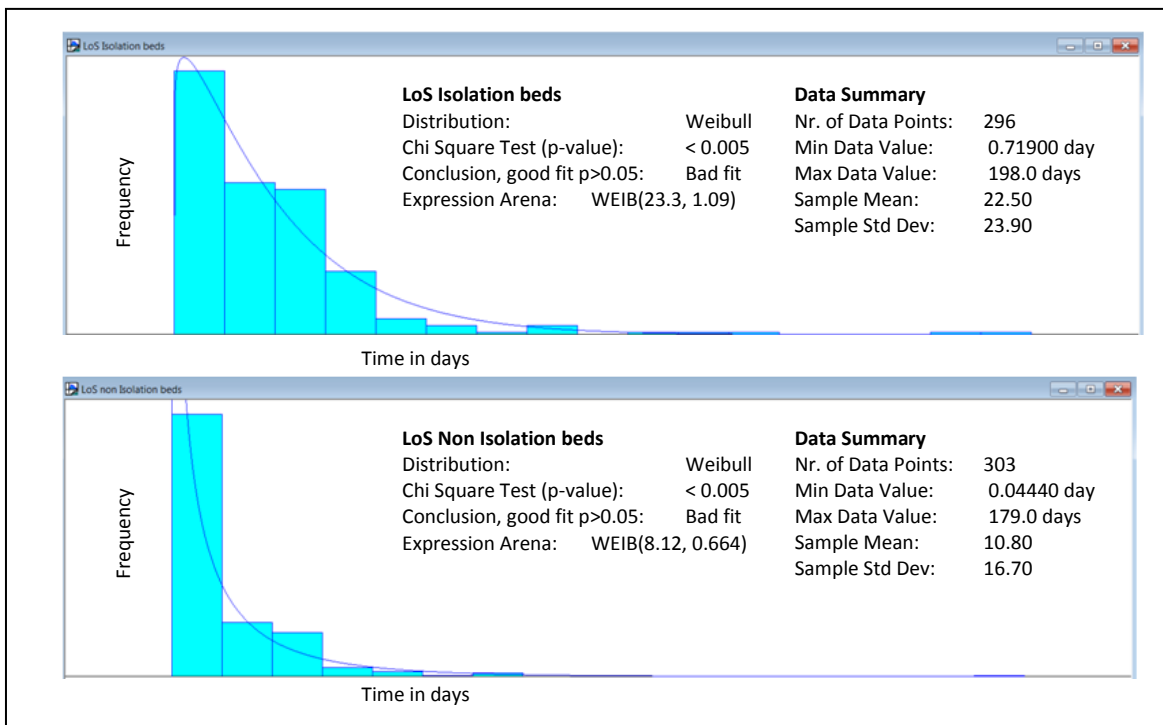


Figure 21 Histogram showing the frequency of the LoS of patients of the **current situation** for isolation beds and non isolation beds conform a Weibull distribution

The LoS for non-isolation beds are following also a Weibull distribution with a p-value that is under the norm of 0.05, the empirical data has therefore a bad fit. The future situation is also visualized in Figure 23.

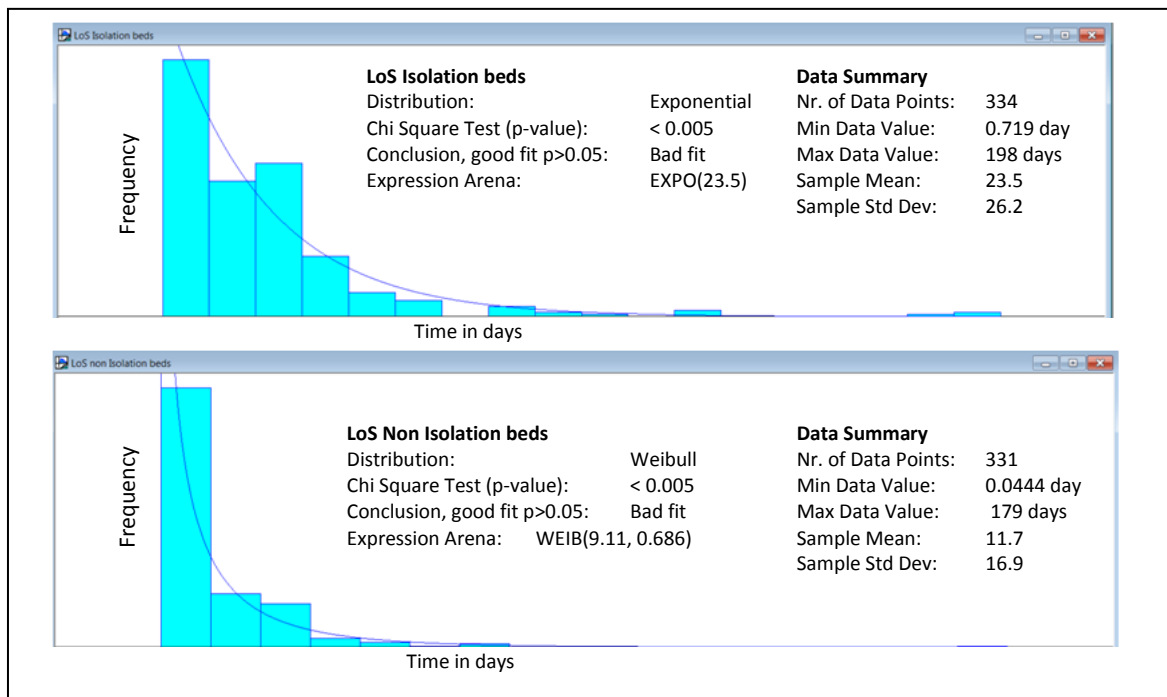


Figure 22 Histogram showing the frequency of the LoS of patients of the **future situation** for isolation beds and non isolation beds conform a Exponential and Weibull distribution

The real LoS histogram for 2009 has not a good fit with a specific distribution. Therefore, LoS data of the year 2008 was also compared with a specific distribution, and the LoS data 2008 till 2009. Both situations also had a bad fit. The outliers in the LoS were also deleted to get a higher p-value; the result was that the p-value was still not above the norm of 0.05. Therefore the original empirical data will be used for simulation the LoS. This executed in Arena as an entity (patient) goes through the LoS model, the entity will select randomly an individual LoS data point the LoS data list. The entity goes further when the specific LoS time is finished.

6.3.3 The number of reservations for the isolation beds

Another input aspect for the simulation model is the number of reservations for isolation beds. The input for the simulation is a reservation of zero, two or four isolation beds for emergency patients and elective patients. Emergency patients always have a higher priority than the elective patients. The reservation is for the patients that are treated in the isolation beds. There is also a possibility in the simulation model that non-isolation bed patients are treated in an isolation bed, when the isolation beds are not occupied by the isolation bed patients. For example when the number of reservations is four, the non-isolation bed patients will be treated in an isolation bed when there are four free isolation beds.

6.3.4 Conclusion input aspects simulation model

There will be a simulation of all the combinations of the different input aspects for the redesign situation in 2009, these were the different arrival patterns of patients, the LoS of patients, and the number of reservation for isolation beds. The number of combinations of isolation and non-isolation beds are 30 (see appendix C) with three different combination of reservation of isolation beds. The total number of simulation in 2009 are then, 30 multiplied with three is 90 different combinations

per scenario. There are in total four scenario's for the simulation of the redesign, see Table 5. The total simulation runs for 2009 will be then 360 (=90 x 4 scenarios) runs.

2009	arrival pattern patients		Length of Stay (LoS)	
	emergency	elective	Isolation beds	Non-isolation beds
1	Beta distr.	Beta distr.	Weibull distr.	Weibull distr.
2	Beta distr.	Schedule	Weibull distr.	Weibull distr.
3	Schedule	Schedule	Weibull distr.	Weibull distr.
4	Schedule	Schedule	Empirical	Empirical

Table 5 Different arrival scenario's for the redesign situation

The difference of combination for the future prognosis related with the current situation is that there will be 42 combinations of isolation and non-isolation beds instead of 30 combinations see appendix C. The total number of combinations for the future prognosis of the year 2015, will be 42 multiply with three is 126 combinations per scenario (see Table 6). The total will be then 504 (=126x4) simulation runs.

2015	arrival pattern patients		Length of Stay (LoS)	
	emergency	elective	Isolation beds	Non-isolation beds
5	Beta distr.	Beta distr.	Exponential distr	Weibull distr
6	Beta distr.	Schedule	Exponential distr	Weibull distr
7	Schedule	Schedule	Exponential distr	Weibull distr
8	Schedule	Schedule	Empirical	Empirical

Table 6 Different arrival scenario's for the future prognosis situation

Scenario four and eight are the scenarios with the best fit of the real data and the input data for simulation. The reason is because the real arrival data is used for the simulation input that is based on the arrival per hour of patients. The input of the LoS simulation data has also a 100% fit because the real LoS data is used for the simulation input. The reason that there are made also other scenarios is because these other scenarios have a more added value and predictive value for simulation in other situations than the only hematology situations.

6.4 Definition of the KPI's

To evaluate the outcome of the different scenarios adequate key performance indicators (KPI's) and performance indicators (PI's) will be defined. In addition proper KPI targets will be identified. The KPI's are more important than the PI's. The KPI's have therefore also a target and the best scenario will be chose according to these targets. According to Cardoen et al. (2010) there are different KPI's and PI's in the healthcare, these are among others waiting time and utilization. Another important PI in the healthcare is the variability. Variability can have a negative impact on the planning and scheduling of patients. The standard deviation (SD) will be the PI for the variability.

6.4.1 Waiting time

Waiting time is a hot item in the last decade; many measurements of the Dutch hospitals are concentrated on reducing the waiting time. The drawback is when reducing the waiting time to zero is that there is a chance to idleness of the expensive resources in the healthcare. The best concept according to Vissers et al. (2001) is a mix between the extreme service concepts, for example, a reservation of the capacity for emergency patients and a system for a waiting list for elective patients. The definition of the waiting time according to the simulation model is the time period

between the arrival of a patient and the time the patient is admitted at an isolation or non-isolation bed. The following KPI's and PI's will be defined in relation to the waiting time; these are in order of priority:

- The average waiting time in days of the emergency patients is a KPI.
- The standard deviation (SD) of the emergency patients is a PI;
- The average waiting time and the SD of the elective patients are PI's;
- The average waiting time and the SD for the isolation beds are PI's;
- The average waiting time and the SD for the non-isolation beds are PI's.

6.4.2 Resources and the utilization

It is interesting to focus on the utilization of the bed resources. In some situations the utilization of the resources should be maximized, because scarce resources are expensive. There is no general rule of an optimal utilization, because its dependence on the variability of the arrival pattern and the number of resources. For example when there are a few resources, the optimal utilization rate will be lower compared to a high number of resources. On the other hand, over-utilized resources that are completely full planned with no time slack is very unstable and has a higher change of large uncertain costs. For example, the slightest change when a treatment takes longer than planned can cause high costs, because of employees are working over time (Cardoen et al., 2010). Therefore a trade-off between over-utilization and under-utilization is preferable. According to Houdenhoven et al. (2007) it is unlikely to have a healthcare process of 100% utilization, because of the inherent variability. The following KPI's will be defined in relation of the bed capacity and utilization:

- The KPI is the total number of beds (summation of the isolation- and non-isolation beds)
- The number of isolation beds is the PI;
- The number of non-isolation beds is the PI;
- The utilization and SD of the isolation beds are the PI's;
- The utilization and SD of the non-isolation beds are the PI's.

6.4.3 Selection process of the best combination

The outcome of the redesign situation and the future prognosis situation will be evaluated with the dimensions of cost, flexibility, time and quality (Reijers, 2005). The KPI's and PI's are now identified. The best combination will be chosen of the following KPI's, this is when the norm of the average waiting time for the emergency patients is less than one day (24 hours) in combination of a minimum of total beds. Extra beds are costly; therefore the best combination has the lowest number of total beds and has a waiting time less than one day for emergency patients.

As mentioned before the fourth and eight scenarios have a 100% fit with the original data, because the real arrival data is used for the simulation input that is based on the arrival per hour of patients and the LoS simulation data is based on the real LoS data. The assumption is that the average of the all the fourth scenarios is leading compared with the fourth or eight scenarios.

When there are more outcomes with the same minimum of total beds, the minimum of the average waiting time of the emergency patients will be chosen in combination with the minimum of the waiting time of elective patients. The flexibility will be mainly focused on the patient flow; the expectation will be that the flexibility of the process will increase, because there is now a possibility

to admit patients in an isolation bed or a non-isolation bed. The quality of care will be the same; assumed that there will be no healthcare risks for patients according to the decision of the hematologists if a patient can be admitted at non-isolation bed, see appendix B. To summarize the selection steps to identify the best combination are the following three steps; the first step is to select the combination that are in the norm of the average waiting time for the emergency patients that is less than one day (24 hours). The second step is that the total beds must be minimal of the selected combinations that are according the norm of one day. The third step is (when there are more combinations) to select the combination with a minimum waiting time of emergency patients and elective patients.

6.5 Validation of the simulation model

A validation of the used simulation model was not possible, because the simulation model is a redesign of the current situation and a future prognosis. In the current situation there are 28 isolation beds, the simulation model is made with also non-isolation beds. Nevertheless, validation is an important step in the simulation process. Therefore a simulation model is made with 28 isolation beds to validate the input data. The conclusion was that there were no huge differences with the historical data and the outcome of the simulation model, except on the average waiting time. The outcome of the simulation model for only the "E00 patients" (hematology patients has occupied 0.85 bed in average elsewhere than E00) has an average bed utilization of 95%, the historical data had a bed utilization in a range of 85-92%. The average waiting time for patients of the simulation model was 7 days with a standard deviation of 8 days, the historical data had a waiting time of 4 days and a standard deviation of 7 days (resource reception data). The standard deviation of the simulation model can be reduced to execute more simulation runs, this is not done because more runs means also longer time per simulation. The simulation assumed that the arrival was according a Beta distribution and the LoS according a Weibull distribution.

6.6 Simulation results

In this paragraph the results of the simulation will be described. First, the results of the redesign will be explained and then the outcome of the future prognosis will be described.

As mentioned before, there are four scenarios made for the redesign situation and the future prognosis. There are therefore different results for the best combination for the lowest waiting time for emergency patients. The combinations were the number of isolation beds, the number of non-isolation beds and the number of reservation of isolation beds. The main KPI is the waiting time for emergency patients, with the norm of one day. Per combination there will be four different waiting times for emergency patients, because of the four different scenarios. This is also for the other KPI's and PI's.

It is unknown which scenario is based on the most real scenario. Therefore a summary is made with an average of the four scenarios to select the best combination. This average will also be used to sort the waiting time per different scenario. Only the combinations that are conform the norm of an average waiting time of emergency patients of one day are summarized in the results.

The average waiting time will be calculated to take the average of the four different scenarios. It is not possible to simply calculate the average of a standard deviation therefore the following formula is used to calculate the average combined standard deviation (s_{12}). N_1 is the number of patients for

scenario 1, N_2 is the number of patients for scenario 2 etc. s_1 is the standard deviation of scenario 1, s_2 from scenario 2 etc. d_1 is the different from the average of scenario 1 minus the average from the scenario 1 till 4 etc. The formula for a combined standard deviation is then:

$$\text{Combined sd, } s_{12} = \sqrt{\frac{N_1 \cdot (s_1^2 + d_1^2) + \dots + N_4 \cdot (s_4^2 + d_4^2)}{N_1 + \dots + N_4}}$$

6.6.1 Results of the redesign

There were four scenarios simulated for the redesign situation. The main difference is the arrival patterns, as mentioned before; the first scenario has an arrival pattern for emergency patients and elective patients according to a Beta distribution. The second scenario has an arrival pattern for emergency patients conform a Beta distribution and the elective patients have an arrival pattern conform a schedule arrival pattern. The third combination has an arrival pattern for emergency patients and elective patients are according to schedule arrival pattern. The first three scenarios have a LoS that is according a Weibull distribution. The fourth combination has another LoS simulation, namely an empirical simulation, and has the same arrival pattern as scenario three, see Table 5.

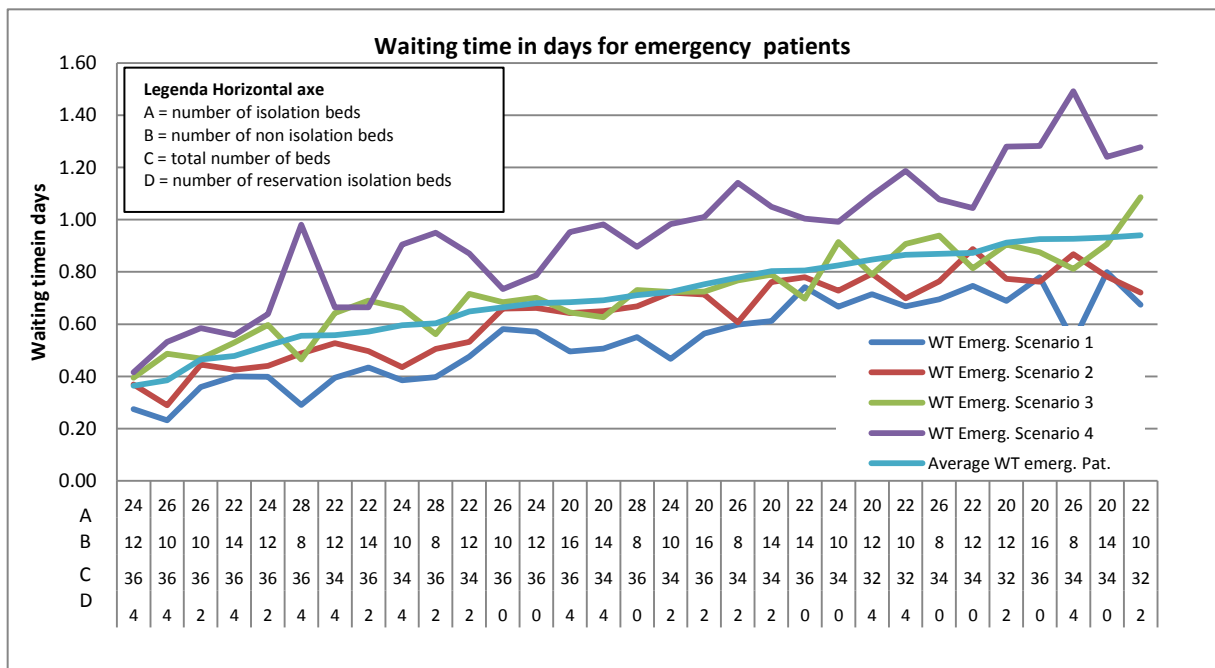


Figure 23 Waiting time for emergency patients per scenario for the redesign

An interesting point of view to evaluate shortly is the outcomes of the different scenarios. Figure 23 is namely based on the average of scenarios 1 to 4. Figure 23 has visualized the outcome of the waiting time of emergency patients per scenario and the average of the different scenarios. The horizontal axis of Figure 23 is a short notation of the possible combinations. For example the first combination (the left combination on the horizontal axis of Figure 23) is 24, 12, 36 and 4 this means 24 isolation beds (in the legend this is notated as 'A'), 12 non-isolation beds ('B'), 36 total beds ('C') and 4 reservation ('D') of isolation beds. The 'C' notation is the number of total beds. The first thing

to notice when looking at Figure 23, is that the lines are mainly following each other quite well on a broad level, with a few exceptions. The conclusion of Figure 23 is that scenario 4 has mainly the highest waiting time for emergency patients for all combinations and scenarios. After scenario 4, scenario 3 has mainly the longest waiting times, then scenario 2 and scenario 1. Therefore in this simulation model is that the waiting time of emergency patients is the longest when the arrival pattern is according to a schedule pattern and simulated with empirical data for the LoS. Scenario 4 has also the best fit with the original data. See Table 7 for the influence of the different arrival patterns and LoS on the waiting time of emergency patients.

2009	arrival pattern patients		Length of Stay (LoS)		Influence of the WT
Scenario	emergency	elective	Isolation beds	Non-isolation beds	emergency patients
1	Beta distr.	Beta distr.	Weibull distr.	Weibull distr.	Low WT
2	Beta distr.	Schedule	Weibull distr.	Weibull distr.	Medium WT
3	Schedule	Schedule	Weibull distr.	Weibull distr.	Medium WT
4	Schedule	Schedule	Empirical	Empirical	High WT

Table 7 Redesign scenarios compared with the waiting time of emergency patients.

The waiting time for elective patients per scenario can be also plotted in a graph, see Figure 24. The mean difference compared with Figure 23 is that in Figure 24 it is not clear which scenario the longest waiting time has. The different scenarios of the waiting time of elective patients are crossing each other more than the waiting time of the emergency patients. The minimum waiting time for elective patients is scenario 1. The other lines of the scenarios are crossing each other. A possible reason is the priority rule of emergency patients, this can disturb the waiting time of elective patients.

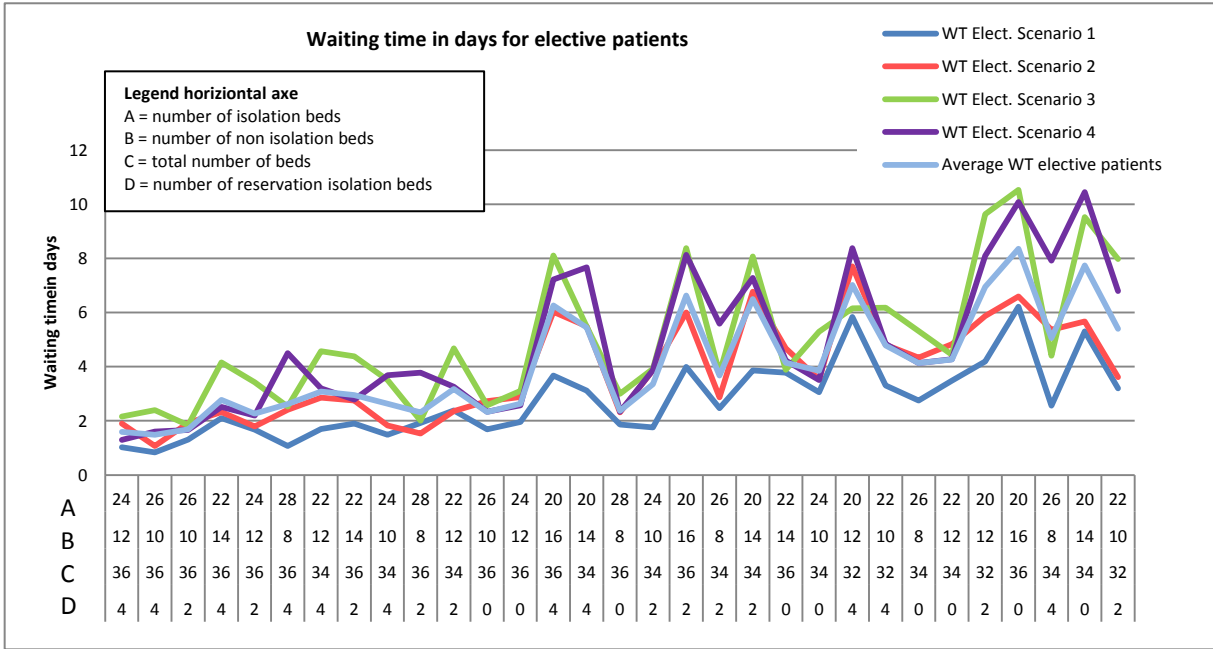


Figure 24 Waiting time for elective patients per scenario for the redesign

The best result for the redesign will be now described. The selection process is among others when the waiting time (WT) for emergency patients is less than one day, in combination of the minimal total beds. In Figure 25 a summary is made that is according the norm of emergency patients of one day. The Figure 25 is based on the average waiting time of scenario 1 till 4 for emergency patients

and elective patients. The selection of the best combination is among others to identify the lowest number of total beds, this is 32 beds in Figure 25. There are more combinations with a total of 32 beds, namely four combinations. Another selection rule was the minimal waiting time for emergency patients and elective patients. The best combination is then the combination 22, 10, 32, 4. The combination 20, 12, 32, 4 is not the best combination, because the waiting time for elective patients is higher than the combination 22, 10, 32, 4

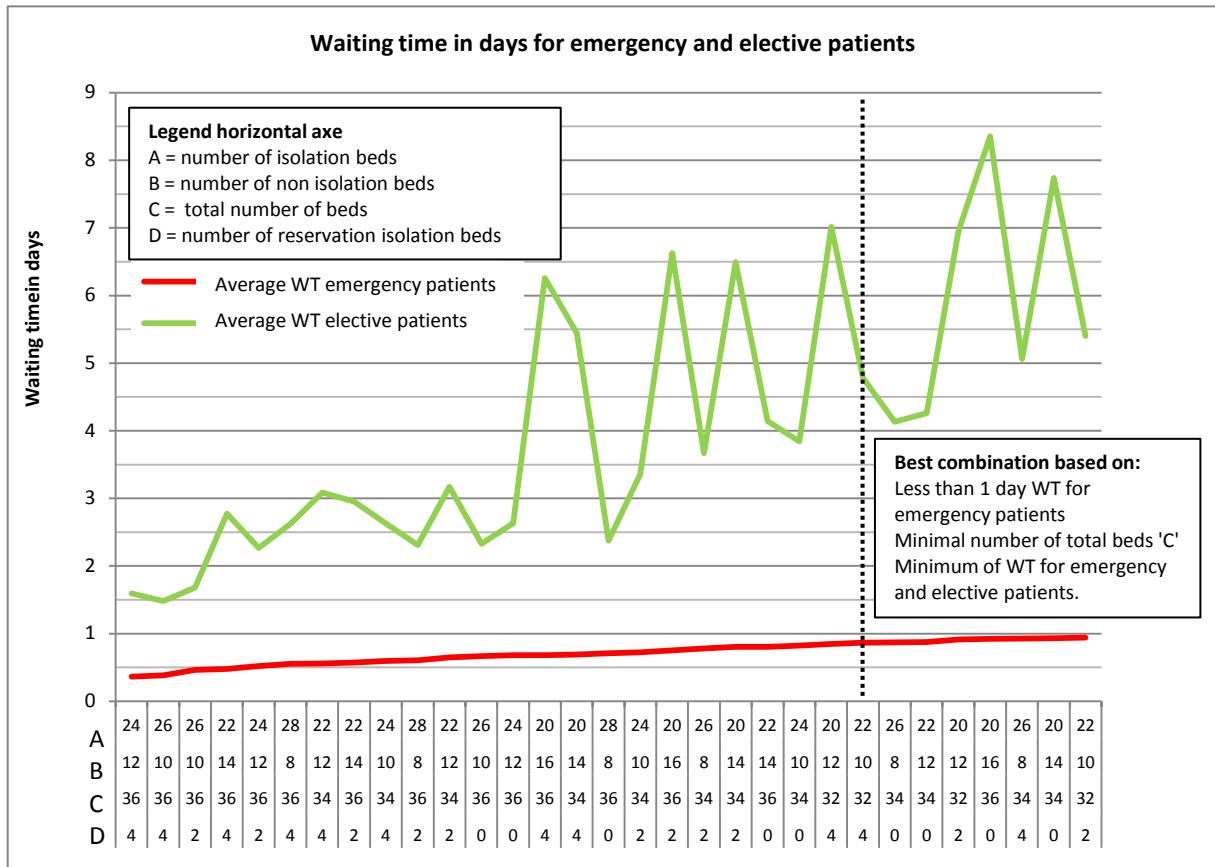


Figure 25 Lowest waiting time for emergency patients for the redesign situation, average of scenario 1 till 4 according to the norm of one day for emergency patients.

The best combination will be therefore 22 isolation beds with a utilization of 0.95, 10 non-isolation beds with a utilization of 0.80 and a reservation with four isolation beds. The total number of beds will be then 32. The waiting time for emergency patients is 0.87 days (21 hours), and for elective patients 4.78 days.

There are also other PI's, these are the standard deviation (SD) of the average waiting time for emergency patients; average waiting time and the SD of the elective patients; average waiting time and the SD for the isolation beds; average waiting time and the SD for the non-isolation beds; the utilization and SD of the isolation beds and the utilization and SD of the non-isolation beds, visible in the table top 25 of appendix D.

It could be that the management of the hematology department will maintain the current number of 28 isolation beds, the lowest average waiting time of emergency patients will then be 13 hours, and 8 extra non-isolation beds will be needed to fulfill the demand of hematology patients in the redesign.

The outcome of the redesign situation and the current situation will be shortly evaluated with the dimensions of cost, flexibility, time and quality (Reijers, 2005). It is clear that the cost will expand when there will be more beds. The flexibility of the process will increase, because there is now a possibility to admit patients in an isolation bed or a non-isolation bed. The waiting time will be reduced. The quality of care will be the same; assumed that there will be no healthcare risks for patients according to the decision of the hematologists whether or not a patient can be admitted at non-isolation bed, see appendix B. The conclusion is based on the expansion of beds that results in extra costs are that the redesign is not a good choice. And therefore it is preferable to maintain the 28 isolation beds in the current situation.

6.6.2 Results of the future prognosis

The future prognosis is also simulated with four different scenarios. There were scenarios 5 till 8 simulated for the future prognosis situation. The main difference is the arrival patterns, as mentioned before; scenario 5 has an arrival pattern for emergency patients and elective patients according to a Beta distribution. Scenario 6 has an arrival pattern for emergency patients conform a Beta distribution and the elective patients have an arrival pattern conform a schedule arrival pattern. Scenario 7 has an arrival pattern for emergency patients and elective patients are according to schedule arrival pattern. The first three scenarios have a LoS that follows an exponential distribution for the isolation beds and a Weibull distribution for the non-isolation beds. The last scenario 8 has another LoS simulation, namely an empirical simulation, and has the same arrival pattern as scenario 3, this is according to a schedule pattern. See Table 6 for more details.

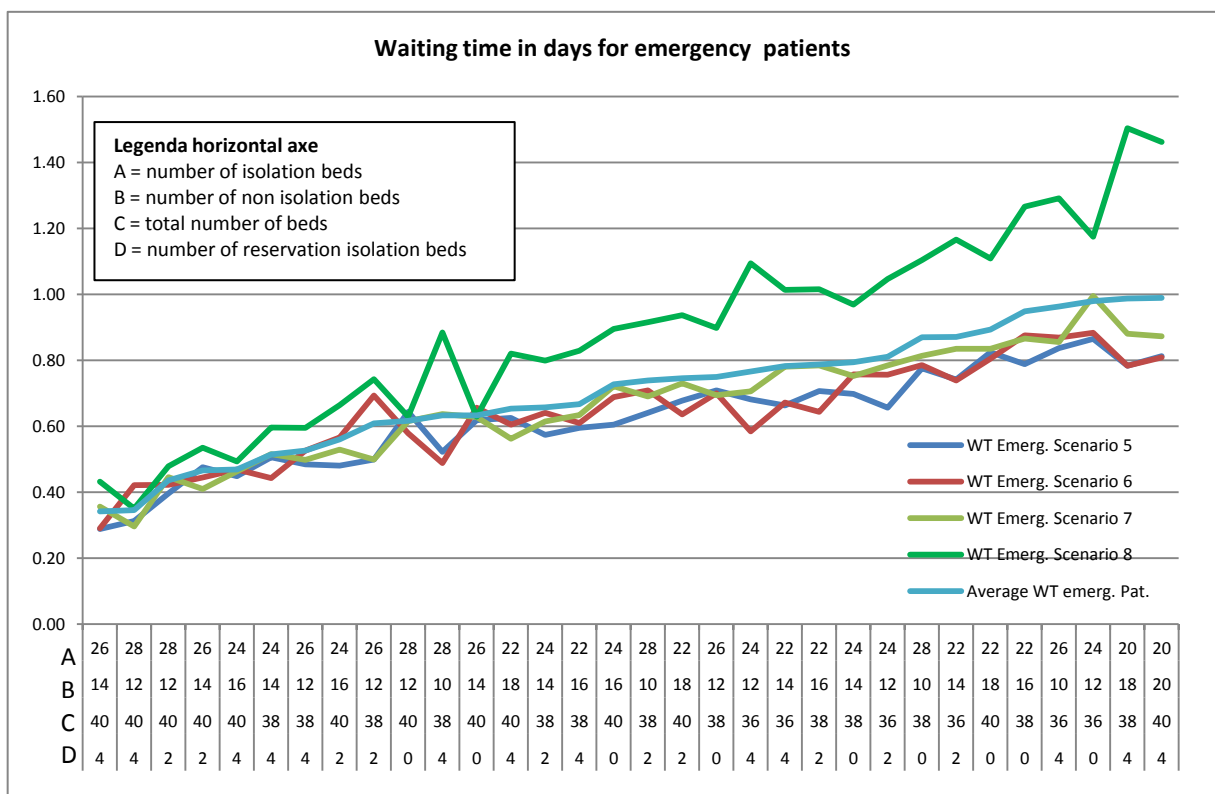


Figure 26 Waiting time for emergency patients per scenario for the future prognosis situation

For the future prognosis situation the waiting time for emergency patients is also plotted per different scenario, see Figure 26. In this figure, the lines are also mainly following each other quite

well on a broad level, with a few exceptions as in Figure 23 of the current situation. The lines in Figure 26 are crossing each other more than in Figure 23. The conclusion of Figure 26 is that scenario 8 has mainly the highest waiting time for emergency patients for all combinations and scenarios. After scenario 8 it is not so clear what the sequences are per scenario. Therefore in this simulation model is that the waiting time of emergency patients is the longest when the arrival pattern is according to a schedule pattern and simulated with empirical data for the LoS. It is out of the scope of this research to formulate more connections with the different outcomes of the simulations.

The main question is to determine the required bed capacity to fulfill the growth scenario. The method from the previous paragraph is used to discover the best combination.

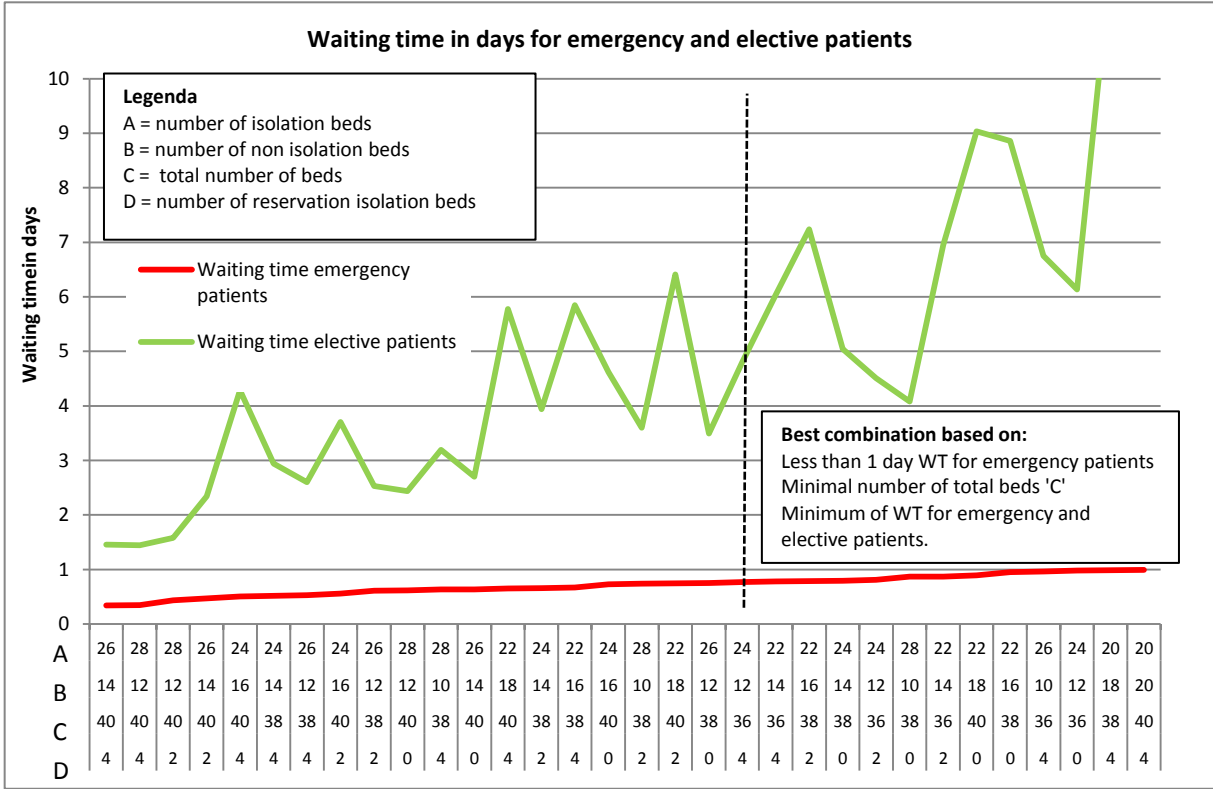


Figure 27 Lowest waiting time for emergency patients for the future prognosis situation, average of scenario 5 till 8 according to the norm of one day for emergency patients.

The conclusion is that the combination of 24 isolation beds with a utilization of 0.96, 12 extra non-isolation beds with a utilization of 0.77 and an allocation rule with four reservations of isolation beds for the hematology patients is the best combination for the future prognosis situation (option 1). The total number of beds is then 36 beds. When the management of the hematology department wants to maintain the 28 isolation beds, 10 extra non-isolation beds will be sufficient to maintain the future growth scenario for 2015 with a reservation of four isolation beds (option 2).

These two combinations can also be evaluated with the dimensions of cost, flexibility, time and quality (Reijers, 2005). An approximation will be that the cost will be lower for option 1, because there are less isolation beds. The number of non-isolation beds for option 1 will be higher although isolation beds are more costly than non-isolation beds this will lead to less costs. The total beds of 36 (24 isolation beds plus 12 non-isolation beds) is also lower than the total beds of 38 (28 isolation beds and then 10 non-isolation beds). The flexibility of the two options will be the same. The average

waiting time for emergency patients is for option 2 lower, namely 0.63 days compared to option 1, namely 0.77 days. The quality of care will be the same for option 1 and 2. The conclusion is that option 1 is better than option 2 based on less cost. Option 2 is better based on lower waiting time for emergency patients, although it is a minimum difference of 0.14 days (3 hours). Although there are reasons to still maintain the 28 isolation beds, a reason could be that there will be costs to rebuild the isolation beds into non-isolation beds. Therefore a graph is made that only visualized the 28 isolation beds with extra non-isolation beds, see Figure 28.

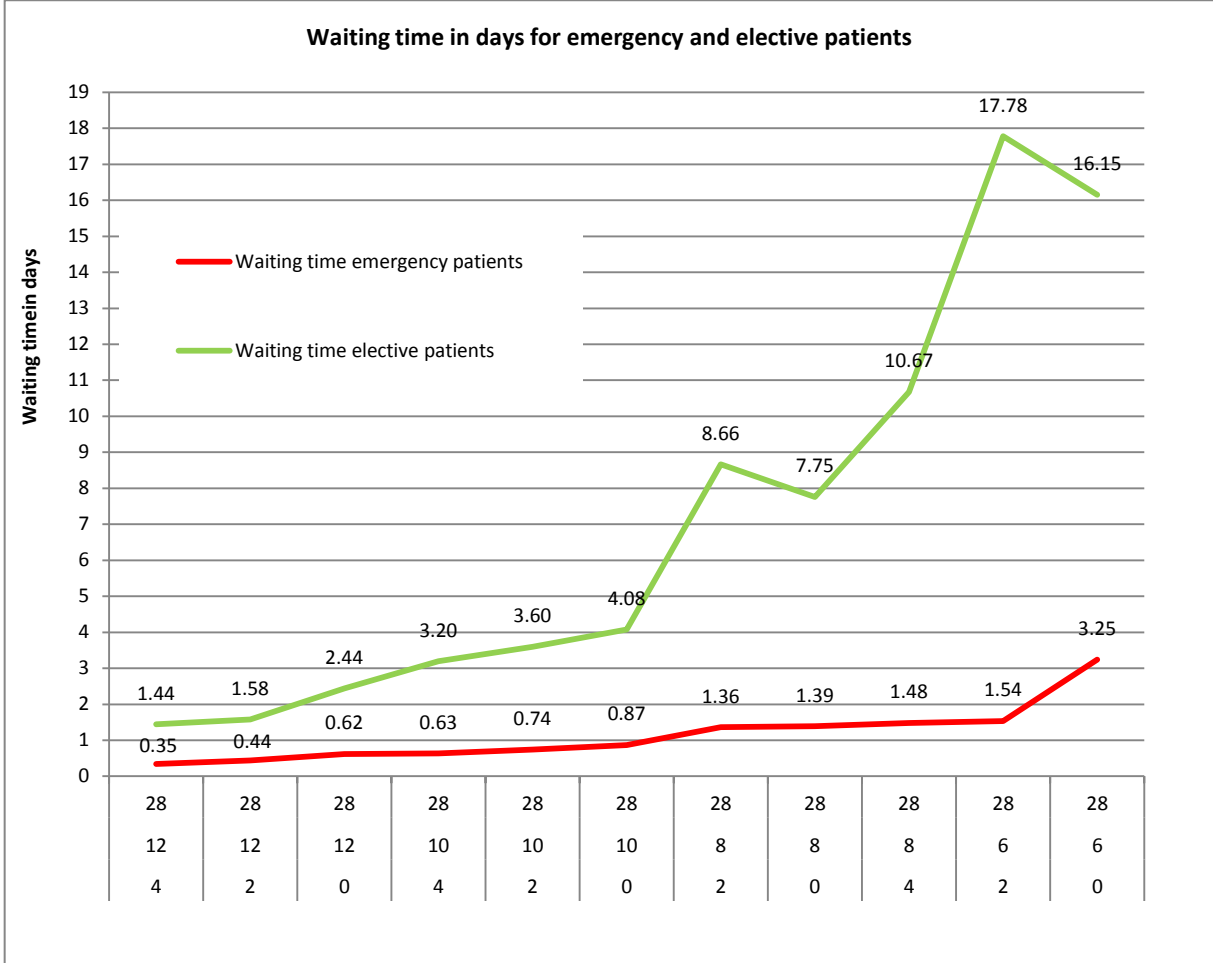


Figure 28 Lowest waiting time for emergency patients for the future prognosis situation, average of scenario 5 till 8 according to 28 isolation beds.

The conclusion of Figure 28 is that 12 or 10 extra non-isolation beds are sufficient enough for the future growth scenario in the norm of 1 day for emergency patients. Eight or six extra non-isolation beds will be exceeding the norm of one day. The reason that there are not 6 or less extra non-isolation beds visualized is because the number of waiting patients of the simulation model exceeded the 150 patients. When this happened the simulation program will give an error and will stop with the simulation.

6.7 Discussion simulation model

The simulation model has several limitations. The simulation model that is made is a simplified representation of the hematology department. A simulation model will rarely capture precisely the system characteristics (Altiok and Melamed, 2007). Therefore an exact outcome is difficult to present.

Another limitation of the simulation model is that the arrival pattern and the LoS pattern are compared with ten different distributions. There are more distributions to compare with, for example Cauchy, Laplace, Logistic, Maxwell. The simulation program Arena had only the ten distributions to compare with.

There will be more patients arrivals in the future prognosis because there will be more SCT's, this is done by picking random individual patient paths from the current situation. The limitation is that there will be other individual patients paths picked when this will be executed again. The arrival of the random picked patients is delayed with two weeks; another delay period was also possible.

As mentioned before according to the management of hematology is that the in the future scenario there will be only more SCT treatments, the number of other treatments will be the same as in 2009.

During an interview with a medical expert there was a discussion about the definition of an emergency patient. There are several levels of urgency for emergency patients. For example some emergency patients must be admitted in one hour, and some emergency patients between in one day. In the input data there is no distinction of the sort of emergency patients, therefore the average waiting time that an emergency patients must be admitted is one day this is 24 hours.

There are other methods to determine the warming up period. In this report this is done when the average utilization of the beds reached the first time at 90%. In the article of Robinson (2002) other method are described to determine the warm up periods.

The outcome of the simulation runs is based from the average waiting time from scenario 1 till 4 (redesign situation) and average waiting time from scenario 5 till 8 (future situation). This is an assumption. The selection of the best combination could be also based for example only on scenario four, because of the 100% fit with the real input data.

7 Conclusion and managerial implications

7.1 Conclusion

In this chapter the sub research and the research questions will be answered. The answers of the sub research questions are:

1. "How should allocation rules be formulated to determine if a patient must be treated in an isolation bed or a non-isolation bed?" The conclusion is that 45 percent of the patients can be treated into a non-isolation bed, for more details see appendix B.
2. "How many isolation beds and non-isolation beds are necessary to fulfill the redesign scenario?" These are 22 isolation beds and 10 non-isolation beds. This is based on the waiting time for emergency patients that are less than one day and the lowest number of total beds. "The number of isolation bed that need to be reserved to optimize the waiting time for isolation beds" are for the combination 22 isolation beds and 10 non-isolation beds are four isolation beds. When the management of the hematology department wants to maintain the 28 isolation beds then 8 extra non-isolation beds will be sufficient, with a reservation of four isolation beds.

The conclusion is based on the expansion of beds that results in extra costs are that the redesign is not a good choice. And therefore it is preferable to maintain the 28 isolation beds in the current situation.

3. "How many isolation beds and non-isolation beds are necessary to fulfill the future growth scenario?" These are 24 isolation beds, 12 non-isolation beds and a reservation of four isolation beds. This is also based on the norm of 1 day for the emergency patients and the lowest number of total beds. When the management of the hematology department wants to maintain the 28 isolation beds then 10 extra non-isolation beds will be sufficient to maintain the future growth scenario for 2015 with a reservation of four isolation beds.

To answer the main question of "How many beds are necessary to fulfill the redesign" are a total of 32 beds if the combination is 22 isolation beds and 10 non-isolation beds.

For the future prognosis scenario this is a total of 36 beds if the combination is 24 isolation beds and 12 non-isolation beds. When the management wants to maintain the 28 isolation beds, then 10 extra non-isolation beds will be sufficient. The total number of beds will be then 38.

7.2 Managerial implications

There is an increasing demand in the healthcare to have an efficient en effective number of beds. Isolation beds are more costly than non-isolation beds. In the current situation all the hematology patients are treated in an isolation bed. The conclusion is that 45 percent of the hematology patients can be treated into a non-isolation bed. The research was also done to determine the bed resource to fulfill the future grow scenario at the hematology department. With a simulation model the total beds are determined to fulfill the patients demand till the year 2015. The outcome of the simulation model was that 24 isolation beds and 12 non-isolation beds are sufficient enough to fulfill the future demand. A reservation of four isolation beds has a good influence on the waiting time for emergency

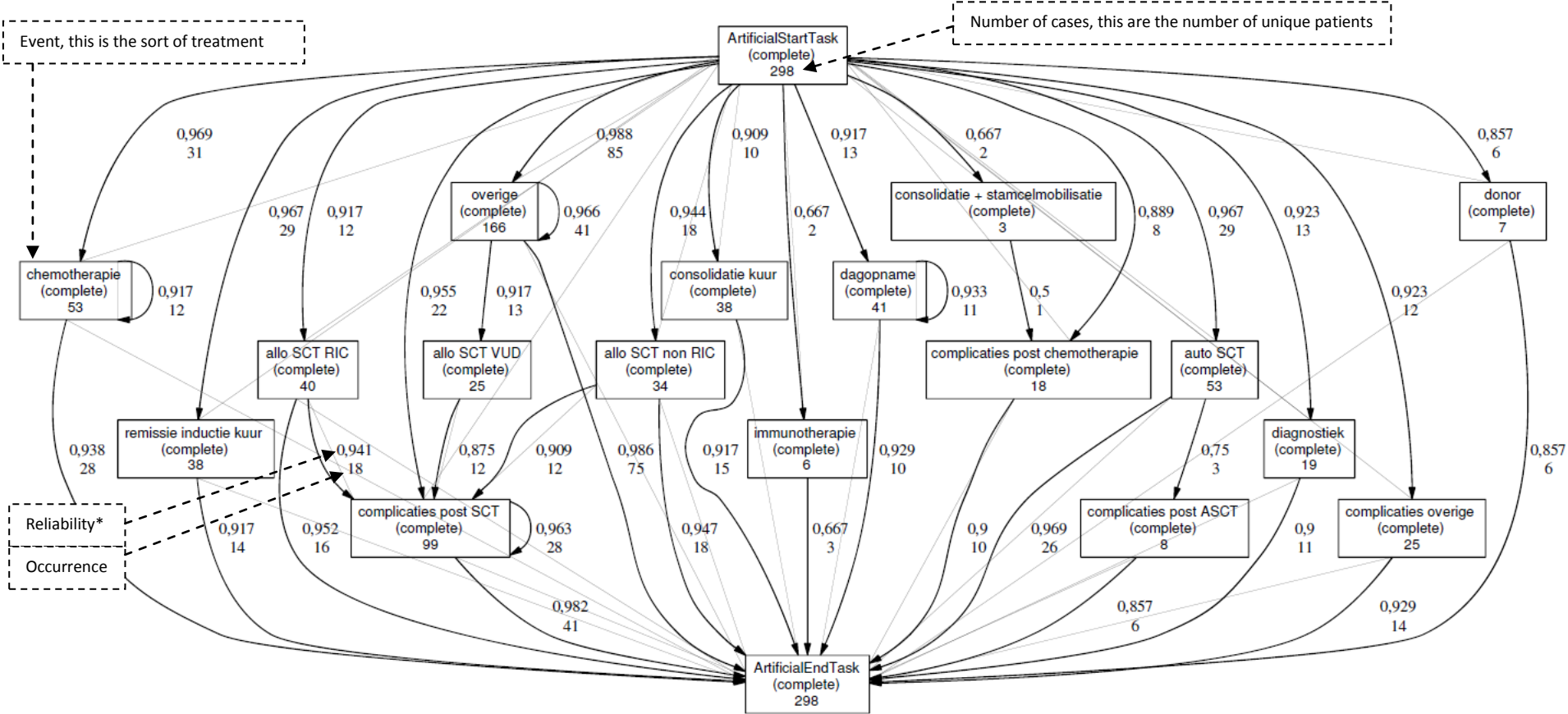
patients. The outcome is based on the norm of 1 day for the emergency patients and the lowest number of total beds. When the management wants to maintain the 28 isolation beds then 10 extra non-isolation beds will be sufficient in the year 2015.

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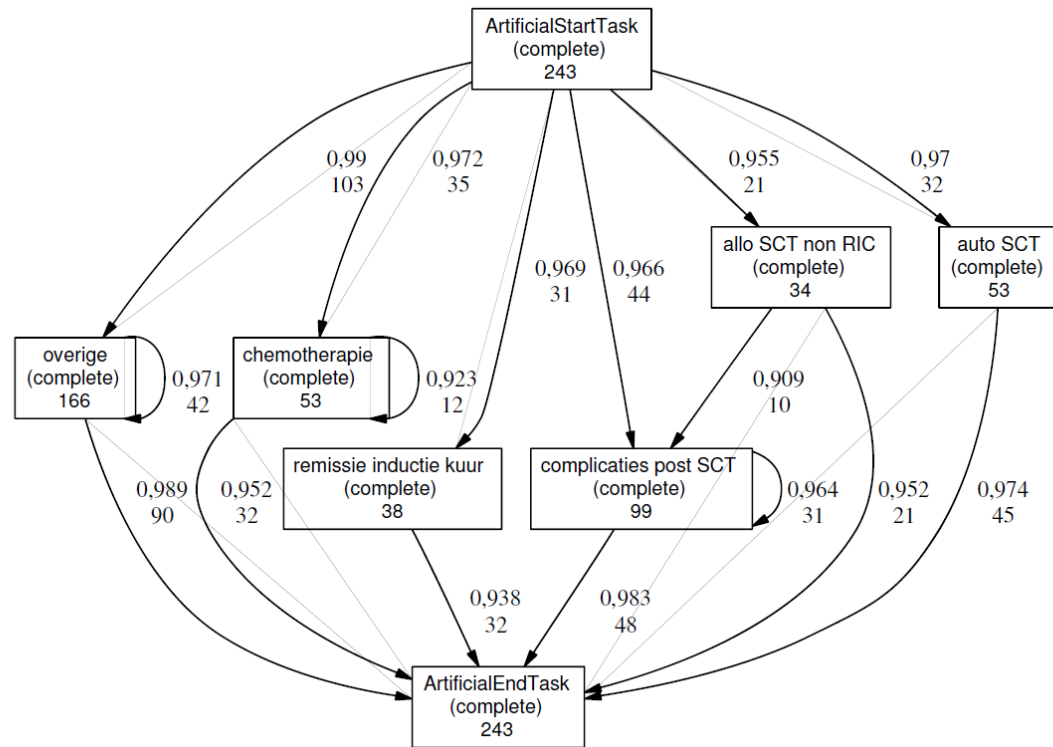
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Appendix A1, Hematology treatment process with the Heuristic mining algorithm

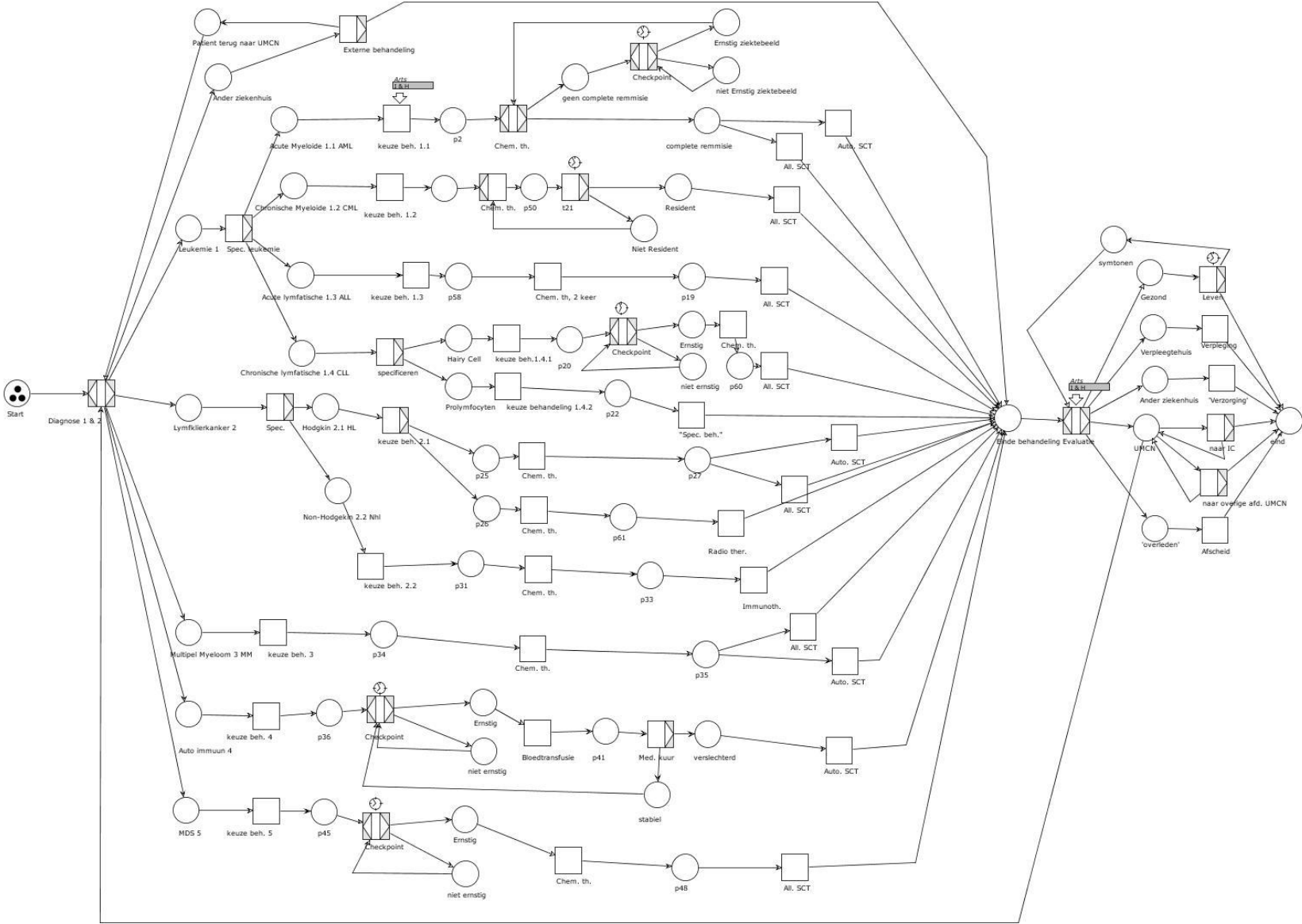


*A high reliability value (close to 1) means a high certainty about the dependency relation between two events (Mans, 2011). For example, the reliability of the “allo SCT RIC” event being followed by the “complicaties post SCT” event is 0.941 this has a high reliability. The bottom number on an arc represents the number of times in the log that the event at the tail of the arc is followed by the event at the head of the arc (e.g. in 18 cases “allo SCT RIC” event being followed by the “complicaties post SCT” event).

Appendix A2, Hematology treatment process with the Heuristic mining algorithm, based on the most frequency path



Appendix A3, Hematology treatment process from interview



Appendix B, Redesign for patients that can treated in a non-isolation bed

Allocation list for isolation or non-isolation bed based on the treatments.

Period 15-09-2005 till 29-09-2009 Source: HRS n=1252

		Perc. Tot.	
Group: Allogeneic SCT	Average LoS (days)	LoS	Sort Bed
1. Allogeneic SCT non RIC	35	13,8%	Isolation bed
Allogeneic SCT VUD	34	11,2%	Isolation bed
Allogeneic SCT RIC	25	9,2%	Non-isolation bed
Immunotherapy	20	0,9%	Isolation bed
Group: Autologous SCT			
2. Autologous SCT (ASCT)	23	10,0%	Isolation bed
Group: Chemotherapy			
3. Remission induction cure	26	10,0%	Isolation bed
Chemotherapy	16	9,7%	Combination
Consolidation cure	22	8,0%	Isolation bed
Consolidation + stem cell mobilization	20	1,0%	Isolation bed
Group: Complications			
4. Complication after SCT	22	18,7%	Combination
Complication others	18	3,7%	Non-isolation bed
Complication after chemotherapy	19	3,4%	Non-isolation bed
Complications after ASCT	14	0,3%	Non-isolation bed

Appendix C Number of combinations of isolation –and non-isolation beds

2009

# combination	Isolations beds	non isolations beds
1	28	0
2	26	2
3	24	4
4	22	6
5	20	8
6	18	10
7	28	2
8	26	4
9	24	6
10	22	8
11	20	10
12	18	12
13	28	4
14	26	6
15	24	8
16	22	10
17	20	12
18	18	14
19	28	6
20	26	8
21	24	10
22	22	12
23	20	14
24	18	16
25	28	8
26	26	10
27	24	12
28	22	14
29	20	16
30	18	18

2015

# combination	Isolations beds	non isolations beds
31	28	10
32	26	12
33	24	14
34	22	16
35	20	18
36	18	20
37	28	12
38	26	14
39	24	16
40	22	18
41	20	20
42	18	22

Table Emerg. Pat. less than 24 hours, based on the lowest waiting time of Emerg. Pat. (time in days), summary: average scenario 1 till 4

	Number	Number	Reserv.	Waiting time		Waiting		Waiting time		Waiting time		Utilization		Utilization	
	Iso.	Non iso.	Iso. beds	Emerg. Pat.	SD	Elect. Pat.	SD	Iso. beds	SD	Non iso. beds	SD	Iso. beds	SD	Non iso.	SD
1	24	12	4	0.36	0.21	1.59	1.84	1.52	2.11	0.54	0.70	0.92	0.12	0.61	0.11
2	26	10	4	0.38	0.24	1.48	1.38	0.66	0.71	1.55	1.79	0.91	0.76	0.67	0.75
3	26	10	2	0.46	0.26	1.68	1.44	1.05	0.68	1.31	2.01	0.95	0.66	0.62	0.66
4	22	14	4	0.48	0.25	2.77	3.16	3.19	3.93	0.21	0.52	0.94	0.27	0.57	0.26
5	24	12	2	0.52	0.24	2.27	2.06	2.36	2.39	0.38	0.56	0.96	0.15	0.59	0.15
6	28	8	4	0.56	0.42	2.62	2.91	0.31	0.28	4.09	4.07	0.89	1.09	0.72	1.08
7	22	12	4	0.56	0.32	3.09	3.49	3.11	3.60	0.71	1.00	0.94	0.47	0.68	0.47
8	22	14	2	0.57	0.24	2.96	2.53	3.42	3.11	0.15	0.35	0.97	0.21	0.55	0.21
9	24	10	4	0.60	0.45	2.63	3.39	1.22	1.43	2.28	3.31	0.92	1.53	0.72	1.52
10	28	8	2	0.60	0.40	2.31	1.98	0.66	0.48	3.27	3.34	0.94	0.78	0.68	0.77
11	22	12	2	0.65	0.34	3.17	2.75	3.27	2.66	0.61	1.23	0.97	0.75	0.63	0.75
12	26	10	0	0.66	0.25	2.33	1.82	1.76	0.79	1.26	2.09	0.98	0.70	0.59	0.70
13	24	12	0	0.68	0.20	2.63	1.19	2.66	1.19	0.41	0.78	0.98	0.18	0.56	0.18
14	20	16	4	0.68	0.34	6.26	5.85	7.47	7.19	0.05	0.19	0.97	0.13	0.53	0.13
15	20	14	4	0.69	0.34	5.44	5.08	6.19	5.46	0.19	0.35	0.97	0.12	0.60	0.12
16	28	8	0	0.71	0.40	2.38	2.20	1.25	0.57	2.61	4.13	0.97	1.78	0.64	1.78
17	24	10	2	0.72	0.40	3.36	2.81	2.13	1.79	2.29	2.78	0.96	0.81	0.71	0.80
18	20	16	2	0.75	0.28	6.63	6.16	7.61	6.78	0.03	0.09	0.98	0.06	0.51	0.06
19	26	8	2	0.78	0.48	3.67	3.85	0.97	0.55	4.76	5.37	0.95	0.15	0.74	0.14
20	20	14	2	0.80	0.28	6.49	5.57	7.61	6.56	0.17	0.30	0.98	0.11	0.59	0.11
21	22	14	0	0.81	0.23	4.14	2.10	4.65	2.52	0.15	0.37	0.99	0.24	0.54	0.24
22	24	10	0	0.83	0.26	3.85	2.47	3.12	1.87	1.75	2.21	0.98	0.57	0.67	0.56
23	20	12	4	0.85	0.36	7.02	6.33	7.39	7.11	0.95	1.19	0.97	0.44	0.71	0.44
24*	22	10	4	0.87	0.41	4.78	3.57	3.00	2.82	3.23	2.98	0.95	0.81	0.80	0.80
25	26	8	0	0.87	0.37	4.13	4.11	1.74	1.04	4.62	6.03	0.98	2.55	0.72	2.55
26	22	12	0	0.87	0.26	4.26	2.50	4.39	2.33	0.70	1.51	0.99	0.99	0.64	0.98
27	20	12	2	0.91	0.42	6.95	6.67	7.46	7.32	0.87	1.68	0.98	0.97	0.68	0.97
28	20	16	0	0.93	0.30	8.36	5.70	9.58	6.50	0.04	0.12	1.00	0.06	0.51	0.07
29	26	8	4	0.93	0.67	5.06	5.15	0.74	0.61	6.83	6.62	0.91	2.13	0.82	2.12
30	20	14	0	0.93	0.29	7.74	6.03	8.55	6.09	0.12	0.24	1.00	0.12	0.57	0.13
31	22	10	2	0.94	0.42	5.40	4.48	3.83	3.47	2.86	3.13	0.97	1.33	0.76	1.32

*Outcome of the best combination.

Table Emerg. Pat. less than 24 hours, based on the lowest waiting time of Emerg. Pat. (time in days), summary: average scenario 5 till 8

	Number	Number	Reserv.	Waiting time		Waiting time		Waiting time		Waiting time		Utilization		Utilization	
	Iso. beds	Non iso.	Iso. beds	Emerg. Pat.	SD	Elect. Pat.	SD	Iso. beds	SD	Non iso. beds	SD	Iso. beds	SD	Non iso. beds	SD
1	26	14	4	0.34	0.18	1.46	1.18	1.46	1.20	0.32	0.56	0.93	0.24	0.62	0.23
2	28	12	4	0.35	0.22	1.44	1.76	0.69	0.67	1.40	2.09	0.92	1.03	0.68	1.02
3	28	12	2	0.44	0.22	1.58	1.10	1.22	0.82	0.85	1.10	0.96	0.36	0.63	0.35
4	26	14	2	0.47	0.17	2.34	2.05	2.24	1.56	0.49	2.05	0.97	1.77	0.60	1.76
5	24	16	4	0.50	0.24	4.28	4.80	5.03	5.46	0.11	0.18	0.96	0.06	0.58	0.06
6	24	14	4	0.51	0.22	2.94	2.43	3.04	2.41	0.51	0.75	0.95	0.27	0.67	0.26
7	26	12	4	0.53	0.25	2.60	1.80	1.71	1.32	1.73	1.68	0.94	0.39	0.74	0.38
8	24	16	2	0.56	0.19	3.71	2.95	4.09	3.23	0.13	0.22	0.98	0.08	0.57	0.08
9	26	12	2	0.61	0.27	2.53	1.63	1.99	1.19	1.20	1.40	0.97	0.26	0.69	0.25
10	28	12	0	0.62	0.21	2.44	1.52	2.07	0.96	0.96	2.07	0.98	1.27	0.60	1.26
11*	28	10	4	0.63	0.41	3.20	3.13	0.74	0.59	3.98	3.92	0.92	0.87	0.78	0.87
12	26	14	0	0.63	0.16	2.70	1.39	2.84	1.45	0.25	0.67	0.99	0.30	0.56	0.30
13	22	18	4	0.65	0.26	5.77	5.05	6.78	5.52	0.06	0.18	0.97	0.11	0.56	0.11
14	24	14	2	0.66	0.23	3.94	2.65	4.12	2.94	0.47	0.72	0.98	0.38	0.66	0.38
15	22	16	4	0.67	0.25	5.85	4.98	6.74	5.81	0.20	0.36	0.97	0.14	0.62	0.13
16	24	16	0	0.73	0.19	4.62	2.66	5.04	2.85	0.17	0.42	0.99	0.22	0.57	0.22
17	28	10	2	0.74	0.38	3.60	2.87	1.36	0.94	4.02	3.76	0.96	0.85	0.76	0.84
18	22	18	2	0.75	0.29	6.41	4.88	7.43	5.20	0.05	0.12	0.99	0.08	0.54	0.08
19	26	12	0	0.75	0.24	3.50	2.44	2.98	1.70	1.26	1.99	0.99	0.75	0.66	0.74
20**	24	12	4	0.77	0.41	4.80	4.20	3.29	3.01	2.52	3.58	0.96	1.34	0.77	1.33
21	22	14	4	0.78	0.32	6.04	5.23	6.59	6.08	0.73	0.78	0.97	0.15	0.71	0.15
22	22	16	2	0.79	0.26	7.24	5.64	8.08	5.62	0.20	0.33	0.99	0.08	0.61	0.08
23	24	14	0	0.79	0.25	5.04	3.14	5.25	2.97	0.55	0.86	0.99	0.36	0.65	0.35
24	24	12	2	0.81	0.33	4.51	3.24	3.61	2.59	1.92	2.29	0.98	0.72	0.74	0.72
25	28	10	0	0.87	0.48	4.08	3.42	2.19	1.17	3.24	4.08	0.98	0.38	0.71	0.38
26	22	14	2	0.87	0.35	6.95	5.20	7.62	6.05	0.59	0.74	0.99	0.20	0.69	0.20
27	22	18	0	0.89	0.23	9.04	5.80	10.41	6.69	0.03	0.08	1.00	0.04	0.54	0.05
28	22	16	0	0.95	0.30	8.86	5.58	10.23	6.34	0.14	0.32	1.00	0.09	0.60	0.09
29	26	10	4	0.96	0.47	6.75	5.94	1.72	1.44	7.48	8.04	0.94	2.44	0.86	2.43
30	24	12	0	0.98	0.30	6.14	4.14	5.31	3.02	1.90	2.34	0.99	0.67	0.74	0.67
31	20	18	4	0.99	0.38	12.12	6.95	14.07	7.64	0.02	0.03	0.99	0.01	0.57	0.02
32	20	20	4	0.99	0.42	12.07	7.35	14.07	7.98	0.01	0.03	0.99	0.02	0.52	0.03

* Outcome of the best combination when maintaining the 28 isolation beds

** Outcome of the best combination when not maintaining the 28 isolation beds

