Master assignment, Industrial engineering and management

Track: Financial Engineering and Management

Draft version

Modeling patients flows through a hospital using ARIMA theory and Markov theory

Author:
S. Weggemans

Supervisors:
R.A.M.G. Joosten, (UT)
E.W. Hans, (UT)
D. Plijter, (ZGT)

August 19, 2012

UNIVERSITEIT TWENTE.

Management summary

In this paper we develop a holistic model which enables Ziekenhuis Groep Twente, ZGT, to predict patient volumes and occupancy rates of (sub)specialisms at outpatient clinics, operating theaters and nursing wards at least one month ahead. Moreover, ZGT is interested in how patients transfer from one (sub)specialisms to another in the outpatients clinics and the nursing wards. The estimation of patient volumes and occupancy rates is useful for allocating nursing beds and staff. Currently, ZGT uses common sense and experience of employees to predict the number of beds, operating time and staff.

The model we propose, consists of three components: the arrival of patients at the three departments, outpatient clinics, operating theaters and nursing wards, the transfers between (sub)specialisms in the departments and the average service time. The first component is modeled by autoregressive integrated moving average (ARIMA) models. The second component is modeled by using Markov theory. The average service times are computed by statistical analysis.

For the arrivals at outpatient clinics (first and repeated visit), operating theaters and nursing wards (one day-admission and more than one day admission), we propose ARIMA-models, which can predict weekly patient arrivals. We compute monthly transition probabilities for transfers between subspecialisms of surgery and the remaining part of the hospital for in- and outpatients. Also we compute weekly transition probabilities for transfers between 11 specialisms for inpatients. We demonstrate that for estimating patient volumes, the subdivision in 11 specialisms is more useful than the subdivision in several small subspecialisms of surgery and one large part, which represents the remaining part of the hospital. Also we argue that weekly transfers yield a better computation of transition probabilities than monthly transfers. This is due to the fact that the average nursing time of a single patient is much closer to one week than one month. We see this confirmed, as we compute the average service times. For 299 of 980 treatments, the nursing time is three days or more, for 181 treatments 5 days or more, for 60 treatments 10 days or more and for 0 treatments of 30 days or more.

The input model for the arrivals and the transition probability matrix can be used for computing patient volumes at a combination of department and (sub)specialism. If we use the average service times, we can also compute the occupancy rates. In Chapter 8

we pay special attention to the applicability and the possibility of the implementation of the model with respect to ZGT. Also we briefly explain the ins and outs of the model in this chapter.

The transition probabilities matrix demonstrates that more than 70% of the inpatients arriving at a specific specialism are also discharged within this specialism within one week. Thus less than 30% of the patients transfer from one specialism to another in the nursing ward, or stay in the hospital for a period longer than one week.

We back-test our model for 20 weeks in 2011 by estimating the expected weekly patient volumes at the nursing wards for 11 specialisms and comparing them with the actual values. Approximately 40% of the weekly patient volume estimates, differ less than 10 patients in comparison with the actual data. About 25% of the estimations are in the range of a difference between 10 and 20 patients in comparison with the actual data. As said, ZGT uses common sense to allocate staff and nursing beds. Since these estimations are not entirely comparable, we also construct a simple measure and compare our model to this measure. This measure uses the 4 year average arrivals. In 53% of the cases, our model estimates the arrivals better than the 4 year average model. Moreover, our model predicts 14% more cases than the 4 year average model, in which the difference between the estimate and the actual data is only 10 patients or less. The 4 year average model estimates 8% more cases than our model, in which the difference is more than 25 patients compared to the actual data.

To illustrate what these findings imply with respect to potential savings, we make a cost comparison of the two models. We calculate costs of wrongly planned nursing beds and staff per group of ten patients per week in case of an over- and underestimation by our model. We compare these costs to the cost estimates of the 4 year average model. For this purpose we use arbitrarily cost estimates of €1,200.− per patient per nursing day. In a scenario in which five of the ten planned beds are really used, the comparison shows a potential costs saving of 2.3 million euro for a period of 20 weeks in favor of our model. In the case of a worst case estimation, this is even higher: a cost reduction of approximately 4.6 million euro in 20 weeks. In these calculations, we assume that the capacity is available for five days a week and that no transfers between specialisms are allowed. We are well aware that we use several assumptions which should be validated with the real world and this may bring down the calculated cost savings estimates.

Overall, we construct a model which adequately models the patient flows within ZGT and estimates patient volumes and occupancy rates at the combination of department and (sub)specialisms and which has the potential to lower future costs.

Preface

The master thesis is the final project before the conclusion of the Master Program of Industrial Engineering and Management, track Financial Engineering and Management at the university of Twente. This graduation project is done in cooperation with the Ziekenhuis Groep Twente, ZGT in Hengelo and Almelo. From February 2012 until now I have been an intern at ZGT at the department Finance and Information.

From the start, the graduation project was very challenging. The assignment was not entirely defined, which led to much freedom to develop the borders of the research. I really appreciate the extent to which this freedom attains: there was a lot of space to develop my own view and models in the research. As time went by, the assignment became clear and I think we developed an adequate model and obtained some promising results in modeling patient flows and predicting patient volumes.

I would like to specially thank Daniel Plijter, Jasper Quik and Dennis Westerhof, all of ZGT, for their support. They introduced me in the health care industry and in particular in ZGT. Daniel's views were useful for the applicability of the research. Jasper's analytical and coding competencies were useful for the modeling part of the thesis. Finally, Dennis could explain the details of health care finance very well.

Next, I would like to thank Reinoud Joosten for being the chief supervisor of my graduation report. At some times we had very lively and pleasant discussions about the report and the research. The feedback was always very useful.

It is thanks to Erwin Hans that I got the opportunity to graduate in a hospital. I would like to thank Erwin for his willingness to put me in contact with ZGT and for being the second supervisor.

Writing the Master thesis, I realize there comes an end to studying. I have always enjoyed the studies I have attended at the University of Twente. I think in the future, I will always look very positively at this time.

Bas Weggemans
Enschede, August 19, 2012

Contents

Chapter 1

Introduction

1.1 Motivation

Staff, nursing beds and operating theatres are scarce and expensive resources in a hospital. This is why management of hospitals would like to allocate these resources as efficient as possible. Furthermore, health care is a complex product: the demand for care is stochastic and the course of a medical treatment is not predetermined. Often multiple specialisms are involved in one treatment. As the health care process is a complex process and can be described in an abundance of details, we develop in this paper a holistic model which uses concepts from Finance in order to model patients arrivals at and patient flows between specialisms in the hospitals of Ziekenhuis Groep Twente, ZGT. A patient path is defined as the successive treatments a single patient undergoes at a specific combination of specialisms and departments of a hospital. These specialisms are e.g. surgery or cardiology. The departments are outpatient clinics, operating theaters and nursing wards. A patient flow is defined as the visits to combinations of a department and a (sub)specialisms of a group of patients in a certain time period. Each department has his own function, the outpatient clinics are for diagnoses purposes and simple treatments, operating theaters for (complex) operations and nursing wards for clinical admissions. The various specialisms are represented at these departments. Currently ZGT uses common sense, historical averages and planned appointments as the basis for allocating staff, operating theaters and nursing beds. Moreover, ZGT has no insight in how patients transfer from one specialism to another specialism. Forecasting demand for care and having insight into transitions of patients through the hospital in a certain time period, should enable the management of ZGT to allocate staff, nursing beds and operating theaters more efficiently than the current manner of allocation, yielding a better occupancy rate and lower costs.

First, we introduce the research problem and research questions. Next, we discuss the relevance and methodology of the study. Also we provide a social and economical context and elaborate on changes in the health care market. Finally, we provide some background information on ZGT.

1.2 Research question

ZGT is interested in predicting patient volumes at the various departments: outpatient clinics, operating theaters and nursing wards of the hospital, at least one month ahead. These estimates of patient volumes enables ZGT to allocate resources as staff, operating theaters and nursing beds more efficiently. Moreover, ZGT is interested in which share of patients transfer from one(sub)specialism to another (sub)specialism in the hospital within a certain time period. Insight into future patient volumes and patient transfers between (sub)specialisms, provides the management of ZGT information required for using resources more efficiently. The research problem is as follows:

> What is an adequate model to predict future patient volumes at least one month ahead at a (sub)specialism at the various departments within ZGT?

Next to the problem statement, we define a research objective, which is:

> Develop a model that enables Ziekenhuis Groep Twente to predict patient volumes at least one month ahead at specific departments within the hospital, taking into account the transition from patients from one (sub)specialism to another (sub)specialism in a certain time period.

In order to answer the research objective, we define the following research questions:

1. Can we develop a model that can predict the number of patient arrivals in a certain time period of (sub)specialisms in the

   a. Outpatient clinics?
   b. Operating theaters?
   c. Nursing wards?

   This research question is answered in Section 6.3.1.

2. Can we develop a model that can compute the probability that a patient will transfer from one (sub)specialism to another(sub)specialism in a certain time period in the

   a. Outpatient clinics?
   b. Operating theaters?
   c. Nursing wards?

   This research question is answered in Section 6.3.2.

3. Can we develop a model that can estimate the service time of patients in the

a. Operating theaters?

b. Nursing wards?

This research question is answered in Section 6.3.3.

4. How can we combine the estimation of the expected number of arrivals at a certain (sub)specialism, the probability of a patient transferring from one (sub)specialism to another (sub)specialism and the average service time to estimate the occupancy rate of specialisms at

   a. Operating theaters?

   b. Nursing wards?

   This research question is answered in Section 6.1.

The modeling part is given in Chapter 3, the results are provided in Chapter 5.

1.3 Relevance of the research

The health care environment is rapidly changing. Social, political and economical causes ask for a more efficient use of resources as nursing wards and staff in the health care industry. The government tries to control the health care expenditures by allowing more competition between health care providers and by reforming the health care market. Until 2003 the health care market was mainly capacity and volume driven. The more capacity a health care provider possessed, the more health care budget the provider received. After the reform of 2003, a health care provider receives a fixed sum of money per treatment per patient. This requires a fundamental reorganization of the health care industry: the usage of nursing beds and operating rooms should be more efficient. That is avoiding over- and undercapacity of operating theaters and nursing beds as much as possible, given the capacity and time constraints. With respect to staff this is allocating staff such that there is neither a shortfall nor an abundance of staff, given the demand for care and a time constraint. Sections 1.5, 1.6 and 1.7 explain in some more detail the different interests of society and the changing health care market.

At this moment in ZGT there is no direct link in the planning process between operating theaters on the one hand and nursing departments on the other hand. The data available is sufficient to forecast the occupancy of the nursing wards, however the current predicting methods are not really sophisticated but based on common sense and experience. Differences in occupancy rates of beds yields financial effects. At this moment the department nursing wards within a hospital is one of the most costly departments. A more efficient usage of nursing wards yields cost reductions. That is why the management would like to have estimates of future patient volumes as accurate as possible.

In this research we combine knowledge from other disciplines, in particular from Finance,

in order to model patient flows and predict patient volumes. We develop a holistic model which provides ZGT insight into patient flows trough the various departments of the hospital, taking transitions from one (sub)specialism to another (sub)specialism into account. The model enables them to predict patient volumes at (sub)specialisms at least one month ahead. Insight into patient flows and expected patient volumes can be used for allocating staff, nursing wards and operating theaters more efficiently. Moreover, the model gives insight what proportion of patients transfers from one (sub)specialism to another (sub)specialism within a certain time period. The model we develop in this study uses the strengths of two different theories, namely ARIMA and Markov theory. The integration of these theories enables one to develop a holistic model of a hospital, which one can use to predict patient volumes of (sub)specialisms at the various departments at least one month ahead. Relatively little studies focus on using financial models in health care optimization and efficiency issues. By far, most studies use theories as queuing theory and the theory of petri nets. This research investigates the applicability of finance theories in health care. This can be seen as the scientific relevance of the study.

1.4 Methodology

The research questions deal with modeling the patient flow within a hospital. Aim is to construct a holistic model which predict patient volumes and keeps track of transitions of patients between (sub)specialisms. We develop a holistic view of the hospital in order to avoid a too much detailed view of a hospital and to deal with the complexity of the health care process in a hospital. A holistic approach is often used in Economics and Finance. In these disciplines the complex reality is described by a holistic model. Consider for instance how in Economics the Keynesian theory models the economy and society.

We use Financial theories in order to model the various aspects of the holistic model. We model patient admissions using ARIMA theory. In Finance, ARIMA-models are used in order to estimate indices and prices of commodities. We use Markov chains for modeling the transition probabilities between different departments in the hospital. Markov chains are the basis of many principles in Finance. The Markov property is again one of the key principles with respect to pricing: the property claims that the future price of a commodity only depends on its current price, irrelevant of the historical prices. In fact, it is one of the key assumptions of the efficient markets (Hull, 2009). In the Efficient market theory it is assumed that the price at this moment, reflects all information and that only this price is necessary to compute the price some small time instant later. In this research, part of the model we develop, also only requires the current information of a patient and not all historic information to compute the next step in his/her patient path. Finally, we use statistical analysis for computing the average service times. We introduce the model in Chapter 3.

In order to validate the model, it requires analysis of data. We use historical data for investigating the patient volumes per specialism and its inter and intra transitions. Also

we use historical data in order to develop a time series which can be used for forecasting future admissions. Finally, we use historical data to compute the average service time of patients.

1.5 Urge from society, a changing world

There is an urge from society to organize health care more cost-efficient. Population aging and co-morbidity have resulted in rising health care expenditures. Statistics Netherlands computed that there is a rising increase in health care expenditures in the period 2004-2008 (CBS, 2010). In 2009 the health care expenditures amount to 83.8 billion euro, an increase of 5.8% compared to 2008. Next, Statistics Netherlands computed that the health expenditures in 2009 per capita increased with 5.2% compared to 2008, confirming the trend that also the health care expenditures per capita are increasing over the years.

Furthermore, there is a shortage of staff in health care. Estimations of the SCP[1] demonstrates that the demand for health care staff will increase from 220.000 vacancies in 2005 to 300.000 vacancies in 2030 (Eggink, Oudijk, & Woittiez, 2010). The Dutch government has realized the need for more health care staff. In 2012 recruitment funds will increase to 852 million euro (VWS, 2012). These developments ask for a more efficient allocation of health care budget. To achieve this, the Dutch government designed a reform of the health care market, in which a more liberal market is introduced. Furthermore, the current economic situation and the introduction of a new expenses claim system have led to uncertainty on the health care market, which has made banks reserved with financing hospitals.

1.6 Changing health insurance market and expenses claim system

One can distinguish three players on the health care market. First there are the patients (demand side), second the health care providers (supply side) and finally the financing institutions, such as health care insurers or government. Often the market is regulated by a health care authority. In the Netherlands major reforms in the health care market have taken place. Both the health insurance market and the expenses claim system have been reformed, the former in 2003, the latter in 2005.

In the Netherlands the health insurance market is a dual system. The non insurable health care risks are financed by a special act and are totally paid by the Dutch government. The government finances this act from tax incomes, paid by employees and employers. This is regulated in the AWBZ.[2] The AWBZ is a collective and obligatory

[1] SCP: Sociaal Cultureel Planbureau, English: Bureau for Social and Cultural Studies.

[2] AWBZ: Algemene Wet Bijzondere Ziektekosten, English: General Act on Exceptional Health Care Expenditures.

health care insurance which covers non insurable health care risks, as e.g. long stay care or nursing homes. Until 2003, every now and then, the law was amended to accommodate wishes from society, resulting in much bureaucracy and non transparency. The intensity of adaptations called for a reform of the act. The redefined act has legislative power as of 2003. The reform allowed more participants on the health care market in order to increase competition. Moreover, before the reform, patients were not confronted with the costs of health care. The new reform should make both patients and health care providers more cost-conscious.

The other demand for health care should be covered in an obligatory private health insurance. Health insurers are obliged to offer a by the government predefined package with treatments, which covers minimum health care benefits. Next to this health insurance one can take an additional health insurance. This part of the health insurance market is liberalized, such that insurers can compete.

The foundation of the insurance system is health equity: all people are allowed admission to health care, regardless their age, mental or physical condition. In the Netherlands an equalization pool and risk pool are used in order to reconcile differences in the customer population of health insurers. These funds are regulated by the government, which pools the risk of the various insured, by transferring funds to the insurer of the more risky insured from the insurer of the less risky insured. This measure should overcome moral hazard by insurance companies.

1.7 New expenses claim system in the Netherlands

The expenses claim system has been reformed. The reason for the reform is trying to change the incentives of the health care providers. The new expenses claim should make the providers more cost-efficient, as they are only compensated per treatment, instead of available capacity. A major reform has taken place in 2005 by the introduction of DBCs[3] and a smaller one in 2012, in which DBC was replaced by DOT.[4] These reforms are an additional challenge for the health care market. The Dutch government tries to introduce a health care system on a free market basis.

A DBC is the total care trajectory starting with a diagnosis and finally ending with some treatment from a specialist in a certain time period (maximum one year). With the introduction of DBC the Dutch health care market became partially competitive. For several treatments, often 'less complex' treatments (or B-segment), a free market has been introduced. The diagnosis and the treatments are administrated in one specific code, the DBC performance code. For complex treatments and some very rare and specific treatments (often in academic hospitals) the Dutch Care authority (NZa[5] deter-

[3]DBC: Diagnose BehandelingsCombinatie, English: DTC, Diagnose Treatment Combination.
[4]DOT: DBC Op weg naar Transparantie, English: DTC, a Road map for more Transparency.
[5]NZa: Nederlandse Zorgautoriteit, English: Dutch Health care authority.

mines the prices (A segment). Over time, the authority will shift more treatments from the A segment to the B segment, so that the number of treatments on which hospitals can compete, will increase. The aim of introducing DBCs is making both hospitals and patients more cost conscious about how much health care actually costs.

Before the DBC expenses claim system and the reform of the AWBZ, hospitals were financed on basis of fixed prices, volume agreements and on basis of the number of inhabitants a hospital served. The hospitals received a fixed sum covering interest expenses, housing expenses and a variable part, depending on the number of admissions, nursing days, outpatient clinic consultations and day care treatments. This way of financing has led to a system in which compensations did not match the executed health care production. Also there was no incentive to organize health care efficient or that is to discharge patients as quickly as possible. The urge for a more transparent compensation system was born. One of the purposes of introducing DBCs was to overcome this problem.

However, the introduction of DBCs has led to an abundance of combinations of performance codes (each combination of outpatient visits, operating theater visits and clinical visits has for each diagnose its own performance code). Therefore, there was a desire for a more uniform system: DOT. DOT is derived from DBCs however; they are more uniform than DBC. In DOT the specific care is divided in several 'DBC care products'. The ultimate combination of care products determines the specific DOT. In DOT a health care provider will receive a fixed price for a care product, regardless the specialism which has executed the treatment, in DBC these prices could have been different. Also the introduction of DOT has led to another expenses claim method towards the health care insurer. DBCs are checked on administrative errors by hospitals themselves and then submitted as a claim to the health insurer, DOTs are approved by an approval authority (grouper) and can then be paid out by a health insurer.

1.8 Ziekenhuisgroep Twente

Ziekenhuisgroep Twente, or short ZGT, is a health care organization in the east of the Netherlands. ZGT has two hospitals, one located in Hengelo and one in Almelo. Furthermore, the group has five outpatient clinics in Geesteren, Goor, Nijverdal, Rijssen and Westerhaar. ZGT was founded in 1998 as a merger of the two hospitals, Streekziekenhuis Midden-Twente in Hengelo and the Twenteborg Ziekenhuis in Almelo. This merger has made ZGT the largest hospital in Twente, only somewhat larger than Medisch Spectrum Twente, Enschede. The service area of ZGT covers the municipalities of Almelo, Hengelo, Borne, Dinkelland, Rijssen-Holten, Twenterand, Tubbergen, Hof van Twente, Hellendoorn and Wierden. Other hospitals nearby, are in Enschede, Deventer, Hardenberg, Winterswijk, Zutphen and Zwolle. In 2010 the capacity of the hospital was 1085 beds. Furthermore, the production of DBCs in the A-segment equaled 213.524 and in the B-segment: 79,965 (ZGT, 2010). ZGT accommodates 25 different specialisms, from which surgery is the largest.

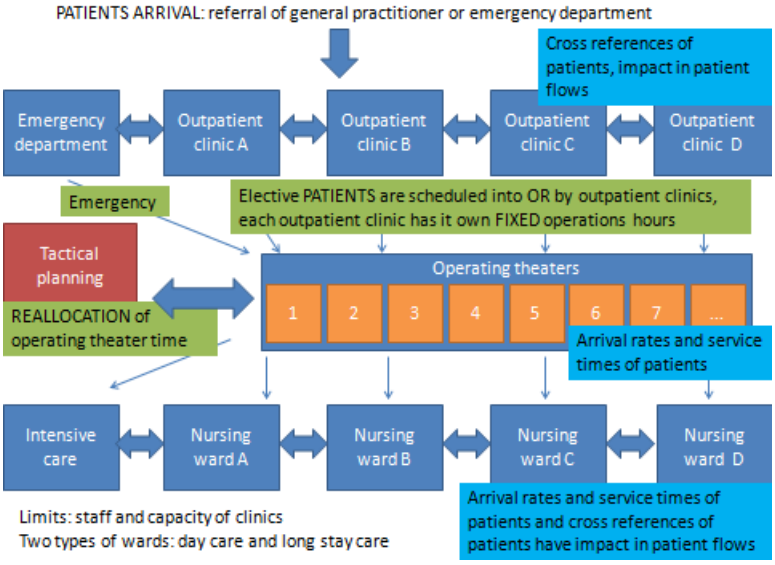


Figure 1.1: Patient flow within ZGT hospital, also general for Dutch hospitals.

In the ZGT a system, called tactical planning, is used in order to optimize the allocation of patients and specialists to operating theaters. This system is used to gain insight into the patient flows, their arrival processes and service times. Historical data and the expertise of specialists are used for optimizing the master schedule of the operation theaters. The patient flow within ZGT is given in Figure 1.1. In a hospital there are two types of patients: outpatients and inpatients. Outpatients are patients who only visit the hospital for a short treatment or diagnosis in an outpatient clinic. Inpatients are admitted at the hospital for a longer treatment. This can be a treatment of several hours (one day admission) or several days (more than one day admission). Both type of admissions require a nursing bed in a nursing ward.

ZGT is in the mid of a reorganization. The board of the hospital would like to make the hierarchical structure of the organization less stratified. Currently there are three divisions in the organization, two divisions deal with the health care process, the third division is facility management. These divisions are lead by managers, reporting to the board of directors. Next to these divisions a Financial and Information department, a Human Resource department and a Board Supporting department exist. All these departments directly report to the board of directors. Figure 1.2 shows the current organization structure.

In order to make the organization less stratified, the board would like to introduce a RVE-structure.[6] RVEs are organized around one specialism. This can be a clinical

[6]RVE, Resultaat Verantwoordelijke Eenheid, English Profit Responsible Unit.

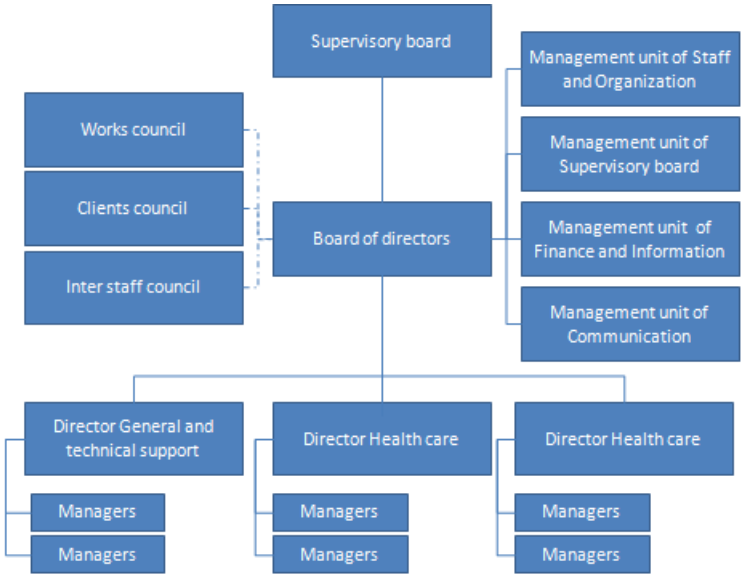


Figure 1.2: The current organization of ZGT hospital, until April 2012.

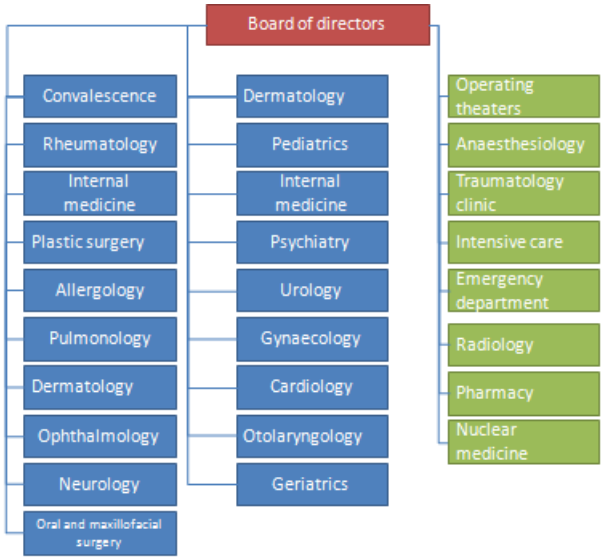


Figure 1.3: New structure of organization of ZGT hospital, per May 2012. Blue specialisms indicate porters and green specialisms are supporting specialisms.

(porter) or a supporting specialism. Figure 1.3 shows the different porter and supporting specialisms[7] in the new RVE-structure. These entities will directly report to the board of directors. The RVEs could be compared with business units in an ordinary company. Goal of the introduction of the RVEs is to introduce a more entrepreneurial attitude within the different specialisms. Currently, in ZGT the entities determine their budget on cost basis principle. The RVEs structure should also make the different units revenue conscious. The reorganization is completed in May 2012.

1.9 Outline of report

The outline of the remainder of the report is as follows. In Chapter 2 we investigate the literature with regard to modeling patient flows in hospitals. In Chapter 3 we introduce a mathematical model in which we model patient flows through a hospital. The model consists of three components. First, we discuss how to model patient arrivals at the three departments. Next, we introduce a model in which the transfers of out- and inpatients between (sub)specialisms are modeled. Finally, we discuss techniques to obtain average service times. Chapter 4 discusses the data requirements as well as the data used in the holistic model. Chapter 5 elaborates on the results. Chapter 6 concludes. Chapter 7 provides a discussion and considers limitations of our research and suggestions for further research. Finally, in Chapter 8 we briefly explain the ins and outs of the model and discuss the applicability and implementation of the model and do recommendations to ZGT.

[7] Porter specialisms, e.g. cardiology, are specialisms where a patient is referred to in order to receive a medical specialist-oriented care; supporting specialisms, e.g. radiology, supports the porter specialisms by e.g. diagnosing and treatment of a patient.

Chapter 2

Theoretical framework

In this chapter we investigate relevant literature. We enlarge on the various disciplines and theories. The existing structure of the hospital is assumed to be given. The aim is not to propose changes in the structure of the hospital which could make the organization of the health care process within ZGT more efficient. Aim of the research is however to provide a holistic view of a hospital which enables one to predict future patient volumes at various combinations of departments and (sub)specialisms, given the current structure of the hospital. The required theory concerns mathematical models of a hospital such that we are able to reconstruct patient paths through a hospital and to compute future patient volumes at combinations of departments and (sub)specialisms. Predicting patient volumes and monitoring patient flows between specialisms requires three components:

1. Modeling patient arrivals in a certain time period.
2. Modeling transitions of patients between (sub)specialisms in a certain time period.
3. Computing average service times of treatments for specific treatments.

The first two require a consideration of various theories and models. The last item only requires a statistical analysis of historical service times. First, we consider theory concerning arrivals at specific departments of a hospital. Second, we focus on how to model transfers of patients between (sub)specialisms in a hospital. Finally, we motivate which theory we select for model building.

2.1 Patient arrivals

There are many ways of modeling patient arrivals at hospitals. In health care research queuing theory is one of the most dominant theories to model arrivals. ARIMA-models can also be used for predicting future arrivals. This section discusses both theories.

2.1.1 ARIMA theory

Autoregressive integrated moving average (ARIMA) models can be used for forecasting. The principle is based on time series analysis. A time series is a sequence of data points

measured at equidistant time intervals. The applicability of time series analysis is wide, for instance in Finance many time series models are used in order to predict the behavior of certain commodity prices. ARIMA-models can yield good predictions in the short term.

Engle and Russel (1998) have described the data conditions under which an ARIMA-model can be used for forecasting: the data generating process should be stationary. The stationarity of the data generating process can be tested using a unit root test.

Several authors have used ARIMA-models in order to forecast patient volumes in hospitals. Kao and Tung (1980) use an ARIMA-model which predicts demand of inpatients in a large public hospital. The authors propose an ARIMA-model for forecasting the monthly admissions per specialism for the next twelve months. They find promising results in predicting the demand as they compare it with the actual demand. Abdel-Aal and Mangoud (1998) predict the monthly patient volume of a primary health care clinic using an ARIMA-model, which also accounts for seasonal effects. Abdel-Aal and Mangoud propose a ARIMA$(4, 2, 0)$ model which fits best in forecasting the patient volumes of this particular clinic. Finally, Lin (1989) also uses an ARIMA-model in order to forecast monthly patient volumes. For several hospitals in the United States the author develops ARIMA-models for forecasting admission, discharge of patients and gains of a hospital. Furthermore, the paper provides some tests in order to check the outcome of the prediction with actual demand.

2.1.2 Queuing theory

Queuing theory is a mathematical theory about waiting lines. It observes a server which can serve persons or objects and a waiting line in front of this server. The theory requires a specific arrival distribution and service distribution. The length of the queue can be either finite or infinite. Network of queues is a modification of queuing theory. In a network of queues multiple queues are linked in a network. Applications of queuing theory are used in all sort of processes in which customers are served at a counter, as. e.g. shops and banks. Moreover, it has applications in traffic engineering and telecommunication. Queuing theory is mainly used to describe the arrivals at hospitals, but could also be used to model consecutive queues in a health care process.

Creemers and Lambrecht (2007) model a hospital in Belgium using a network of queues. The authors consider the health care process as a consecutive chain of locations in a hospital a patient visits. They link the outpatient clinic, the operating theater and the nursing wards, using queuing theory. The authors propose a model in which these locations have a $G|G|n$-structure.[1] The authors determine the arrival and service process for the several locations in the health care process. Figure 2.2 provides an example of

[1] In this case: the arrival process has a general distribution, the service process has a general distribution and the length of the waiting line is n.

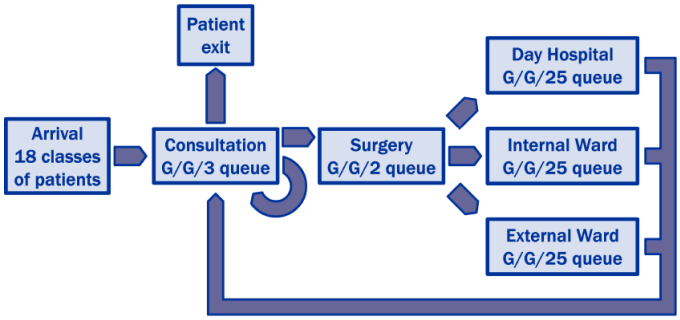


Figure 2.1: Network of queues of a hospital in Belgium (Creemers & Lambrecht, 2007).

network of queues, applied to hospitals. Queuing models assume that the arrival process possesses the memoryless property. Poisson and Erlang distributions have this property. It is the question however, whether patient admissions at a hospital are distributed as a Poisson or Erlang distribution. Schwartzman (1970) models patients arrivals, using a Poisson distribution. Utley et al. (2003) however claim that patient arrivals do not necessarily possess the memoryless property.

2.2 Patient transitions between (sub)specialisms

There are also several theories with regard to modeling patient transitions from one (sub)specialism to another (sub)specialism. Markov theory seems natural as it comes to model system transitions. Also the theory of Petri nets is used to model transitions within a system. Both theories are explained in more detail in this section.

2.2.1 Markov models

Markov chains represent a system subject to going from one state to another state (transition) with a certain probability. A Markov chain has a finite number of states and transitions. Markov chains are used in order to compute the one-step transition probability of going from one state to another state, but becomes more powerful as it is a convenient method for computing the long run transition probability of going from one state to another. Markov chains have an abundance of applications, e.g. Economics, Operations research or Game theory.

Several authors have used Markov chains in order to model patient transfers between specific locations within a hospital. A patient transfer can be seen as a single patient transferring from one physical location to another physical location and can be described by a system transition in a Markov chain.[2] Perez et al. (2004) use Markov models in or-

[2]We choose physical locations, one particular treatment can occur at different specialisms. Moreover, this also enables one to model transitions within one (sub)specialism or process.

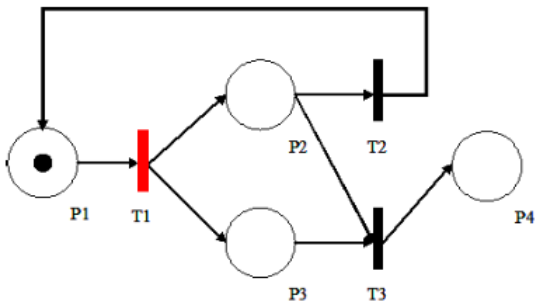


Figure 2.2: A Petri net as in the paper of Leite. The red T_1 indicates that it is activated (Leite *et al.*, 2010).

der to model patients transfers in an intensive care unit in a hospital in Colombia. They consider different steps in the process and provide an approximation of the likelihood that events occur in some order. Furthermore, they provide an estimate for the average length of stay. Akkerman and Knip (2004) also use Markov models in order to give an estimation of the length of stay at a cardiac surgery department of a Dutch hospital.

2.2.2 Petri nets

A Petri net is a bipartite graph[3] in which the vertices represent transitions and places. In the representations of Petri nets, the vertices representing transitions are depicted by bars, the places are depicted by circles. The edges are always directed arcs. At circles tokens are stored; the transition is only activated if the input at places (circles) is equal or larger than the weight of the directed arc. Petri nets are used to model systems in which transitions can take only place if a minimum input is satisfied. In health care, for instance: a patient can only go to the next step in a health care process if all preconditions, e.g. several small medical examinations, are met. Other applications of Petri nets are in software engineering. Research in the field of health care and petri nets aims at improving data mining. Maruster et al. (2001) use a Petri net model in order to model the successive events in a health care process. The Petri net model is designed in order to model successive events in patient flows of a single patient. For specific treatments the authors develop a Petri net which is used for representing the patient flow within one specialism. Further research will deal with modeling the patient flow of multi multidisciplinary patients. Leite et al. (2010) model an intensive care unit using stochastic Petri nets. The authors conclude that Petri nets are useful for checking manual processes within the successive chain of events in a patient flow. As much hospitals still use manual processes the authors conclude that the use of Petri nets can prevent the

[3] A graph in which the vertices can be divided in two disjoint sets A and B, in other words every edge connects a vertex in set A to one in set B.

occurrence of deadlocks.

2.3 Selection of theory: ARIMA and Markov theory

ZGT would like to have an indication of future patient volumes and insight into the transfers of patients between specialisms in a certain time period. A single theory described above is not sufficient to provide a holistic model. To approach our goal, we choose ARIMA and Markov theory.

Time series are applied to forecast future patient volumes. This manner of forecasting also allows us to account for patient fluctuations. It is known that patient volumes vary over time. Time series have the opportunity to include this effect as it uses historical data for predicting the next value. Queuing theory is less useful for this purpose as it assumes a fixed arrival distribution. Historical data allows one to provide an ARIMA-model which can predict future patient volumes.

Petri nets are useful for modeling processes in which there is a necessity to specify a set of minimum conditions before a system can undergo a transition from one state to another. Petri nets however are not useful for forecasting purposes and computing transition probabilities. ZGT is interested in the transfers a patient can make between several (sub)specialisms. The abundance of possible transitions, makes queuing theories less appropriate. A matrix representing all transitions is more efficient and elegant and this is where Markov chains become interesting. Predicting patient volume and the occupancy rate of a combination of departments and (sub)specialisms, it is indispensable to keep track of how a patient transfers from one (sub)specialism to another (sub)specialism during his patient path. We define a patient path as the consecutive chain of (sub)specialisms a patient visits for the treatment of one disease. A patient path can exist of several visits. Taking the whole patient history of one patient into account, requires an abundance of data storage and computation efficiency. If one is able to develop a model which only requires the last visit in order to determine the next visit, one can save a lot of computation time. This is one of the aspects in which lies the power of Markov theory. The Markov property states that the probability of going from one state to another state[4] only depends on the last state and not on the history of all its predecessors. Moreover, Markov chains can possess a limiting distribution. The limiting distribution is a powerful tool to compute the transfers between (sub)specialisms in the long run.

To conclude we use the combination of ARIMA-models and Markov models to model patient arrivals and patient transfers between (sub)specialisms at departments.

[4] In this study going from one (sub)specialism to another (sub)specialism in a certain time period.

Chapter 3

Model

In this chapter we introduce mathematical theory, models and assumptions used in order to model the patient flow within a hospital. The model we use consists of three components: patient arrivals at various combinations of departments and (sub)specialisms, transfers of patients between (sub)specialisms within a department and the average service time for specific treatments. For the arrival process we use ARIMA theory, for modeling patient transfers between (sub)specialisms we use Markov theory and finally we use statistical analysis for computing the average service times.

Data limitations require to subdivide the hospital into three departments: outpatient clinics, operating theaters and nursing wards. The data at the three departments have other characteristics which makes it impossible to reconstruct a patient path by using the data of the various departments in one model. However if we split the model, we can reconstruct the patient path.[1] This is explained in more detail in Chapter 4. The specialisms are represented at the three departments. Figure 3.1 provides a schematic overview of the hospital in the three departments and depicts where the three different model components, are applied. The red bars in the picture represent the arrivals and are modeled by ARIMA theory. The blue boxes are the three departments and the green boxes are the (sub)specialisms within the departments. The black arrows within and between the departments represent the transition probabilities of a Markov chain. The number of specialisms and black arrows depicted in Figure 3.1, are not exhaustive. Finally, the orange box depicts the computation of the average service times of (sub)specialisms at the operating theaters and nursing wards.

Patient arrivals are modeled using ARIMA theory. Due to the stochastic character of the incidence of the demand for health care, one would like to have a model that can

[1] Recall that a patient path is defined as the consecutive (sub)specialisms a single patient sees, during a treatment of one disease. A patient flow is defined as the visits to combinations of a department and (sub)specialisms of a group of patients in a certain time period. For determining a patient flow we have to know the patient paths of individual patients. The sum of transfers of single patients from one (sub)specialism to another (sub)specialism in a certain period is equal to the patient flow from this (sub)specialism to the other (sub)specialism in this period.

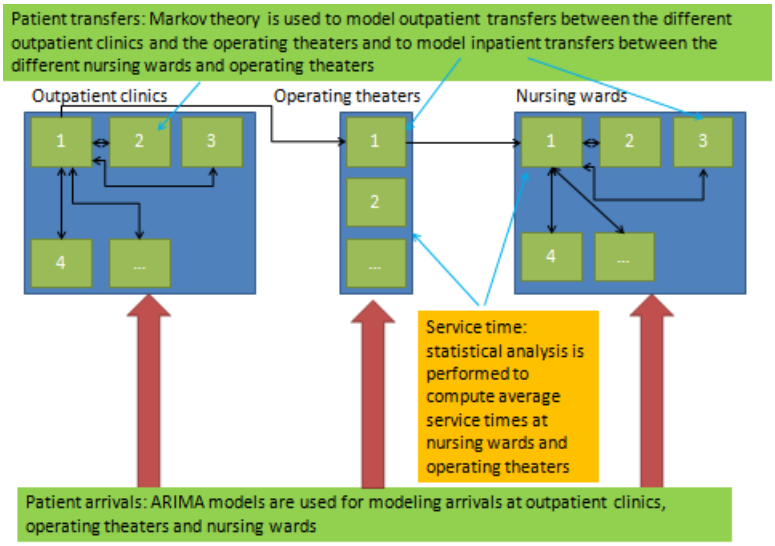


Figure 3.1: A graphical representation of the subdivision of the hospital ZGT in the three departments. The numbers at the green boxes in the departments represent the specialisms. In the figure we indicate where we apply ARIMA theory, Markov theory and statistical analysis.

predict the number of arrivals at a specific combination of a department and specialism in a certain time period. One can fit an ARIMA-model onto historical data points and use this model to predict future patient arrivals at a certain combination of department and specialism. At ZGT there is an abundance of historical data about patient arrivals at several departments and specialisms. For the combination of a specific department and (sub)specialism, we use the ARIMA theory to estimate an ARIMA-model which predicts the future patient arrivals at this combination. The theory about ARIMA-models is discussed in Section 3.1. In this section we introduce an ARIMA-model for ZGT.

Typically, a patient arrives at a hospital after a referral of a general practitioner. In a hospital elective patients first visit an outpatient clinic. Emergency patients are admitted at the emergency department, but this can be seen as special type of an outpatient clinic. At this point a decision will be made for further treatment. This decision is one of the following: an outpatient treatment in the same (sub)specialism, a referral to another (sub)specialism in the outpatient clinics, an appointment for an operation, an admission to a nursing ward or the discharge of the patient. Patients enter a nursing ward after being referred from an outpatient clinic or after being operated. The intensive care could be seen as a special nursing ward. The transfers are considered to be the transitions from one state to another state of a Markov chain.

We use two Markov chains in order to model transfer of patients from one (sub)specialism

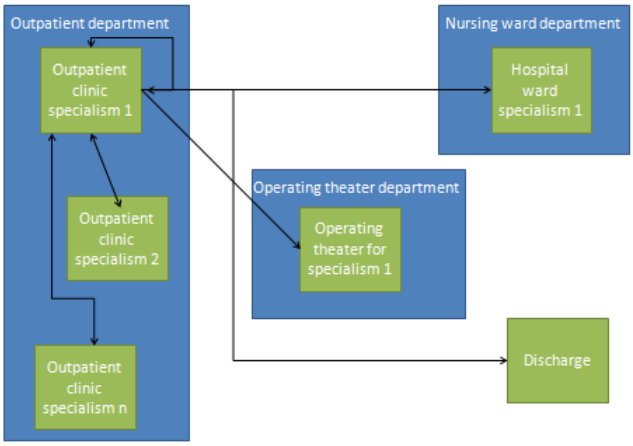


Figure 3.2: A graphical representation of a Markov chain of the transfers of outpatients.

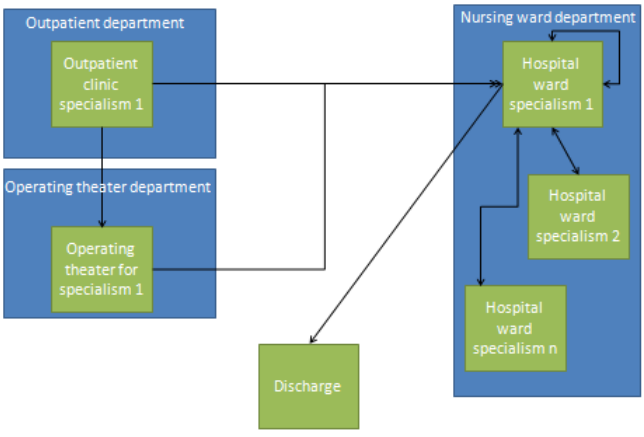


Figure 3.3: A graphical representation of a Markov chain of the transfer of inpatients.

to another (sub)specialism. This is due to data limitations which are discussed in Chapter 4 and Chapter 7. The first process describes the transfers of outpatients between specialisms in the outpatient clinics and the operating theaters. Figure 3.2 depicts the transfers of the outpatients. The second process deals with the transfers of inpatients between operating theaters and nursing wards. The transfers of the inpatients is shown in Figure 3.3. For simplicity, in both figures just one outpatient ward or hospital ward is considered. It assumes that patients can flow to and from a finite number of other outpatient clinics/nursing wards. As the transitions between various (sub)specialisms are of interest, the choice to use Markov theory seems natural. Section 3.2.1 provides the Markov chain for outpatient transfers and Section 3.2.2 for the inpatient transfers.

The last component of our model concerns the computation of average service times. The average service times are necessary when it comes to computing the occupancy rate of different combinations of (sub)specialisms and departments. The first two components: arrivals and transfer probabilities, are sufficient to compute the expected number of arrivals at a combinations of departments and (sub)specialisms. The last component: service time, adds a time dimension. Incorporating the average service times provide an estimate for how long a specific combination of department and (sub)specialism is occupied. The equations for computing the average service time are in Section 3.3.

Since ZGT, uses common sense and experience to estimate the number of nursing beds and operating time per (sub)specialism, we construct another simple performance measure to compare the results of our model to another model. We can compare the performance of both models using back-testing. Also we develop a method for a cost comparison between the two models. This is explained in Section 3.4.

3.1 Patient arrivals and ARIMA theory

The incidence of demand for care is uncertain. One cannot predict with certainty at which moment a person requires medical care within a hospital. However, using historical data, one can predict future patient volumes. ARIMA theory is suitable for this purpose. We require the number of arrivals at a certain combination of department and (sub)specialism at consecutive time periods. The number of arrivals are called data points. The ARIMA-model is used to provide a fit[2] onto this data points. The ARIMA-model can be used to predict the patient volumes of a next time period. In Figure 3.1, the figure with an overview of the holistic model, the prediction of patient arrivals, is illustrated by the red arrows.

ARIMA-models are used in Statistics and Econometrics in order to predict future points of a time series $\{W_t\}$ for time $t = 1, ..., T$. Alexander (2001) provides a theoretical framework for ARIMA-models and time series analysis. ARIMA-models are denoted

[2]The ARIMA-model describes an equation which should fit the data points best. ARIMA can be used to predict patient volumes at a combination of department and specialism in the next time period.

as ARIMA(p, d, q)-models in which p is the number of autoregressive terms, d denotes which difference of the original series $\{W_t\}$ we take and q is the number of moving average terms. The application of ARIMA-models requires that the data are stationary. Stationarity can be obtained by taking differences of the original series. Also, the residuals of the estimated ARIMA series should follow a normal distribution and should not possess autocorrelation. Often, we compute for one series of arrivals, several ARIMA-models. We can use the Akaike criterion to identify the best fit among the estimated ARIMA series. We explain all this, in the next paragraphs.

Data can possess seasonal patterns. ARIMA-models can deal with seasonality by incorporating seasonal autoregressive and/or moving average terms. We can investigate whether data possess seasonal effects. This is described in Section 3.1.1.

Stationarity

A time series is said to be strongly stationary if and only if for the joint density function F_W the following holds:

$$F_W(W_{t+\tau}, .., W_{t+k+\tau}) = F_W(W_t, .., W_{t+k}). \tag{3.1}$$

for all τ and all W_t, $t = 1, ..., T$. For a time series, however, it is sufficient to have a weakly stationary process. A time series is weakly stationary if the expected value and its variance are finite and independent of t, moreover the autocovariance function should only depend on k and not on t:

$$\gamma_{t,k} = cov(W_t, W_{t-k}) = E((W_t - E(W_t))(W_{t-k} - E(W_{t-k}))) = \gamma_k. \tag{3.2}$$

Unit roots tests, or Dickey-Fuller tests are performed in order to establish whether a time series is weakly stationary. To explain the usage of the test, we require the difference operator:

$$\Delta W_t = c + \beta W_t + \alpha_1 \Delta W_{t-1} + ... + \alpha_m \Delta W_{t-m} + \varepsilon_t. \tag{3.3}$$

The test checks the significance of the appearance of β in the model of Equation 3.3. The null hypothesis denotes $\beta = 0$, whereas the alternative hypothesis is $\beta < 0$. The Dickey-Fuller test can only be applied to AR(1) models.[3] A moving average process is always stationary. An autoregressive process can be weakly stationary from upon some lag τ. The augmented Dickey-Fuller test is a portmanteau test of the Dickey-Fuller test and enables one to test the significance of all coefficients in Equation 3.3 and to determine the number of lags m to include in the model.

One can check that the expected value and the variance of W_t are finite whenever $\beta < 0$ in Equation 3.3. Often, an original time series is not stationary, but the differenced series is. For instance, once modeling stock prices, the log returns of stock prizes are not stationary, but their difference are. Equation 3.3 is used in order to establish the d^{th} differences of the original series.

[3] AR is an abbreviation of autoregressive, AR(1) denotes an autoregressive process with one autoregressive term. MA is the abbreviation of moving average.

ARMA equation

If the data series is (weakly) stationary, an ARIMA-model can be applied. It is sufficient to use an ARMA (autoregressive moving average) model if the data series is stationary.[4] The ARMA model is given by:

$$W_t = \sum_{i=1}^{p} \alpha_i L^i W_t + \sum_{i=1}^{q} \theta_i L^i \varepsilon_t + \varepsilon_t. \tag{3.4}$$

in which L is the lag operator:

$$L^k W_t = W_{t-k} \tag{3.5}$$

and in which α_i are the coefficients of the ith autoregressive terms and θ_i are the ith coefficients of the moving average terms. ε_t are the residuals. Residuals are the observable estimates of the unobservable statistical errors. ε_t is an independent and identically distributed random variable with mean zero and variance σ^2. This is exactly the definition of a white noise process. A white noise process implies no autocorrelation. Sometimes a constant term is also included in Equation 3.4.

Autocorrelation in the residuals

Box-Pierce or Ljung-Box tests are statistical tests for checking the white noise condition. The Ljung-Box test is preferred over the Box-Pierce test. The test investigates whether any group of autocorrelations at lag j of a time series are different from zero for a fixed number of k legs. The null hypothesis is the assumption that the data are independently distributed. The alternative hypothesis is that the series is not. The test is applied to the residuals of the fitted series, e.g. the ε_t, $t = 1, .., T$ in Equation 3.4. The Ljung-Box test statistic[5] follows a chi-squared distribution with T degrees of freedom and is a number for testing the autocorrelation up to order k, or that is $corr(W_t, W_{t+m}) = 0$ for $m = 1...k$ and $m < k < T$.

Normality of the residuals

A Jarque-Bera[6] test can be performed in order to check whether the residuals in Equation 3.4 are normally distributed. For large samples the test statistic has a chi-squared distribution with two degrees of freedom. The null hypothesis of the statistical test is that the error terms are normally distributed. If it is rejected we may conclude the data are not.

[4] We drop the "I" from ARIMA, I only indicates which difference we take in order to make the data stationary.

[5] The Ljung-Box statistic is $T(T+2)\sum_{j=1}^{k} \frac{\rho_j^2}{T-j}$, in which ρ_j is the sample correlation at lag j.

[6] A Jarque-Bera test whether data is normally distributed, the test statistic is $JB = \frac{n}{6}(s^2 + \frac{(k-3)^2}{4})$.

Identifying the best fit

Finally, the Akaike or Schwarz criteria are used for indicating the goodness of fit of a model. Statisticians prefer the Akaike information criterion. The Akaike criterion is based on the number of parameters and the maximum value of the likelihood function of a fit and is just a number. The smaller the number, the better the fit. The lowest Akaike criterion among several fits of one series, indicates the best fit.

Software packages, like Eviews and Matlab, can do statistical tests, as the Ljung-Box test, the Jarque-Bera tests and compute the Akaike criterion.

3.1.1 Seasonality effects

Data might possess seasonal effects. For instance an ice cream vendor sees an increased sales during the summer months and lower sales during the other months. ARIMA-models can account for seasonal effects. If one suspects a cyclical effect after n periods one should take the nth difference to take this seasonal effect into account. The nth difference of a series W_t can be obtained by using the difference operator:

$$d(W_t, n) = (1 - L)^n W_t \tag{3.6}$$

in which L is the lag operator as in Equation 3.5. The notation of a seasonal ARIMA-model is $(p, d, q)X(P, D, Q)$, in which p, d, q are as before. P denotes the number of the seasonal autoregressive terms, Q the number of seasonal moving average terms, D the number of seasonal differences. Often we add a single number to this notation to indicate which seasonal difference we take, e.g. if we observe monthly data and one expects a yearly pattern, one could take the 12^{th} difference for investigating this suspicion.[7]

Yaffee and McGee (2000) provide an action plan for investigating whether a series contains seasonal effects. One can do this by looking at the $(0, 0, 0)$-ARIMA series. Seasonality events occur at regular time intervals, e.g. monthly or quarterly. By eyeballing, one might discover a cyclic pattern in the residual plot of the $(0, 0, 0)X(0, 0, 0)$-ARIMA series.[8] Next, one can compare the residual plot of both the $(0, 1, 0)X(0, 0, 0)$- and the $(0, 0, 0)X(0, 1, 0)$-ARIMA series[9] in order to observe a seasonal pattern. Finally, by looking at the plot of the autocorrelation function one might indicate at which lag we observe autocorrelation. Typically, we find strong autocorrelation at the lag at which we suspect a cyclic pattern and no autocorrelation at other lags. For instance, while analyzing monthly data in which one suspects a yearly pattern, one will find strong autocorrelation at the 12^{th} lag.

[7] An ARIMA-model in which the seasonal components are first differenced and we subsequently take the 12^{th} difference, is denoted by $(0, 0, 0)X(0, 1, 0)12$.

[8] That is a plot in which the residuals are plotted. For comparing it also contains the actual data and the proposed model.

[9] We compare the first ordinary difference to the first seasonal difference.

3.1.2 Action plan for determining an ARIMA-model for a series

This subsection contains an action plan or summary of how to find an ARIMA-model for a time series W_t, $t = 1, .., T$. For a series W_t, $t = 1, .., T$ one does the following.

1. Investigate seasonality effects as described in Section 3.1.1.
2. Determine whether W_t, $t = 1, .., T$ is (weakly) stationary. This can be done by using an Augmented Dickey-Fuller test.
3. If the series is stationary, the ARMA equation (Equation 3.4) can be applied. If the data is not stationary, take d^{th} difference until stationarity is obtained and apply the ARMA equation to the stationary series.
4. Test whether the residuals are white noise. This can be done by using the Ljung-Box test.
5. Test whether the residuals are normally distributed. This can be done by using the Jarque-Bera test.
6. Presumably for different values of p and q the conditions of steps 2-5 are satisfied. Now compute the Akaike criterion in order to identify the best fit. The fit with the lowest Akaike criterion indicates the best fit.

As a rule one tries to find the simplest ARIMA-model which can forecast a series accurately. That is, one would like to have the least possible autoregressive and moving average terms possible. Also including a seasonal component increases the complexity of the ARIMA-model. If one finds no evidence for a seasonal pattern, one should not incorporate a seasonal component in the ARIMA-model.

3.1.3 Validation of estimated arrival series

One would like to know whether the series forecasts the expected number of patients reliably. Mean squared errors are used for indicating the error in the measurement between the actual values and the predicted values. As we use historic data we can compare the estimated series with the actual (or historic) data. Let $\hat{W}_t$ be the estimated series by time series analysis of W_t. The error between the computation of $\hat{W}_t$ and W_t is denoted by e_t and is called the bias.[10] The mean squared error is a measure indicating the difference between an estimator and the actual data (Albers & Nijdam, 2007). The MSE of an estimator $\hat{\theta}$ with respect to the estimated parameter θ is defined as follows:

$$MSE(\hat{\theta}) = \mathbb{E}[\hat{\theta} - \theta]^2 \tag{3.7}$$

Now if we are interested in the MSE of the mean of a series W_t , we compute the MSE as follows:

$$MSE(\bar{W}) = \mathbb{E}[(\bar{W} - \mu)^2] = (\frac{\sigma}{\sqrt{n}})^2 = \frac{\sigma^2}{n} \tag{3.8}$$

[10] $e_t = \hat{W}_t - W_t$.

For our study we are thus interested in the difference of the actual and the predicted data, or also known as $MSE(e_t)$. A MSE of zero implies a perfect fit between the estimated value and the actual value. The MSE developed here only checks to what extent the proposed ARIMA-model fits onto the series of arrivals. The MSE is also equal to the sum of the variance of the errors and the bias squared. The smaller MSE, the smaller the variance of the error terms and the bias. Whenever MSE is close to zero, the error between the true value and the estimation is also small, and thus the deviation in the error with respect to the mean is small.

3.2 Patient transfers and Markov chains

We use a Markov chain in order to model the process of patient transfers between (sub)specialisms between the outpatient clinics and/or the operating theaters and the nursing wards and/or the operating theaters. Markov chains are a mathematical description of a system in which a transition from one state to another can be described with a certain probability. The transition probability does not depend on the previous states. A Markov process is said to be memoryless.

Definition of a Markov chain

Ross (2007) provides a mathematical definition of the Markov chain. Let $\{Z_N, n = 0, 1, 2, \dots\}$ be a stochastic process which can take on a finite or countable number of possible values. $Z_n = i$ means that the process is in state i at time n. Furthermore, it supposes that whenever the process is in state i, there is a fixed probability M_{ij} that it will be in the next state j. Formally, a Markov chain is defined as follows:

$$M\{Z_{n+1} = j | Z_n = i, Z_{n-1} = i_{n-1}, ...Z_1 = i_1, Z_0 = i_0\} = M\{Z_{n+1} = j | Z_n = i\} = M_{ij} \tag{3.9}$$

for all states $i_0, i_1, \dots, i_{n-1}, i, j$ and all $n \geq 0$. The process described in Equation 3.9 is known as a Markov chain. The equation states that the conditional distribution of a future state Z_{n+1}, given the past states $Z_0, Z_1, \dots, Z_n$, only depends on the previous state Z_n. This condition is known as the Markov condition.[11] For the transition probability, M_{ij}, the following holds:

$$i, j \geq 0 \qquad M_{ij} \geq 0 \qquad \sum_{j=0}^{\infty} M_{ij} = 1, \qquad i, j = 0, 1, ... \tag{3.10}$$

Or equivalently, we require i, j to be nonnegative. The transition probabilities should be greater or equal to zero for all i, j and in matrix representation a row sum should be equal to one.[12] The transition probabilities M_{ij} are denoted in a transition matrix $\mathbf{M}$.

[11] The Markov condition is also known as the memoryless property of a Markov chain.

[12] The sum of the probabilities of starting in a state fixed i and ending and a fixed state j should sum to one.

Homogeneity and limiting distribution

A Markov chain is homogeneous if the transition probabilities do not change over time. That is the probability of going from state i to state j at time $t = 1$, is equal to the probability of going from state i to state j in some future period. A Markov chain is said to be an ergodic chain if it is possible to go from every state to every state. Moreover, a Markov chain is called regular if some power of the transition matrix has only strictly positive elements. Winkler (1995) provides theory on limiting distributions of Markov chains. Let the limiting distribution be $\mathbf{L}$. We require the Markov kernel[13] to be primitive. A Markov kernel is primitive if there exists an n such that $M^n(i,j) > 0$ for all i, j.[14] Now if $\mathbf{M}$ has a primitive Markov kernel on a finite space with invariant (or limiting) distribution $\mathbf{L}$, then uniformly for all distributions v

$$\lim_{n\to\infty} v\mathbf{M^n} = \mathbf{L}. \tag{3.11}$$

$\mathbf{L}$ is also known as the stationary distribution. A Markov process should possess the Markov property, as defined in Equation 3.9. According to the literature, there are no known tests in order to test the Markov property directly. Some indirect tests could be done, as the order of dependence (Perez et al., 2004). Furthermore, the process should contain the stationary property. Bickenbach and Bode (2003) provide some statistical tests to examine the reliability of estimated Markov transition matrices. Furthermore, they discuss tests for spatial independence and homogeneity. The authors propose a likelihood ratio and Pearson χ^2 test in order to test the Markov property. Also they provide a method for constructing the transition probabilities, using maximum likelihood.

Measure whether homogeneity property holds

As this requires huge and complex computations, we use the notion of independence for testing the Markov property. In probability theory, two events are said to be independent if the occurrence of one of the events is neither more, nor less probable, than the other event. The definition is as follows:

$$\mathbb{P}(\psi \cap \omega) = \mathbb{P}(\psi)\mathbb{P}(\omega). \tag{3.12}$$

If two events ψ and ω are independent, the conditional probability becomes $\mathbb{P}(\psi|\omega) = \mathbb{P}(\psi)$[15] and the Markov equation (Equation 3.9) reduces to:

$$M\{Z_{n+1} = j\} = M_{ij}. \tag{3.13}$$

[13] A function p: $S \times S \to \mathbb{R}$ is called a Markov kernel if 1) For each $x \in S$, the mapping $A \to p(x, A)$ is a probability function on (S, S) and 2) For each $A \in S$, the mapping $x \to p(x, A)$ is a S measurable function.

[14] A regular Markov chain and a primitive Markov chain coincides when the Markov kernel coincides with the transition kernel of the Markov chain.

[15] Formally $\mathbb{P}(\psi|\omega) = \frac{\mathbb{P}(\psi\cap\omega)}{\mathbb{P}(\omega)} \overset{\text{by independence}}{=} \frac{\mathbb{P}(\psi)\mathbb{P}(\omega)}{\mathbb{P}(\omega)} = \mathbb{P}(\psi)$.

For a homogeneous Markov chain one can demonstrate that Equation 3.9 can be rewritten as follows:

$$\begin{aligned}
&M\{Z_{n+1}=j|Z_n=i,Z_{n-1}=i_{n-1},...Z_1=i_1,Z_0=i_0\}=M\{Z_{n+1}=j|Z_n=i\}=\\
&M\{Z_n=j|Z_{n-1}=i,Z_{n-2}=i_{n-2},...Z_1=i_1,Z_0=i_0\}=M\{Z_n=j|Z_{n-1}=i\}=\\
&\ldots\\
&M\{Z_2=j|Z_1=i,Z_0=i_0\}=M\{Z_2=j|Z_1=i\}=\\
&M\{Z_1=j|Z_0=i\}=M_{ij}. \qquad (3.14)
\end{aligned}$$

If we are able to demonstrate that we deal with an independent probability process or that is the condition in Equation 3.12 is satisfied, the following holds:

$$\begin{aligned}
&M\{Z_{n+1}=j|Z_n=i\}=M\{Z_{n+1=j}\}=\\
&M\{Z_1=j|Z_0=i\}=M\{Z_1=j\}. \qquad (3.15)
\end{aligned}$$

In this research we shall compute the transition probability of transferring from one (sub)specialism to another (sub)specialism in the outpatient clinics/nursing wards for different time intervals. The different transition probabilities are called realizations. The computed transition probabilities are derived from time intervals which are disjoint. Since the time intervals are disjoint the independence assumption follows. If the different realizations over time do not differ too much, we may assume the homogeneity property holds.

Now we shall introduce a criterion which is useful for measuring this difference. This criterion is also useful in investigating the Markov property. Assume that we compute different realizations $t=1,..,T$ of the transition probabilities. Each realization concerns another time interval and thus the intersection of the time intervals is an empty set. [16] The transition probability realizations at different time intervals t, $1 \leq t \leq T$, are denoted by $M_{ij}(t)$. As criterion whether the Markov property holds, we use the following equation:

$$\lim_{t\to\infty} \max_{1\leq t\leq T} \|M_{ij}(t)-\bar{M_{ij}}\| \leq \varepsilon \qquad j \geq 0 \ i \text{ fixed} \qquad (3.16)$$

in which $\bar{M_{ij}}$ is defined as follows:

$$\bar{M_{ij}} = \frac{1}{T}\sum_{t=1}^{T} M_{ij}(t). \qquad (3.17)$$

Equation 3.16 states that the maximum over t of the different T transition probabilities realizations and its average for a certain fixed i should be less or equal than ε. For this paper we assume two epsilons, namely $\varepsilon = 0.05$ and $\varepsilon = 0.10$. The two epsilons are sufficiently small for accepting the homogeneity property. In practice we also use

[16] Formally, for all t: $t=1 \cap t=2 \cap \ldots \cap t=T=\emptyset$.

somewhat different criterion. In this criterion we exclude n-highest and m-lowest number of a series of realizations $M_{ij}(t)$, $t = 1, .., T$ and apply the adapted series to Equation 3.16. As we suspect that the data contains measurement errors due to for instance wrong data processing, we can exclude these externalities if computing the norm in Equation 3.16.

Measure for existence of the limiting distribution

The Chapman-Kolmogorov equations enables one to compute the M_{ij}^{n+m} transition probabilities. These equations should be interpreted as computing the probability of starting in state i and ending in state j in exactly $n+m$ transitions through a path which takes into state k at the nth transition. The equation is:

$$M_{ij}^{n+m} = \sum_{k=0}^{\infty} M_{ik}^{n} M_{kj}^{m} \qquad \text{for all } n, m \geq 0, \text{ all } i, j. \tag{3.18}$$

We use the Chapman-Kolmogorov equations in order to test the limiting probabilities of the Markov chains. We compute the M^n transition probabilities for $i = j$ and $k = 0$. We assume that the time periods are indifferent.[17]

3.2.1 Markov chains and the transfers of outpatients

First we consider the transfers of outpatients. In Figure 3.1 the transfers of outpatients are depicted by the black arrows between the green marked specialisms in the departments outpatient clinics and operating theaters. A more detailed view is provided in Figure 3.2. There are n states S_i which represents the various locations an outpatient can be referred to, namely an outpatient clinic of another (sub)specialisms, the department operation theaters, the department nursing wards or discharge. $i = 1, 2, ..., n-3$ denotes an outpatient clinics of a (sub)specialism. $n-2$ represents the department operating theaters, $n-1$ the department nursing wards and n represents discharge. We observe the transitions during some time interval t. The number of patients are thus considered in a certain time interval, t, which is defined as follows: $[t_{\tau+1} - t_\tau)$. The time points $t_{\tau+1}$ and t_τ, are the two time points, between which we measure an inflow and outflow of patients from one location to another location. The transition probability thus denotes the probability that a patient will transfer from state S_i to state S_j within $[t_{\tau+1} - t_\tau)$, and has formal definition:

$$P\{S_{n+1} = j | S_n = i, S_{n-1} = i_{n-1}, ...S_1 = i_1, S_0 = i_0\} = P\{S_{n+1} = j | S_n = i\} = a_{ij} \tag{3.19}$$

or

$$a_{ij}(t) := \text{the probability that a patient is sent from state } i \text{ to state } j \text{ in } [t_{\tau+1} - t_\tau)$$

[17] For now we assume that the data should not necessarily be gathered from consecutive periods.

Patients who transfer from state i to state j somewhere in time interval $[t_\tau - t_{\tau+1})$ contribute to the transition probability. This allows patients to enter, to leave the system or to transfer from one state to another on an arbitrary time point t_t during the time interval t.[18] We can not distinguish between the time length a patient is in the t interval, e.g. a patient entering a state at day one of the interval will be seen equally, as a patient entering the state at the last day of the interval. The estimated transition probability $\hat{a}_{ij}$ of the transition probability a_{ij} can be computed as follows:

$$\hat{a_{ij}} = \frac{\sum_{t=1}^{T} r_{ij}(t)}{\sum_{t=1}^{T}\sum_{j=1}^{n} r_{ij}(t)} \tag{3.20}$$

in which $r_{ij}(t)$ denotes the number of patients transfered from state i to state j in time period t.[19] The estimated transition probability $\hat{a_{ij}}(t)$ is the average of transition probabilities over all realizations t, $t = 1, ..., T$.[20] One obtains the transition probability $\hat{a_{ij}}(t)$ of one realization t by dropping the summation from 1 to T in both numerator as the denominator in Equation 3.20. The accompanying transition matrix $\mathbf{A}$ is as follows:

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1,n-3} & a_{1,n-2} & a_{1,n-1} & a_{1,n} \\ a_{21} & a_{22} & \dots & a_{2,n-3} & a_{2,n-2} & a_{2,n-1} & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ a_{n-3,1} & a_{n-3,2} & \dots & a_{n-3,n-3} & a_{n-3,n-2} & a_{n-3,n-1} & a_{n-3,n} \\ 0 & 0 & \dots & 0 & 0 & 1 & 0 \\ 0 & 0 & \dots & 0 & 0 & 1 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 & 1 \end{bmatrix}$$

The last three rows are special as they only contain 0 or 1. We only consider transfers of outpatients in the hospital from one (sub)specialisms to another (sub)specialism.

We assume that patients who are operated will always be nursed in a nursing ward and not in an outpatient clinic, which is why $a_{n-2,n-1} = 1$.

The elements of the second last row represent the transition probabilities of going from a nursing ward of (sub)specialism i to an outpatient clinic of (sub)specialism j. As we have argued that a normal patient path in a hospital exists of subsequently a visit to an outpatient clinic, (possibly) to an operating theater and finally to a nursing ward, we assume that patient cannot transfer from a nursing ward to an outpatient clinic and thus $a_{n-1,n-1} = 1$.[21]

[18] We also check whether a patient, who is in the hospital during interval t remains in the hospital during interval $t + 1$.

[19] $r_{ij}(t)$ is equal to the patient flow from (sub)specialism i to (sub)specialism j in the interval $t = [t_{\tau+1} - t_\tau)$.

[20] Note that a realization coincides with an interval in this case.

[21] Of course also, patients could transfer from a nursing ward to an operating theater, however as this transition matrix concerns the transfer of outpatients, we do not incorporate these transition probabilities here.

Finally, the last row represents the transition probabilities of going home[22] to an outpatient clinic of (sub)specialism j. We do however estimate the arrivals using ARIMA theory. We incorporate the state 'discharge', to model the transition probability of a transfer of an outpatient from (sub)specialism to the state 'discharge'.

The probabilities of the last three rows are not estimated, since they are all logical zero or one.

Now the total number of expected outpatients TAO_j in the outpatients clinic of (sub)specialism j in interval t are:

$$\mathbb{E}[TAO_j] = \sum_{i=1}^{n-3} X_i^O \hat{a_{ij}} + X_j^O [a_{j,\hat{n-2}} + a_{j,\hat{n-1}} + \hat{a_{j,n}}] \tag{3.21}$$

in which X_i^O is a specific number of outpatients for (sub)specialism. X_i^O has mean μ_i^O. We use time series analysis in order to estimate this parameter μ_i^O. This is explained in section 3.1. $X_j^O[a_{j,\hat{n-2}} + a_{j,\hat{n-1}} + \hat{a_{j,n}}]$ in Equation 3.21 deals with the transfers of patients from the outpatient clinic to respectively an operating theater, a nursing ward of (sub)specialism j and discharge. The total number of expected outpatients in (sub)specialism is equal to the sum of new outpatients arriving from other (sub)specialisms and outpatients already being in this (sub)specialism. $\mathbb{E}[TAO_j]$ can be seen as the patient volumes in the department outpatient clinics at (sub)specialism j.

Assumptions for the transfers of outpatients

This subsection lists the assumptions for the Markov process describing the transfers of outpatients. These assumptions are specific for modeling the patient paths through the hospital.

- Patients can enter an outpatient clinic by a referral from a general practitioner and a referral from another outpatient clinic.
- For clinical admissions there exists one unique number. However, for successive outpatient clinic visits of one patient path, there exists non unique number. We assume that outpatient clinic visits occurring the same or adjacent time state are part of the same patient path. Also, if the patient visits an outpatient clinic in the next time period, this will be seen as part of the same patient path.

3.2.2 Markov chains and the transfers of inpatients

We construct a similar model for the transfers of the inpatients. In Figure 3.1 the transfers of inpatients are depicted by the black arrows between the green marked specialisms in

[22] We assume home is the opposite of a discharge.

the departments operating theaters and nursing wards. A more detailed view is provided in Figure 3.3. We define similar states for the Markov chain of the transfers of the outpatients. Let denote U_i the states of this process, $i = 1, .., n$, in which $i = 1, ..., n-3$ are the several nursing wards of a (sub)specialism, $i = n-2$ the department operation theaters, $i = n-1$ the intensive care and $i = n$ discharge. The formal Markov chain is:

$$P\{U_{n+1} = j|U_n = i, U_{n-1} = i_{n-1}, ...U_1 = i_1, U_0 = i_0\} = P\{U_{n+1} = j|U_n = i\} = b_{ij}. \tag{3.22}$$

The transition probability b_{ij} can be interpreted as follows:

$b_{ij}(t) :=$ the probability that a patient is sent from state i to state j in $[t_{\tau+1} - t_\tau)$

Note that the last state is an absorbing state. The estimate $\hat{b_{ij}}$ of the transition probability $b_{ij}(t)$ is computed as follows:

$$\hat{b_{ij}} = \frac{\sum_{t=1}^{T} s_{ij}(t)}{\sum_{t=1}^{T}\sum_{j=1}^{n} s_{ij}(t)} \tag{3.23}$$

in which $s_{ij}(t)$ is the number of patients transferred from location i to location j in interval t.[23] The transition matrix $\mathbf{B}$ for this process is:

$$\mathbf{B} = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1,n-3} & b_{1,n-2} & b_{1,n-1} & b_{1,n} \\ b_{21} & b_{22} & \dots & b_{2,n-3} & b_{2,n-2} & b_{2,n-1} & b_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ b_{n-3,1} & b_{n-3,2} & \dots & b_{n-3,n-3} & b_{n-3,n-2} & b_{n-3,n-1} & b_{n-3,n} \\ b_{n-2,1} & b_{n-2,2} & \dots & b_{n-2,n-3} & 0 & b_{n-2,n-1} & b_{n-2,n} \\ b_{n-1,1} & b_{n-1,2} & \dots & b_{n-1,n-3} & b_{n-1,n-2} & b_{n-1,n-1} & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 & 1 \end{bmatrix}$$

The transition probability $b_{n-2,n-2}$ is equal to zero as we assume that a patient can not stay within an operating theater during the whole time interval t. Next we assume that a patient in the intensive care unit cannot directly be discharged. That is why $b_{n-3,n-3}$ and $b_{n-1,n}$ are both equal to zero. Again, the last row is an absorbing state, representing the discharge process.

The total expected number of inpatients TAH_j for a nursing ward j in interval t is:

$$\mathbb{E}[TAH_j] = \sum_{i=1}^{n-1} X_i^N \hat{b_{ij}} + X_j^N \hat{b_{j,n}}. \tag{3.24}$$

$i = 1, \dots, n$. X_i^N represents the number of inpatients at a nursing ward for (sub)specialism j and has mean λ_i which is estimated using time series. $X_j^N \hat{b_{j,n}}$ of Equation 3.24 represents the expected number of inpatients who transfer from (sub)specialism j to the state 'discharge'. $\mathbb{E}[TAH_j]$ can be seen as the expected number of patients in the department nursing wards at (sub)specialism j.

[23] Again, we also check whether a patient, who is in the hospital during interval t remains in the hospital during interval $t+1$.

Assumptions for the transfers of inpatients

This subsection lists the various assumptions for the Markov process describing the transfer of inpatients.

- A patient can enter a nursing ward through a transfer from another nursing ward, or from an operation in an operation theater or a referral from an outpatient clinic. A patient can not enter the nursing ward otherwise.
- An admission is used in order to determine transfers from the various specialisms. This means that a patient who is admitted more than once, will be seen as two different patients.
- The origin of a patient at a new arrival or transfer is determined by linking the process of transfers of outpatients to the process of the transfers of inpatients. Unique combinations of patient numbers, DBC trajectories numbers and registration dates for operation are used in order to determine the origin.[24] If the combination of patient number and DBC trajectory number is in the outpatient clinic data but not in the operation data, than this indicates an outpatient clinic referral. If the combination of patient number, DBC trajectory number and registration number is in the operation data this indicates surgery in an operation theater, and thus that its origin is an operation theater. If however, the registration date is missing, this indicates a surgery in an outpatient clinic and the origin is an outpatient clinic. Finally, if the physical location of a patient is the intensive care unit, the origin is intensive care.
- Days will be used as the smallest time interval on which transitions are considered. A patient can only be at one particular specialism and department during a day. Thus, if a patient transfers, this occurs at the end of the day exactly, so that at the start of the new day the patient is at the new specialism.
- Patients on the intensive care can not immediately be discharged. These patients are first sent back to a normal nursing ward.

3.2.3 Action plan for establishing Markov chains

This section contains the consecutive steps how to construct a Markov chain from the data. It discusses the construction of states, transitions and state time. Also the concepts of homogeneity, Markov property and limiting distribution are discussed.

1. First choose the subdivision of states and time length of one state. A state change is denoted by a transition. In the health care path a (sub)specialism can be such a state. The transition is then defined as the transfer from one (sub)specialism to another (sub)specialism during the time length of the state. The right choice of the length of the time interval and size of the state are of major importance. In

[24] See Section 1.7 for a discussion on DBC, see Chapter 4 for all patient data characteristics.

Chapter 5, Chapter 6 and Chapter 7 we exhaustively discuss the consequences of choosing a certain subdivision of the hospital and the length of the time interval.

2. Determine the number of transitions, or transfers from one (sub)specialism to another (sub)specialism, for the independent time intervals.

3. Use Equation 3.20 to compute the transition probabilities for the different realizations.

4. Use Equation 3.16 to investigate the homogeneity and Markov property of the Markov chain. If for all computed realizations the condition of Equation 3.16 is satisfied, than the series is homogeneous, meaning that the transition probabilities will not differ much over time. Also this indicates that the Markov property holds.

5. Use Equation 3.18 to investigate limiting distribution of the Markov chain.

3.3 Service times and occupancy rate of (sub)specialisms at operating rooms and nursing wards

The service time of patients is required in order to estimate how long a patient will stay in the hospital after admission. We subsequently estimate the average service time for operations and for nursing time. We compute the average time of a series Y_i, $i = 1, .., N$ service times, by computing the sample mean $\bar{Y}$, which is:

$$\bar{Y} = \frac{1}{N} \sum_{i=1}^{N} Y_i. \tag{3.25}$$

The variance σ^2 is estimated by S^2

$$S^2 = \frac{1}{N-1} \sum_{i=1}^{N} (Y_i - \bar{Y})^2. \tag{3.26}$$

The average and the variance for each specialism are determined.

Occupancy rate

Along with the expected patient volume, the estimated service time allows one to estimate the expected occupancy rate of specialism i. The computation of average service times, is depicted by the orange box in Figure 3.1. Let b_{ij} be the transition probability an inpatient transfers from state i to j, as defined in Section 3.2.2, let X_i^N be the number of inpatients for specialism i at a nursing ward, determined by time series analysis and let Y_j^N be the simple mean of the services times for specialism j over all its treatments

in the department nursing wards. Than for example the expected occupancy rate O_j^N for (sub)specialism j at the nursing ward is derived as follows:

$$\mathbb{E}[O_j^N] = \sum_{i=1}^{n-1} X_i^N \hat{b_{ij}} \bar{Y_j^N} + X_j^N \hat{b_{j,n}} \bar{Y_j^N}. \tag{3.27}$$

The occupancy rate for (sub)specialism j at the outpatient clinics can be obtained similarly. Let a_{ij} be the transition probability an outpatient transfers from state i to state j, as defined in Section 3.2.1, X_i^O the number of outpatients in the outpatient clinics of specialism i and $\bar{Y_i^O}$, the average service time of M treatments in the outpatient clinics of specialism i, than the expected occupancy rate O_j^O for (sub)specialism j at the outpatient clinics is equal to

$$\mathbb{E}[O_j^O] = \sum_{i=1}^{n-3} X_i^O \hat{a_{ij}} \bar{Y_j^O} + X_j^O [a_{j,\hat{n-2}} + a_{j,\hat{n-1}} + \hat{a_{j,n}}] \bar{Y_j^O}. \tag{3.28}$$

3.4 Back-testing and performance of the model

Back-testing is a technique used in social and natural science in order to test the performance of a model. We use back-testing for comparing the model results with the real results. Back-testing can be seen as part of the validation process. For this procedure we use predicted values of the ARIMA-models and the estimated Markov probabilities.

We do not use the average service times as the actual occupancy rate is not registered sufficiently accurate. Hospitals only register admissions of patients in whole days. So we can not distinguish between an admission of 1 hour and 23 hours. For performance purposes one would like to have the most accurate duration of an admission.

Back-testing our model involves the following steps:

1. Compute the series of estimates of arrivals for subsequent values of t, using the proposed ARIMA-model for the combination of departments and (sub)specialisms. Also estimate the Markov transition probabilities.

2. Compute using either Equation 3.21 the expected number of outpatients at a combination of an outpatient clinic for (sub)specialism j or Equation 3.24 the expected number of outpatients at a combination of a nursing ward for (sub)specialism j.

3. Compare the outcome of Equation 3.21 and Equation 3.24 at time t with the true value at time t.

4. Compare the difference of the outcomes of Equation 3.21 and Equation 3.24 and the true value at time t with the difference of another performance measure and the true value at time t.

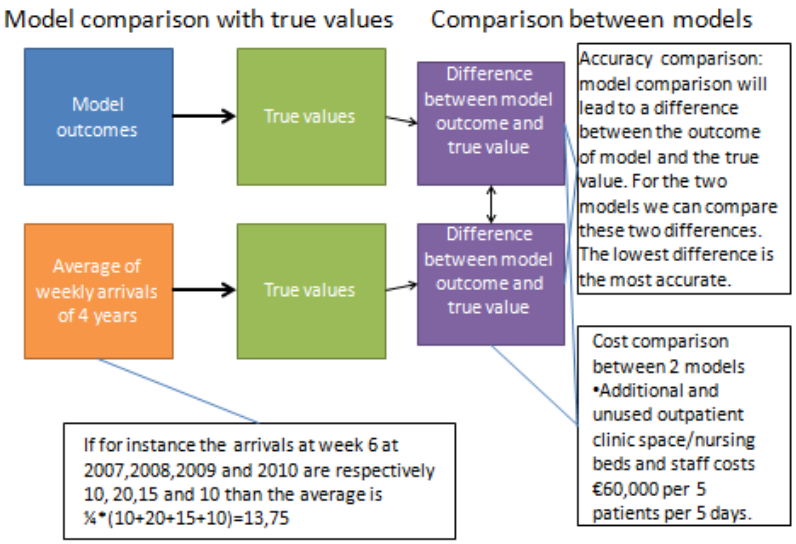


Figure 3.4: Overview of back-testing.

For reconstructing the series of estimates of arrivals for subsequent values of t applying the proposed ARIMA-model, we use the following equation:

$$\hat{X}_t = \hat{X_{t-1}} + \sum_{i}^{p} \alpha_i L^i \Delta \hat{X}_t + \sum_{i=1}^{q} \theta_i L^i \varepsilon_t + \varepsilon_t, \tag{3.29}$$

in which $\hat{X}_t$ is the estimated number of arrivals at t. In fact, it is a method to predict the next arrival estimate for time t, if all values or estimates are known up an till time $t-1$.

We use back-testing for comparing our model values with the true values and comparing our model with another measure. Figure 3.4 provides an overview of the two different back-tests and the comparison between the two models. Also, we introduce arbitrarily costs, so that we can compare both models with respect to the costs of outpatient clinic space, nursing beds and hiring staff in case of an over- and underestimation of the patient volume.

Comparing with true values

The estimated arrivals at the outpatient clinics and the nursing wards for (sub)specialisms are compared with the true values. If the difference between comparison of the model outcome and the true value is zero, than the model estimates the patient volume at the combination of department and (sub)specialism correctly. The closer the difference is to zero, the better the estimation.

Comparison with another model

Also we compare the estimated patient arrivals at the outpatient clinics and the nursing wards for (sub)specialism with another performance indicator. Currently, ZGT uses common sense and experience of employees in order to estimate the required number of nursing beds and operating time, which is more difficult to replicate. That is why, we construct a simplified model and use it to compare it with our model. We choose the average volume over four years at a (sub)specialism as a comparison number, which we can compare with our predicted model values. This average is calculated by summing the true number of arrivals of a (sub)specialism at a certain department at the same time points each year and divide it by four. This step can be seen as a model comparison. We use this average as we have five years of data.[25] We compare the true figures of the last year with the estimated figures for the last year obtained by our model.

Cost comparison

Finally, we perform a cost comparison. The two models predict patient volumes at the specialisms in the department outpatient clinics and nursing wards. We introduce arbitrary costs for the capacity of the outpatient clinics, the nursing wards and staff.[26] We assume that keeping open an outpatient clinic or nursing ward, costs €60,000.- per ten patients per week.[27] For opening an extra outpatient clinic/nursing wards, the costs are also assumed to be €60,000.−.

In order to get an understanding of the sensitivity of the model, we consider two scenarios. We assume that the capacity for an outpatient clinic and a nursing ward, are both ten patients. Moreover, we also assume no transfers between the different specialisms in case of under- or overcapacity. In the first scenario we assume that we don't use the planned capacity at all in case of an overestimation. In the case of an underestimation, we assume the maximum excess of ten patients. We call this the worst case scenario. In a second scenario we assume that five out of ten are occupied in case of an overestimation. In case of an underestimation, the excess is five patients. Both scenarios assume a time horizon of five days. Note that the costs for the average scenario are half of the costs of the worst case scenario. These two scenarios are very artificial, because we expect in reality that the planning is more flexible.

[25] The data we use is described in detail in Chapter 4. Data about inpatients and outpatients are available for the period 2007-2011, data about operations are available for the period 2008-2011.

[26] Note the difference between capacity and patient volume. Capacity is the number of patients an outpatient clinic or nursing ward can hold. Patient volume is the number of patients present in the outpatient clinic or nursing ward during a certain time period.

[27] This figure is based on ten patients. Figures of the NZa demonstrate that in 2008 the average costs per patient per nursing day are approximately €1,267.− for a hospital with more than 600 beds (NZa, 2008). For an easy calculation, we choose these costs to be €1,200. The total costs for ten patients per week are thus $5 * 10 *$ €1,200.− = €60,000.−. The amount includes all costs made for one nursing day and is an average for all specialisms.

Chapter 4

Data

This chapter describes the data used for the research. We discuss the data itself and the modifications we make to the data. The reliability of the data is discussed in Chapter 7. First we discuss the data warehouse used in ZGT. Next we discuss the data used for modeling the arrivals at the combinations of departments and (sub)specialisms using ARIMA-models. After that, we discuss the data we use for determining the transition probability that a patient will transfer from one (sub)specialism to another in a certain time period. We deal with the outpatient and inpatient transfer process separately. At the end of this chapter, we elaborate on the data used for determining the average service times for various treatments.

4.1 Data warehouse

The data warehouse of an organization is a database in which all available information is stored. There are many ways of storing data into the data warehouse and accessing data from it. In order to determine the transition probabilities of our Markov chains, we rely on historical patient information obtained from the data warehouse. ZGT uses Chipsoft-EZIS (EZIS[1]) registration system to record all patient details, both clinically and financially, regarding outpatient clinic visits, operations and hospitalization. Chipsoft is a Dutch software developer which has developed the EZIS patient registration system. The program is a work flow management system, which supports medical staff in order to register clinical details about patients. Within ZGT, the program is used in the outpatient clinics, the operating theaters and the nursing wards for storing patient details about diagnoses, treatments, visits, operations and admissions. Medical staff can view the health status of a patient in the system and update it immediately during a visit/operation/admission in ZGT. Financial and planning support staff use the system for financial and logistic purposes. This registration system is the backbone supplier of the data warehouse of ZGT with respect to clinical patient details. The staff of ZGT is responsible for entering and updating data in this data warehouse. Nurses, doctors

[1] EZIS: Elektronisch Zorg Informatie Systeem, English: Electronic Health care information system.

and supporting employees daily enter patient details in EZIS. EZIS is a software package which stores information into the data warehouse, but is not principally used for data analysis within ZGT.

The data warehouse is daily filled with data from information systems such as EZIS, but also with other information systems. ZGT uses the software package Business Objects for analyzing data and retrieving data from the data warehouse. Business Objects is used worldwide in all sorts of enterprises in order to access and analyze data in a data warehouse. Business Objects allows one to build queries for analyzing data in the data warehouse. Users can select characteristics (dimensions) and measures from an universe in order to compile a certain report. For this research we use Business Objects for accessing and retrieving data from the data warehouse. The universes we access are mainly filled with data from the EZIS system. Finally, we use software packages as Eviews and Matlab for developing ARIMA-models and Excel for constructing the Markov transition probabilities and computing the average service times.

The data warehouse consists of several universes. The most important database is the DBC universe. This universe contains data of all closed and open DBC trajectories. DBC trajectories are specific per patient and treatment. The DBC universe contains information about treatments in the outpatient clinics, the operating theaters and nursing wards. More detailed data about outpatients can be found in the universe outpatients, more detailed data about operations is in the operations universe and finally more detailed data about inpatients is in the nursing wards universe. Figure 4.1 provides an overview of all software packages used.

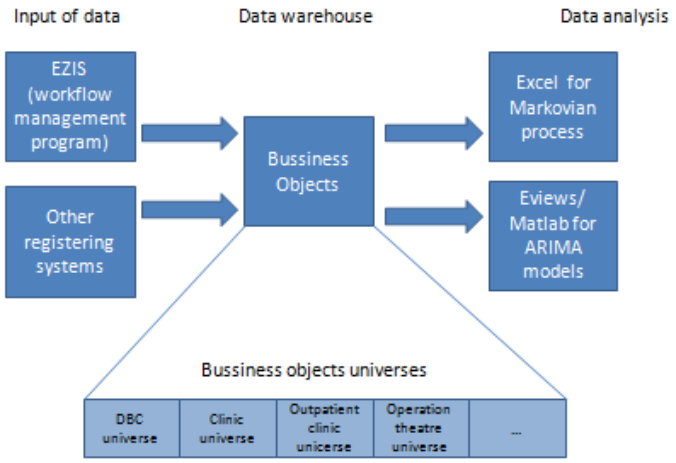


Figure 4.1: Overview of data mining, gathering data, data warehouse and data analysis in ZGT.

4.2 Data

As discussed in Chapter 3 the model we use, consists of three components, namely the patient arrivals at various combinations of departments and (sub)specialisms, the Markov transition probabilities that a patient transfers from one (sub)specialism to another and the average service times. ZGT stores data about outpatient clinics visits and nursing wards admissions from 2007. Data about operating theaters is stored from 2008 onwards.[2] This data is also used in all sorts of other reports within ZGT. For the three components we use the following data:

- For arrivals at the outpatient clinics and the nursing wards we use data from 2007-2011. The data contains the admissions in the period 2007-2011 for the sub(specialisms). For the arrivals at the operating theaters we use data from 2008-2011. The data contains the operations of the (sub)specialism in the period 2008-2011. Fitting an ARIMA-model onto data points requires sufficient data points. The more data points available, the better and easier one can obtain an ARIMA-model. The data characteristics and modifications are discussed in Section 4.3.

- For the determining the transition probabilities that a patient transfers from one (sub)specialism to another in a given department and time period, we use data from 2010 and 2011. The data contains the dates at which a patient has visited a combination of department and (sub)specialism. Computing transition probabilities requires a lot of manual effort and time. That is why we only compute transition probabilities for 2010 and 2011. The details of the data and modifications we make, are discussed in Section 4.4.

- For determining the average service times we only use 2011 data, as this reflects the most recent figures about treatments, such that we can take the newest developments and techniques into account. The data contains the gross operating time per treatment and of clinical admissions it contains the gross admission time. We elaborate on the data in Section 4.5.

Subdivision of hospital and time length of interval

We consider two subdivisions of the hospital. We do this in order to identify what the best subdivision would be for computing transition probabilities in the Markov chain. With this respect the time length of the interval and the size of the (sub)specialisms are important. The size of the (sub)specialisms can not be too small. If the size is too small, there exists a possibility that no or very little transfers will occur between two subspecialisms. The time length of the interval can not be too long, as the time becomes too long, most patients will be absorbed in the state 'discharge'. The share of this state

[2]For the data of the departments outpatient clinics and nursing wards, no accurate or reliable data is available before 2007, for the department operating theaters this is the case with data which are before 2008.

compared to the other states will become very large. Little fluctuations in the other states are more difficult to detect in that case. In order to investigate the influences we make two subdivisions. The first subdivision has small subspecialisms and a large time interval. The second subdivision only concerns specialisms but has a smaller time interval. The first subdivision is as follows:

1. General surgery and surgery for children.
2. Oncology, lung surgery and gastrointestinal surgery.
3. Traumatology and emergency incidents.
4. Vascular surgery.
5. Other surgery.

The time length for this state is one month. It appears that the time length of the interval is too large and the size of the subspecialisms are too small. This is also clarified in Section 5.2.3. The second subdivision is:

1. Cardiology.
2. Gastroenterology.
3. Gynecology.
4. Internal medicine.
5. Neurology.
6. Obstetrics.
7. Pediatrics.
8. Pulmonology.
9. Surgery.
10. Urology.
11. Other.

For this subdivision we use the time period of one week. We shall see in Section 5.2.3 that this subdivision is more suitable. Also the time length of one week is a better interval than one month. As this subdivision is more suitable for computing Markov transition probabilities, we only estimated ARIMA-models using weekly arrival figures for the eleven specialisms mentioned above.

4.3 Data for patient arrivals and time series analysis

Time series analysis is performed on the three departments of the hospital, namely the outpatient clinics, the operating theaters and the nursing wards. We use ARIMA-models to develop a forecasting model for estimating the number of weekly arrivals to the several (sub)departments at a certain department. The arrivals to the outpatient clinics are divided into a first outpatient clinic visit and a repeated outpatient clinic visit. The arrivals to a nursing ward are divided into a one day clinical admission (heavy and light) and a more than one day clinical admission. The length of time interval between two subsequent data points of the number of arrivals at a certain department and (sub)specialism on which we fit the ARIMA-model, should be equal to the length of time interval for which we compute the Markov transition probabilities. This is done in order to avoid timing differences, if we compute the estimated patient volumes at the combinations of department and (sub)specialism.

4.3.1 Data characteristics for patient arrivals and time series analysis

This subsection describes the data characteristics of a data series of patient arrivals at a combination of a (sub)specialism and a department which we can use for estimating an ARIMA-model. We use Business Objects for retrieving arrival data from the data warehouse. We require the characteristics: execution date, patient number, registration code, (sub)specialism and the number of treatments. The execution date is used for determining the period in which a treatment takes place. The (sub)specialism denotes the operator of the treatment, whereas the registration code denotes the type of treatment and its department. We require patient number and the number of treatments in order to make sure that we count all patients and treatments at a given time. Time series analysis requires the establishment of a series of which the data points are one equidistant time interval e.g. weeks or months. The characteristics allows us to determine the number of arrivals at a certain (sub)specialism and department in a certain fixed time interval. We estimate ARIMA-models, using weekly patient arrivals at the combination of a (sub)specialism and one of the three departments: outpatient clinics, operating theaters or nursing wards. Estimating an ARIMA-model requires sufficient data points. That is why we choose weekly data arrivals instead of monthly data points. We shall see that for computing the transition probabilities, the length of the time interval is also very important. This is explained in Section 4.4.

4.4 Data for Markov process and transition matrices

The data we use are from 2010 and 2011. Remember that we compute the transition probabilities for the transfer of outpatients and inpatients. For reconstructing the patient path we require patient data from the outpatient clinics, operating theaters and nursing wards. The patient data we use, contains patient information on treatments on a specific day, performed by a certain (sub)specialism.

In order to analyze the data, we have to modify the data. Computing the transition probabilities of the transfers of outpatients, requires different modifications to the data than for the transfers of inpatients. The Subsections (4.4.2-4.4.3) describe the characteristics and modifications. The transfers of outpatients and inpatients are modeled as two separate processes. These processes should be linked to each other. This is discussed in Section 4.4.4.

4.4.1 Data characteristics for Markov states

In order to compute the transition probabilities a patient transfers from a combination of a department and a (sub)specialism to another during a time period, we have to know how a patient transfers from one (sub)specialism to another in a certain time period. We have to reconstruct a patient path. Remember that a patient path is defined as the successive treatments a single patient undergoes at a specific combination of specialisms and departments of a hospital. We can construct the patient path using specific patient characteristics of visits to outpatient clinics, operations and admissions in nursing wards. In Business Objects we make a query which retrieves the required data from the data warehouse. We use the following patient characteristics, such that we can reconstruct the patient path.

- Start and end date of DBC trajectory. This two dates mark the start and end date of one DBC trajectory. By law, a DBC trajectory has a maximum length of one year. Remark that these data not necessarily coincides with the admission dates of a patient.
- DBC trajectory number. This is an unique number for each specialism and each treatment. DBCs will be replaced by the DOT structure. See also the discussion in Section 1.7.
- Patient code. This an unique registration number of a patient within ZGT.
- Specialism (e.g. surgery, neurology etc.) and subcategory of specialism (e.g. oncology and traumatology).
- Execution date, this date indicates the specific dates on which a treatment is executed.
- Admission number, this an unique number of the admission of a patient at a nursing ward.
- Registration code, this code indicates the type of care. This can be either a first outpatient clinic visit or a repeated outpatient clinic visit (the patient already has seen a specialist at an outpatient clinic) or an operation or an one day clinical admission (light or heavy) or a more than one day clinical admission. This code is based on the old expenses claim system for hospitals, in which the number of

outpatient clinic visits, the number of nursing days and the number of operations were important. See also the discussion in Section 1.6.

4.4.2 Transfer of outpatients

First we consider the transfers of outpatients. A transition is defined as the transfer of a single outpatient from one (sub)specialism in the outpatient clinics to another, in a certain time period. Furthermore, we consider transfers of outpatients to the departments operating theaters and nursing wards. Also we include discharges. We check which outpatient clinics a patient has attended during the time period, whether he/she has been scheduled for an operation, underwent an operation, is redirected to a nursing ward or is discharged. We proceed as follows as we construct the transition matrix.

- First we filter the outpatient data on the data belonging to the time period for which we are going to construct the transition probabilities.
- Next, we sort the data of outpatient clinics subsequently on patient code, execution date and registration code.
- A treatment of a patient is recorded on several lines. Each line indicates for a specific patient, one treatment at a specific (sub)specialism at a specific date. We determine for each line whether this is the first, or the last day or some day in between.
- Next, we determine whether the patient has been transferred from one (sub)specialism to another (sub)specialism. This is the most important step in reconstructing the patient path of a single patient. The transfer can be to an outpatient clinic of a certain (sub)specialism, the department operating theaters, the waiting list for operating theater, the department nursing wards of a certain (sub)specialism or discharge. The waiting list procedure is described in Section 4.4.4.
- All transfers are counted and used for the computation of the transition matrix.
- In Excel, we create a pivot table in order to easily obtain the number of patients per combination of start and end specialism and/or subcategory. From these numbers we can compute the transition probabilities for this particular time period.

We check whether a patient visits an outpatient clinic in the next period, such that we can distinguish between discharge on the last day of the length of the time period and a scheduled visit in the adjacent period. We link the inpatients and operating data to the data of the outpatients by matching patient numbers. If a patient number is only in the inpatients data, then a patient in this time period is sent to the nursing ward and the patient is included in the state 'nursing ward'. If both the patient number is contained in the operating and nursing ward data, this indicates that the patient has underwent surgery. In this case the patient is added to the state 'with operation'.

4.4.3 Transfer of inpatients

This section deals with the transfers of inpatients. Remember that the transfer an inpatient can make, is between (sub)specialisms in the nursing ward in a certain time period, but also includes a transfer from the operating room to the nursing wards. Obviously, a transfer to the state 'discharge' is also included. Constructing the transition matrix for this process, we proceed as follows.

- We filter the data on the time period for which we would like to establish the transition probabilities.

- We sort the data subsequently on patient code, execution date, DBC trajectory code, admission number and registration code. The admission number is obtained from the Business Objects universe clinic. Using the unique combination of patient number and execution date, the admission number is added to the major file.

- Next, we link the operations and the outpatient clinic visits to the nursing wards admissions. We search in the operations and outpatient clinics data for a specific patient number. If the patient number is also in the operations data this means that the patient underwent an operation in the same month. This patient will be placed in the state 'operation'. A patient who is in the outpatient patient database and has been scheduled for an operation in an outpatient clinic, is included in the state 'outpatient clinic'. If a patient is both in the outpatient and the operation data, then we put this patient in the state including 'operation', as we assume that the natural flow of a patient through a hospital is outpatient clinic to operating theater to nursing ward.

- Again a treatment of several days is registered on more than one line. We determine for each line whether this is the first or the last day or some day in between. Each line indicates for a specific patient one treatment at a specific specialism and subcategory at a specific date.

- Next, we determine whether the patient has been transferred from one (sub)specialism to another (sub)specialism. The transfer can be to a nursing ward of a certain (sub)specialism or discharge.

- All transfers are counted and used for the computation of the transition matrix.

- In Excel, we create a pivot table in order to easily obtain the number of patients per combination of start and end specialism and/or subcategory. From these numbers we can compute the transition probabilities for this particular time period.

It is checked whether a patient which is in the department nursing wards at the last day of the period, continues his/her stay in the hospital, or is discharged at this day.

4.4.4 Linking transfers of outpatients and inpatients and the waiting list state

We include a waiting list state in order to obtain a more realistic model of a patient path of a single patient through a hospital. The waiting list state is used in order to keep track of patients who are registered for operation during some state period, but however are not operated in the same state period. We also need this information in order to distinguish whether a patient has been operated in the operating theater or in an outpatient clinic. The registration date is used for this purpose: only for an operation in an operation theater this date is registered. For each operation it has been registered on which date a patient enters the waiting list. We construct a data file which enables us to determine in which period a patient respectively enters, is on and leaves the waiting list. This file is constructed as follows.

- First we collect operations details per patient for all specialisms in a specific year.
- The data we use, is obtained from two different Business Objects universes: DBC universe and operation theaters universe. We use two different universes as we require information from both universes: DBC universe is necessary for determining the flow through the hospital. The operating theater universe is used for obtaining the date of entering the waiting list. The operation details from both universes are linked by using specific patient characteristics per operation. We use the combination of patient code and execution date in order to link both universes. Since this list serves for determining whether a patient in the outpatient clinic is directly or not directly sent for operation, the DBC universe is filtered only on outpatient clinic visits. We link the information from the DBC database and the list established, using the unique combination of patient number and DBC trajectory number.
- The data is sort on patient number, execution date and registering date.
- For each operation it is determined in which period it has taken place. Also if the entry date of the waiting list is not in the same month in which the operation has taken place, the states in which the patient is on the waiting list, are determined.

For the waiting list state there are four distinct cases during a time period: a patient enters the waiting list, is on the waiting list, leaves a waiting list or enters the outpatient clinic and is operated in the same time period.

4.5 Data for service times

For determining service times of operations and admissions, we use data of 2011. Again we use Business Objects for retrieving the required data from the data warehouse. We use the universes DBC, operating theaters and nursing wards, in order to gather the required information. The operating theater universe contains the gross operation time per patient or that is the difference a patient leaves and enters an operating theater. As

we are interested in the time a patient blocks an operation theater, we use these two time points for computing the service time. For the admission we have the start and end time of the admission of a patient, this is stored in the nursing wards universe. The times do have a data-hour-minute format so that we can compute the operation and admission time per patient on a minute accuracy basis. The specific treatment details are stored in the DBC universe. We use Excel macros for linking the DBC and admission universe and DBC and operations figures. We assume that the times are correctly registered by the hospital staff. As a DBC is a specific treatment, we compute per DBC the average service time and its standard deviation.

Chapter 5

Results

In this chapter we discuss the results. Recall that our model consists of three pillars: patient arrivals, transfers of out- and inpatients and average service times. The first pillar is estimated using ARIMA-models, the second using Markov transition probabilities and the third using statistical analysis. First, we discuss the results for ARIMA-models. Next, we discuss the results for the transition probabilities that a patient transfers from one (sub)specialism to another. Moreover, we discuss the results of the average service times. At the end of the chapter, we discuss the results of a back-test and a cost comparison between our model and a simple model which uses the average arrival rates.

Remember that we work with two subdivisions of the hospital. These subdivisions are listed in 4.2. We use the two subdivisions in order to determine the most adequate size and time length of the Markov states. The first subdivision is into (sub)specialisms of surgery and the remaining part of the hospital is in the state 'other'. For this subdivision the time length is one month. The second subdivision is into 11 specialisms. The time length is one week.

It appears that the size of (sub)specialisms is too small and that the time length of one month is too long. We shall discuss this in depth in Section 5.2.3. For time series analysis, we only consider the subdivision in the 11 specialisms.

5.1 Results for time series analysis

This section discusses the results of the estimation of the arrival process for the 11 specialisms, using time series analysis. We established ARIMA-models using weekly patient arrivals for the departments: outpatient clinics, operating theaters and nursing wards. The outpatient clinic visits are divided in first and repeated visits. The nursing ward arrivals are divided in a one day admission (light and heavy)[1] and a more than one day admission.

[1] There are only four specialisms which can have a heavy one day clinical admissions.

	Number of observed specialisms	Number of stationary series	Number of series with normal divided residuals	Number of series satisfying autocorrelation condition	most common ARIMA model
Outpatient clinics					
first arrival	11	11	9	11	7x (3,1,4)
repeated arrival	11	11	5	11	2x (3,1,3)
Operating theater	11	11	5	10	3x (3,1,4) and 3x (4,14)
Nursing wards					
one day (heavy)	4	4	3	4	none
one day (light)	11	11	10	11	2x (3,14) and 2x (4,14)
more than one day	11	11	7	11	3x (3,1,2) and 3x (3,1,4)

Figure 5.1: Summary of ARIMA-models for the various departments.

Figure 5.1 lists for the best fits,[2] the most common number of the autoregressive and moving average terms and the results for statistical tests, as the Augmented Dickey-Fuller test, the Jarque-Bera test and the Ljung-Box test. For each series of arrivals we fit 25 models. Determining the best fit of the ARIMA(p, d, q)-model,[3] we start with $p = 0$ and then increase q from 0 to 4. Next, we increase p to 1 and again increase q from 0 to 4. We repeat this until p and q are both 4, so that we obtain 25 series.[4] We keep d at one. We shall see in Section 5.1 that it is sufficient to difference data only once, to obtain a stationary series.

Figures A.1-A.5 of Appendix A contain the details of the ARIMA-models for the best fits of the 11 specialisms per outpatient clinics (first and repeated visit), operating theaters and nursing wards (one day admission, heavy or light, or more than one day admission). The figures contain the coefficients of the autoregressive and moving average terms. Also, the results for the Augmented Dickey-Fuller test, the Jarque-Bera test and the Ljung-Box test are provided in these tables. All tests are at a significance level of $\alpha = 5\%$.[5]

The next paragraphs discuss the results of statistical tests. We perform these tests in order to make sure that we can use ARIMA-models at all. We elaborate on stationarity of the data, on the normality of the residuals and the existence of no autocorrelation from a certain lag in the residuals.

[2] For each arrival series we fit 25 ARIMA-models, we use the Akaike criterion to identify the best fit. The lowest Akaike criterion indicates the best fit. Figure 5.1 summarizes the results for ARIMA-models with the lowest Akaike criterion per combination of department and specialisms.

[3] Recall that p, is the number of autoregressive terms, q the number of moving average terms and d denotes how many times we have to difference the original series to obtain a stationary series.

[4] Both p and q can attain the values of 0,1,2,3 and 4. So that we have $5^2 = 25$ different fits.

[5] Or otherwise stated, some Jarque-Bera tests are at a significance level of alpha equal to 10%.

Stationarity

All series are stationary if we take the first difference. Augmented Dickey-Fuller tests show that non of the original series are stationary.

The augmented Dickey-Fuller demonstrates that the original series are not stationary at $\alpha = 5\%$ significance, however, the first difference of all series, are stationary at $\alpha = 5\%$. The results are given in Figures A.1-A.5.

Normality assumption and autocorrelation of residuals

For many configurations we accept the assumption that the residuals are normally distributed and that there is no autocorrelation.

We use the Jarque-Bera test in order to test whether the residuals are normally distributed. The Jarque-Bera test shows that for most series, the assumption that the residuals are normally distributed, is accepted at $\alpha = 5\%$ significance.

Furthermore, we test the autocorrelation of the series by using the Ljung-Box test. We test whether the series contains no autocorrelation from lag 20 till lag 253. Again, for most series we accept the assumption of no autocorrelation. However, for some series the normality and autocorrelation assumption is rejected. The results are in Figures A.1-A.5.

Best fit: Akaike criterion

The Akaike criterion is computed to identify the best fit of 25 computed fits per series of arrivals. The fit with the lowest criterion is the best. For the ARIMA-models with the lowest Akaike criterion, details are given in Figures A.1-A.5.

For every series of arrivals, the Akaike criterion for the 25 fits are in Figures A.6-A.11. We see that the Akaike criterion does not decrease much as we increase p ad q in the ARIMA(p, d, q). This suggests that the number of autoregressive and moving average terms is sufficient. We compute per series of arrivals only 25 different ARIMA-models. We do this to reduce computation time: allowing additional autoregressive or moving term requires a quadratic increase of series to be estimated. Moreover, for ARIMA-series with many autoregressive and moving average terms, we face the problem that Matlab can not compute the inverse matrices which are used in the determination of the Akaike criterion. In Eviews we have to input all the different fits manually.[6]

So given the constraint that we only use 25 different fits,[7] we have found the best fit

[6] If we for instance would like to investigate the best ARIMA-model, using the Akaike criterion, in which we allow both ten autoregressive and ten moving average terms, we get 121 possible fits for this ARIMA-model. Using Eviews, this means for all 59 series for which we develop an ARIMA-model that we have to estimate and judge over 7,000 ARIMA-models manually.

[7] In the range $p = 0$ to $p = 4$ and $q = 0$ to $q = 4$.

for our ARIMA-models. In theory, adding much more ARIMA autoregressive and moving average terms, might yield a sharp decrease in the Akaike criterion.[8] However, adding additional terms do certainly increase the complexity of the ARIMA-model. As a rule, we try to minimize the number of autoregressive and moving average terms in an ARIMA-model in order to avoid an unnecessarily complicated model. As argued, it is too time consuming to estimate for all the 11 specialisms at the different departments, ARIMA-models using Eviews with more than four autoregressive and four moving average terms.

All computations, estimated ARIMA coefficients and outcome of test statistics, are digitally available.

5.1.1 Seasonality of time series

We investigate the presence of seasonal patterns in the data, using the action plan of Yaffee and McGee (2000). We shall see that there is no evidence of the existence of a seasonal component in the data and we may model the arrivals using an ordinary non-seasonal ARIMA-model.

We use the action plan as described in Section 3.1.1 in order to determine whether the patient arrivals at the various specialisms and departments exhibit seasonal effects. We respectively look at the residual plots of the $(0,0,0)X(0,0,0)$-, $(0,1,0)X(0,0,0)$-, $(0,0,0)X(0,1,0)$-, $(0,0,0)X(0,1,0)50$- and $(0,1,0)(0,1,0)12$-ARIMA[9] models and at the plots of the autocorrelations at certain lags, to identify seasonal effects. We research the possibility that data contains quarterly and yearly patterns. Yaffee and McGee (2000) suggest that one can identify seasonality effects by looking for a cyclic trend at some equidistant time intervals in the residual plots of the mentioned series. We look whether we can detect spikes in the data that occur at regular time intervals. Moreover, if looking at the plots of the autocorrelations at certain lags, one would expect strong autocorrelation at the lag at which we suspect a seasonal effect and no autocorrelation at the other lags.

Figures 5.3- 5.7 show the residual plots of the $(0,0,0)X(0,0,0)$-, $(0,1,0)X(0,0,0)$-, $(0,0,0)X(0,1,0)12$-, $(0,0,0)X(0,1,0)50$- and $(0,1,0)X(0,1,0)12$-ARIMA- model respectively, for the first visits at the outpatient clinics of the specialism surgery. We shall see that the plots of these ARIMA-models do not contain seasonal components.

[8] We recommend to do further research in adding more autoregressive and moving average terms. Possibly, adding more of these terms will lead to a better prediction as more historical data are taken into account.

[9] Recall that the notation of seasonal $(P,D,Q)X(p,d,q)$ARIMA-models is as follows: P denotes the number of seasonal autoregressive terms, D the seasonal difference, Q the number of seasonal moving average terms, p the number of ordinary autoregressive terms, d the ordinary difference and q the number of ordinary moving average terms. Often a single number is added to this notation to indicate at which lag we suspect seasonality. For instance $(P,D,Q)X(p,d,q)12$ denotes an ARIMA-model with a seasonality component at lag 12.

Looking at the plot of the residuals of the $(0,0,0)X(0,0,0)$-ARIMA-model, Figure 5.3, we observe that data is certainly not stationary. Moreover, we do not discover a cyclic trend at some equidistant time points. Now, if we look at Figure 5.4, the non-seasonal first difference ARIMA series, we see that the data seems stationary. Again we do not observe a clearly cyclic pattern. This is confirmed in the plots which we see in Figure 5.5 and Figure 5.6 in which we respectively take a monthly and quarterly seasonal difference. The plot of both a seasonal and ordinary differenced series, Figure 5.7, also does not show a clear pattern.

We perform a Box Pierce test, to test the influence of autocorrelation at certain lags. The plots of the residual partial correlation and the residual partial autocorrelation, confirm the non-seasonal trend. Figures A.12-A.15 respectively contain the plot of Autocorrelation function (ACF) and the Partial correlation function (PCF) of the $(0,1,0)X(0,0,0)$-, $(0,0,0)X(0,1,0)12$-, $(0,0,0)X(0,1,0)50$- and $(0,1,0)X(0,1,0)12$ ARIMA-model.

Figure 5.2 summarizes the results for the plots of the Autocorrelation function (ACF) and the Partial correlation function (PCF) with regard to seasonality. One can see that in this case, there is no evidence for a seasonal trend, as for all models there is still autocorrelation at lags other than the lag at which we might suspect autocorrelation.

model	should contain autocorrelation at lag	autocorrelation at lags	seasonal evidence ?
(0,0,0)X(0,1,0)	not applicable	1, 13, 16 and 18	no
(0,0,0)X(0,1,0)12	12	2, 3, 5, 11 and 14	no
(0,0,0)X(0,1,0)50	50	11, 31, 35 and 50	no
(0,1,0)X(0,1,0)12	12	1, 11, 12, 13, 19 and 35	no

Figure 5.2: Summary of plots of the ACF and the PCF for the various ARIMA-models of arrivals at the department outpatient clinics (first vists) for the specialism surgery. The second column indicates the lag at which we expect autocorrelation, whereas the third indicates the lags at which autocorrelation is observed.

Both, the residual plots, as the ACF and PCF plots, do not provide sufficient evidence for a seasonal pattern. As it is convenient to have the simplest ARIMA-model, we choose for an ARIMA-model without a seasonal pattern.

In Appendix A.2, Figure A.16-A.33 we provide for the one-day and the more than one day clinical admission of the specialism surgery and for the more than one day clinical admission of the specialism cardiology, the comparison between a non seasonal model and a seasonal model. All comparisons show no evidence of the existence of a seasonal component in the data, so we may model the arrivals, using an ordinary non-seasonal ARIMA-model.

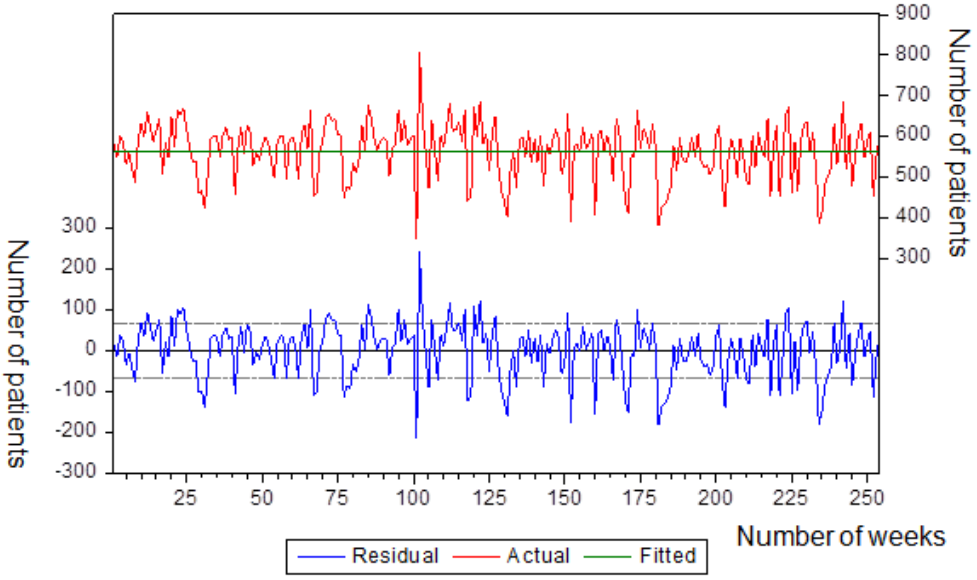


Figure 5.3: Plot of $(0,0,0)X(0,0,0)$ ARIMA-model of arrivals at the department outpatient clinics (first visits) for the specialism surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

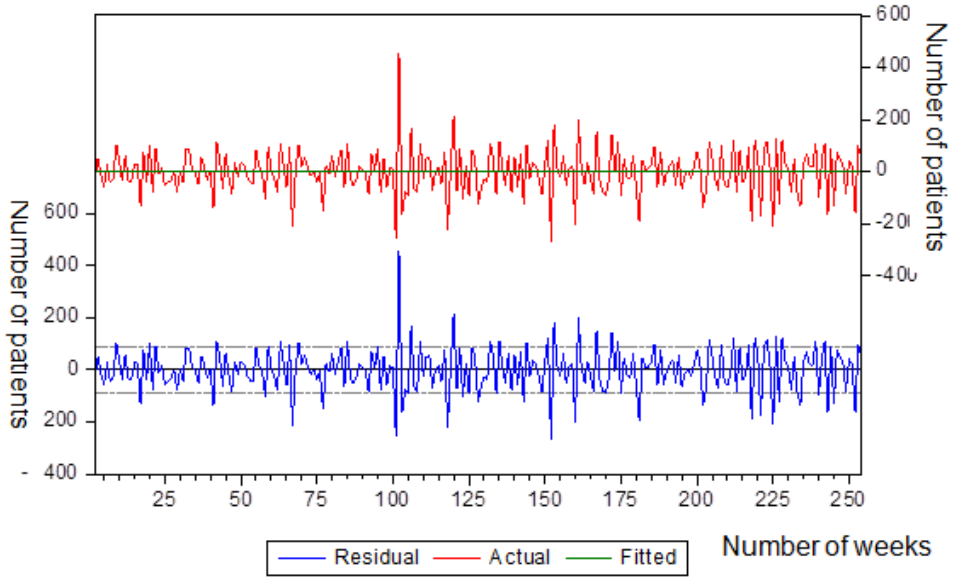


Figure 5.4: Plot of $(0,1,0)X(0,0,0)$ ARIMA-model of arrivals at the department outpatient clinics (first visits) for the specialism surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

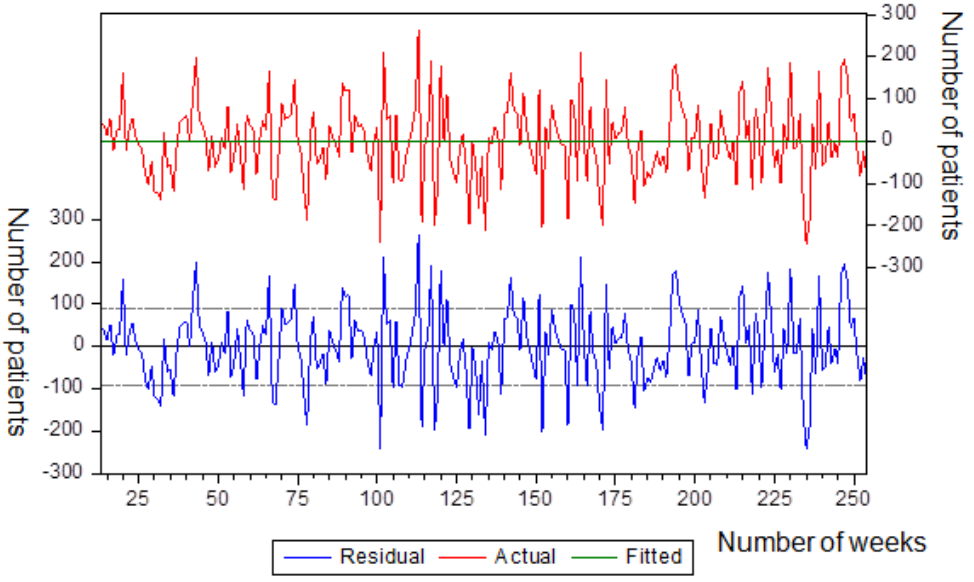


Figure 5.5: Plot of $(0,0,0)X(0,1,0)12$ ARIMA-model of arrivals at the department outpatient clinics (first visits) for the specialism surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

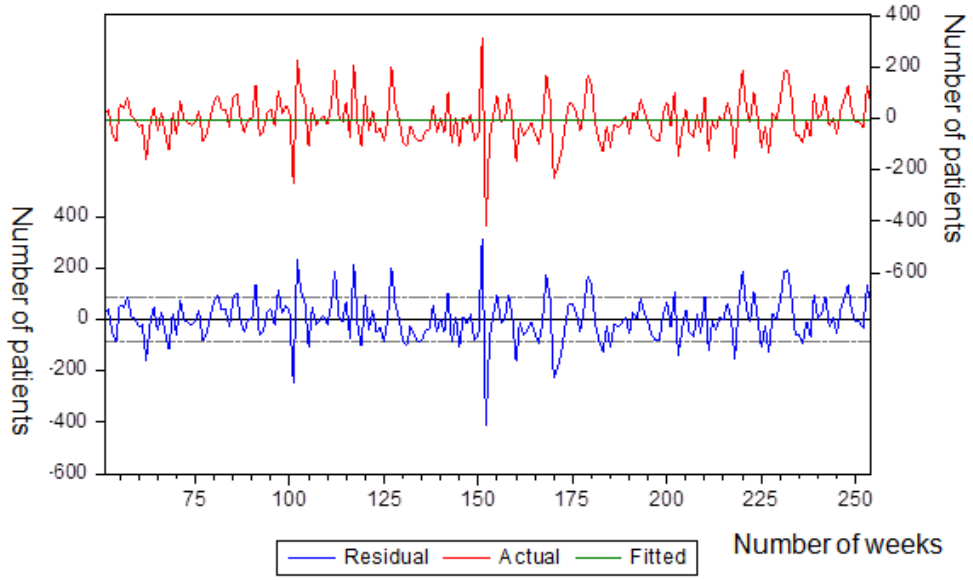


Figure 5.6: Plot of $(0,0,0)X(0,1,0)50$ ARIMA-model of arrivals at the department outpatient clinics (first visits) for the specialism surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

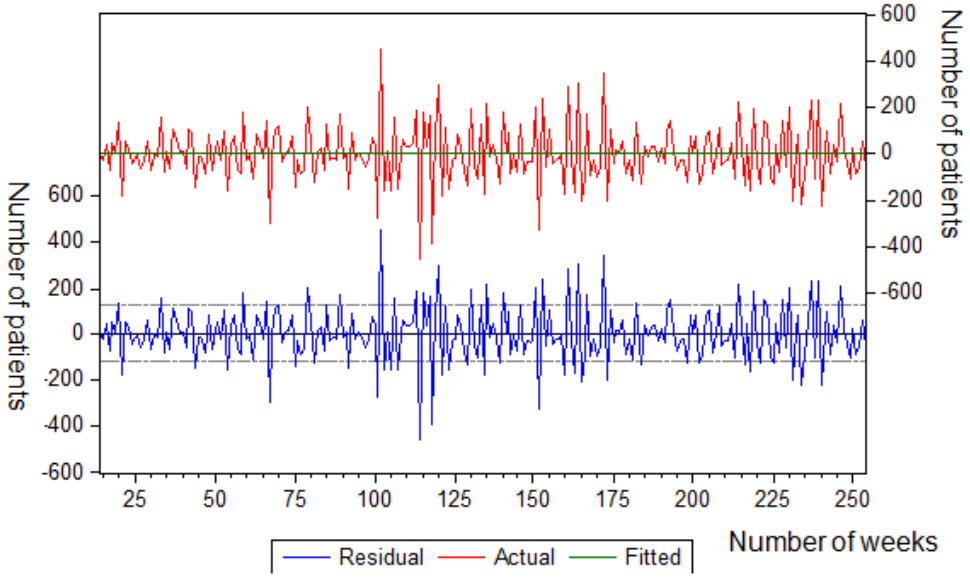


Figure 5.7: Plot of $(0,1,0)X(0,1,0)12$ ARIMA-model of arrivals at the department outpatient clinics (first visits) for the specialism surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

5.1.2 Performance of time series analysis

The ARIMA-models enable us to find estimates of the patient volumes which are to a certain extent accurate. The difference between the real data and estimated data are small. Moreover, if we look at the plot of the fitted and actual data, we observe that the ARIMA-models do follow the increases and decreases of the patient arrivals.

First, we compare the time series predictions with actual data. As discussed in Section 3.1.3, we can use the mean squared error for analyzing the actual data with the fitted data. Using Matlab, we compute the MSE. In Figures A.37-A.42 of the Appendix one can find the MSE for all time series and all scenarios. An MSE of zero indicates a perfect fit. The maximum MSE for all configurations of all computed series is 1.76. As the MSE is defined as the sum of the bias squared and the variance of the residuals, a low MSE indicates also a small difference between the true and the estimated value. The MSE is computed as the difference between actual number of arrivals and the estimated number of arrivals. We estimate patient volumes in whole patients, the figure of 1.76 indicates that the difference between the true and estimated is small for all series of patient arrivals. Moreover, the variance of the residuals is also small.

Figure 5.8 shows the fitted, actual and the residuals for the cardiology of the more than one day clinical admission, using a $(4,1,2)$-ARIMA-model. Figure 5.9 shows the same plots, but for the specialism urology, first outpatient clinic visits, using a $(3,1,4)$-

ARIMA-model. The plots are obtained, using Eviews. Looking at the figures, one can see that it is impossible to have a perfect fit, however the ARIMA-model can predict the trend of the arrivals. This is due to the fact that ARIMA-models use historical data. Increases and decreases of patient volumes can be predicted with ARIMA-models, but can only be detected somewhat later, as the actual data of the previous time periods are already slightly decreasing and increasing. Furthermore, one can notice that the fitted line has less extreme peaks than the actual data. This due to the nature of the fitting procedure. Matlab and Eviews use the method of ordinary least squares for finding an ARIMA fit onto the data. The method of ordinary least squares is vulnerable for huge deviations in the data and will average out the outliers, while obtaining a fit. So the ARIMA-models have a slight delay in predicting patient volumes and face difficulty in detecting huge outliers in the patient volumes.

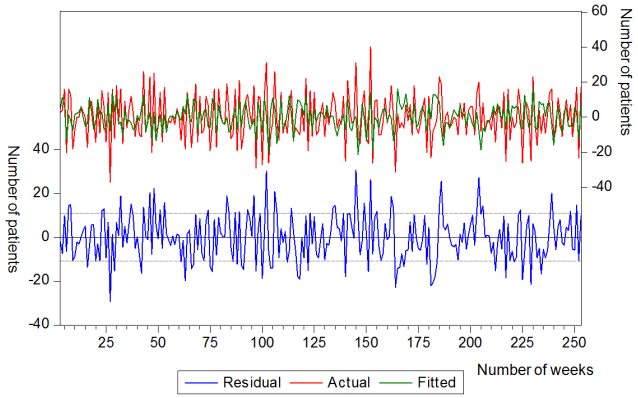


Figure 5.8: Plot of a (4,1,2)-ARIMA-model for the department nursing wards (more than one day admission) for the specialism cardiology. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

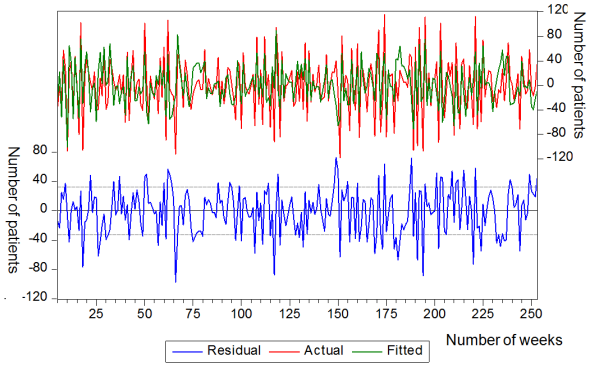


Figure 5.9: Plot of a (3,1,4)-ARIMA-model for the department outpatient clinics (first visit) for the specialism urology. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

5.2 Results for Markov transition probabilities

The results of the Markov transition probabilities are split in two parts: the transfers of the outpatients and the transfers of the inpatients. We discuss the subdivision of the hospital, the time length of the interval and the Markov property, homogeneity and limiting distribution of the proposed Markov chains.

5.2.1 Transfer of outpatients

Figure 5.10 gives the Markov transition probability matrix of the transfers of outpatients, using the subdivision in which the specialism surgery is divided in several subspecialisms and the remaining part of the hospital in the 'other state'. We compute the monthly transition probabilities in the period 2010-2011, giving us 24 realizations of the transition probability matrix of the transfers of outpatients. Using Equation 3.20 we obtain the expected average transition probabilities over the 24 realizations.

The transition matrix provides the monthly transition probabilities. Furthermore, we distinguish which departments a patient is referred to. This can be: the outpatient clinics, the operating theaters or the nursing wards. For the operating theaters we provide separate figures for the patients who are transfered to the operating theaters within in the same state time period and the patients who have to wait for a transfer to the operating theater. The last group of patients have to wait for at least one state time period. Also the transition probabilities of a discharge and being on a waiting list are given in Figure 5.10. Recall that the waiting list is an absorbing Markov state. We see this confirmed in Figure 5.10. We see that the transition probability for the transfers of the patients who are on a waiting list of the various (sub)specialisms, are all equal to one.

All results of the 24 realizations of the transition probabilities for the transfers of outpatients for the five subspecialisms of the specialism surgery, the other part of the hospital, the waiting list and discharge, are available digitally.

5.2.2 Transfer of inpatients

Figure 5.11 provides the average of 24 realizations of the monthly transition probabilities of transfers of inpatients between four subspecialisms of surgery[10] and the remaining part of the hospital in one other state. We distinguish between the origin of the patients. This can be: the outpatient clinics, the operating theater, the nursing wards or the intensive care. The waiting list state and the discharge state are also provided in Figure 5.11.

Again, all results of the 24 realizations of the transition probabilities for the transfers of inpatients for the four subspecialisms of the specialism surgery, the other part of the hospital, the intensive care, the waiting list and discharge, are available digitally.

[10] In the nursing wards the subspecialism 'other surgery' is not existing. All other subspecialisms of surgery do exist in the nursing ward.

The average over the 50 realizations of the expected weekly transition probabilities of transfers of inpatients is provided in Figure 5.12. These transition probabilities concern the second subdivision in 11 specialisms.[11] The aim is to investigate the inter specialism transition probabilities. Recall also that the aim of two different subdivisions is to investigate the influence of the size of the (sub)specialisms on the Markov state. Also the time period for both computations, is different. This is all explained in Section 5.2.3. Again, Figure 5.12, distinguishes between the origin of the inpatients, which can be the outpatients clinics, the operating theaters, the nursing wards or the intensive care. We compute for 50 realizations the weekly transition probabilities for a transfer of inpatients from one specialism to another specialism.

All results of the 50 realizations of the eleven specialisms, the waiting list and discharge, are available digitally.

5.2.3 Subdivision and length of time interval

We recommend to work with a time period of one week. Also we recommend a subdivision of (sub)specialisms into sufficiently large (sub)specialisms. The subdivision into eleven specialisms seems more suitable than the subdivision into (sub)specialisms of surgery and one large other state. We explain this in the next two paragraphs.

The purpose of computing the transition probabilities according to two different subdivisions of the hospital and the two different lengths of the time interval of the states, is twofold. First we would like to know what the influence is of the size of the (sub)specialisms. The subspecialisms of surgery are small and might face little or no transfers of patients during the state time. Moreover, we are interested in the influence of the length of a time interval. The longer the state time, the higher the probability that a patient might transfer from one (sub)specialism to another. However, the state times can not be too large, as we than risk that the vast majority of all transfers will occur in the state 'discharge': the longer the state time, the higher the probability that the patient will also be discharged within the state time. For example, in Figure 5.11 one can see that the transition probability that a patient who is already in the nursing ward, transfers from traumatology to oncology is equal to $0,00\%$, and so there are many other transition probabilities. Moreover, one can see that the discharge probabilities in Figure 5.11 are all very high.[12]

Data analysis demonstrates that the subdivision into the subspecialisms of surgery and one large state 'other', leads to insufficient transitions per state for some of the subspecialisms. There are too many states with a very low number of, or even no, transitions. Figure B.1 provides the aggregate number of all transitions per (sub)specialism of surgery

[11] See Section 4.4 for the subdivision.

[12] For all but the intensive care and waiting list, the estimated discharge probabilities are higher than 75%.

		Surgery						Other		Discharge	Sum
		General surgery and surgery for children	Oncology, lung surgery and gastrointensinal surgery	Other	Traumatology and ER	Vascular Surgery	Waiting list	Other	Waiting list	Discharge	
Nursing wards											
Surgery											
	General surgery and surgery for children	0,94%	0,59%	0,00%	0,56%	0,24%	0,00%	23,93%	0,00%	73,72%	100,00%
	Oncology, lung surgery and gastrointensinal surgery	1,38%	1,12%	0,00%	0,63%	0,00%	0,00%	31,93%	0,00%	64,94%	100,00%
	Other	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	100,00%
	Traumatology and ER	0,33%	0,19%	0,00%	2,43%	0,10%	0,00%	13,17%	0,00%	83,78%	100,00%
	Vascular Surgery	0,78%	0,36%	0,00%	0,96%	1,56%	0,00%	26,89%	0,00%	69,45%	100,00%
Other											
	Other	1,04%	0,78%	0,01%	1,34%	0,88%	0,00%	17,41%	0,00%	78,55%	100,00%
Discharge											
Surgery											
	General surgery and surgery for children	0,51%	0,29%	0,00%	0,66%	0,17%	0,00%	9,19%	0,00%	89,18%	100,00%
	Oncology, lung surgery and gastrointensinal surgery	0,39%	0,56%	0,00%	0,16%	0,11%	0,00%	11,60%	0,00%	87,17%	100,00%
	Other	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	57,50%	0,00%	42,50%	100,00%
	Traumatology and ER	0,41%	0,07%	0,00%	1,00%	0,07%	0,00%	5,35%	0,00%	93,10%	100,00%
	Vascular Surgery	0,35%	0,16%	0,00%	0,22%	0,58%	0,00%	20,31%	0,00%	78,38%	100,00%
Other											
	Other	0,36%	0,40%	0,00%	0,33%	0,46%	0,00%	9,92%	0,00%	88,54%	100,00%
Operating theater without waiting											
Surgery											
	General surgery and surgery for children	3,23%	0,25%	0,00%	0,12%	0,25%	0,00%	7,64%	0,00%	88,52%	100,00%
	Oncology, lung surgery and gastrointensinal surgery	1,18%	2,46%	0,00%	0,86%	0,53%	0,00%	7,70%	0,00%	87,27%	100,00%
	Other	0,00%	0,00%	0,00%	50,00%	0,00%	0,00%	50,00%	0,00%	0,00%	100,00%
	Traumatology and ER	0,53%	0,05%	0,00%	4,42%	0,16%	0,00%	7,61%	0,00%	87,22%	100,00%
	Vascular Surgery	2,15%	1,08%	0,00%	2,96%	2,42%	0,00%	12,37%	0,00%	79,03%	100,00%
Other											
	Other	2,70%	2,88%	0,00%	1,72%	1,14%	0,00%	9,20%	0,00%	82,36%	100,00%
Operating theater with waiting											
Surgery											
	General surgery and surgery for children	2,11%	0,91%	0,00%	1,66%	0,15%	0,00%	14,35%	0,00%	80,82%	100,00%
	Oncology, lung surgery and gastrointensinal surgery	0,56%	2,39%	0,00%	0,70%	0,14%	0,00%	18,59%	0,00%	77,61%	100,00%
	Other	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	100,00%
	Traumatology and ER	2,59%	0,39%	0,00%	1,17%	0,39%	0,00%	13,73%	0,00%	81,74%	100,00%
	Vascular Surgery	1,62%	0,32%	0,00%	1,29%	1,29%	0,00%	28,16%	0,00%	67,31%	100,00%
Other											
	Other	1,54%	2,33%	0,00%	0,84%	1,05%	0,00%	14,89%	0,00%	79,35%	100,00%
Outpatient clinics											
Surgery											
	General surgery and surgery for children	0,00%	2,42%	0,00%	9,66%	2,07%	0,00%	83,92%	0,00%	1,93%	100,00%
	Oncology, lung surgery and gastrointensinal surgery	3,44%	0,00%	0,00%	1,69%	1,17%	0,00%	91,57%	0,00%	2,14%	100,00%
	Other	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	100,00%
	Traumatology and ER	17,75%	1,52%	0,00%	0,00%	1,45%	0,00%	77,45%	0,00%	1,83%	100,00%
	Vascular Surgery	1,41%	1,17%	0,00%	1,04%	0,00%	0,00%	95,57%	0,00%	0,80%	100,00%
Other											
	Other	4,41%	5,69%	0,04%	3,99%	6,36%	0,00%	77,61%	0,00%	1,90%	100,00%
Waiting list											
	General surgery and surgery for children	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	0,00%	100,00%
	Oncology, lung surgery and gastrointensinal surgery	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	0,00%	100,00%
	Traumatology and ER	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	0,00%	100,00%
	Vascular Surgery	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	0,00%	100,00%
	Other	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	100,00%

Figure 5.10: Average over 24 realizations of the expected monthly transition probabilities of transfers of outpatients in the period 2010-2011. The transition probabilities are from to probabilities, thus the origins are the lines, the destinations are the columns. Note that the probabilities are in %, the percentages represent a probability between 0 and 1.

		Intensive care	Surgery Nursing ward				Waiting list	Other Nursing ward	Waiting list	Discharge	Sum
		Other	General surgery and surgery for children	Oncology, lung surgery and gastrointensinal surgery	Traumatology and ER	Vascular Surgery	Waiting list	Other	Waiting list	Discharge	
Intensive care											
Surgery											
	General surgery and surgery fo	40,00%	20,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	40,00%	100,00%
	Oncology, lung surgery and gas	42,86%	0,00%	14,29%	0,00%	0,00%	0,00%	0,00%	0,00%	42,86%	100,00%
	Other	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	100,00%
	Traumatology and ER	57,14%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	42,86%	100,00%
	Vascular Surgery	50,00%	0,00%	0,00%	0,00%	0,00%	0,00%	25,00%	0,00%	25,00%	100,00%
Other											
	Other	2,28%	1,82%	8,65%	1,77%	6,67%	0,00%	31,14%	0,00%	47,67%	100,00%
Nursing wards											
Surgery											
	General surgery and surgery fo	1,72%	10,34%	0,00%	0,00%	0,86%	0,00%	3,45%	0,00%	83,62%	100,00%
	Oncology, lung surgery and gas	3,86%	0,00%	11,20%	0,77%	0,39%	0,00%	7,72%	0,00%	76,06%	100,00%
	Traumatology and ER	0,00%	0,32%	0,00%	5,48%	0,32%	0,00%	1,94%	0,00%	91,94%	100,00%
	Vascular Surgery	2,61%	0,33%	0,65%	0,00%	2,94%	0,00%	1,63%	0,00%	91,83%	100,00%
Other											
	Other	0,45%	0,03%	0,21%	0,11%	0,18%	0,00%	5,67%	0,00%	93,35%	100,00%
Operating theater											
Surgery											
	General surgery and surgery fo	0,98%	2,54%	0,06%	0,02%	0,02%	0,00%	0,54%	0,00%	95,84%	100,00%
	Oncology, lung surgery and gas	5,81%	0,07%	5,09%	0,02%	0,05%	0,00%	0,63%	0,00%	88,33%	100,00%
	Traumatology and ER	0,68%	0,00%	0,00%	4,84%	0,03%	0,00%	0,78%	0,00%	93,68%	100,00%
	Vascular Surgery	11,08%	0,00%	0,30%	0,00%	11,68%	0,00%	1,27%	0,00%	75,67%	100,00%
Other											
	Other	0,30%	0,03%	0,02%	0,02%	0,00%	0,00%	2,29%	0,00%	97,34%	100,00%
Outpatient clinic											
Surgery											
	General surgery and surgery fo	0,24%	3,19%	0,00%	0,04%	0,04%	0,00%	4,35%	0,00%	92,15%	100,00%
	Oncology, lung surgery and gas	0,56%	0,00%	6,54%	0,11%	0,06%	0,00%	3,38%	0,00%	89,34%	100,00%
	Traumatology and ER	0,25%	0,05%	0,04%	3,44%	0,00%	0,00%	1,48%	0,00%	94,74%	100,00%
	Vascular Surgery	0,91%	0,12%	0,06%	0,24%	6,33%	0,00%	1,34%	0,00%	90,99%	100,00%
Other											
	Other	0,40%	0,04%	0,11%	0,03%	0,03%	0,00%	5,65%	0,00%	93,74%	100,00%
Waiting list											
	General surgery and surgery fo	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	0,00%	100,00%
	Oncology, lung surgery and gas	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	0,00%	100,00%
	Traumatology and ER	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	0,00%	100,00%
	Vascular Surgery	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	0,00%	0,00%	100,00%
	Other	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	100,00%

Figure 5.11: Average over 24 realizations of the expected monthly transition probabilities of transfers of inpatients in the period 2010-2011. The transition probabilities are from to probabilities, thus the origins are the lines, the destinations are the columns. Note that the probabilities are in %, the percentages represent a probability between 0 and 1.

		Intensive Care		Clinic											Discharge	Waiting list	Sum
		Internal Medicine	Other	Surgery	Cardiology	Internal Medicine	Neurology	Other	Pulmonology	Gynecology	Obstetrics	Urology	Pediatrics	Gastroenterology	Discharge	Waiting list	
Intensive Care																	
	Cardiology	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	**100,00%**
	Surgery	0,00%	53,85%	0,00%	23,08%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	23,08%	0,00%	**100,00%**
	Gastroenterology	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	**100,00%**
	Internal Medicine	2,72%	1,09%	0,82%	8,17%	1,09%	4,09%	38,96%	0,54%	1,09%	0,27%	0,27%	0,54%	0,27%	40,05%	0,00%	**100,00%**
	Pediatrics	7,14%	0,00%	0,00%	7,14%	0,00%	0,00%	28,57%	0,00%	14,29%	0,00%	0,00%	0,00%	0,00%	42,86%	0,00%	**100,00%**
	Pulmonology	0,00%	20,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	80,00%	0,00%	**100,00%**
	Neurology	0,00%	16,67%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	83,33%	0,00%	**100,00%**
	Other	0,22%	0,11%	1,97%	10,08%	0,77%	1,10%	3,72%	1,31%	3,61%	2,30%	38,44%	0,88%	0,22%	35,27%	0,00%	**100,00%**
	Obstetrics	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	50,00%	50,00%	0,00%	**100,00%**
Nursing ward																	
	Cardiology	0,09%	0,33%	22,33%	1,04%	0,14%	0,09%	0,80%	0,05%	0,80%	0,09%	0,24%	0,05%	0,00%	73,94%	0,00%	**100,00%**
	Surgery	0,16%	0,94%	0,47%	37,46%	0,16%	0,00%	0,94%	0,00%	0,16%	0,16%	0,78%	0,16%	0,00%	58,62%	0,00%	**100,00%**
	Gastroenterology	0,00%	0,00%	0,00%	1,02%	18,09%	0,34%	0,34%	0,00%	0,00%	0,00%	0,34%	0,34%	0,00%	79,52%	0,00%	**100,00%**
	Gynecology	0,00%	0,00%	0,00%	0,99%	0,00%	15,84%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,99%	82,18%	0,00%	**100,00%**
	Internal Medicine	0,07%	0,55%	0,27%	1,03%	1,23%	1,51%	24,67%	0,00%	0,41%	0,34%	0,21%	0,00%	0,00%	69,71%	0,00%	**100,00%**
	Pediatrics	0,00%	0,20%	0,00%	0,10%	0,00%	0,00%	0,20%	24,05%	0,00%	0,00%	0,00%	0,39%	1,17%	73,90%	0,00%	**100,00%**
	Pulmonology	0,18%	0,89%	0,53%	0,36%	0,00%	1,42%	1,78%	1,78%	35,52%	0,00%	0,18%	0,00%	0,00%	57,37%	0,00%	**100,00%**
	Neurology	0,11%	0,21%	0,21%	0,21%	0,00%	0,00%	1,07%	0,21%	0,54%	15,79%	0,11%	0,00%	0,00%	81,53%	0,00%	**100,00%**
	Other	0,00%	0,06%	0,12%	0,12%	0,00%	0,06%	0,47%	0,59%	0,35%	0,59%	15,98%	0,06%	0,06%	81,54%	0,00%	**100,00%**
	Urology	0,00%	0,77%	0,00%	0,77%	0,00%	0,00%	0,39%	0,00%	0,00%	0,39%	1,16%	11,58%	0,00%	84,94%	0,00%	**100,00%**
	Obstetrics	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,32%	0,00%	0,00%	0,49%	0,00%	0,97%	9,58%	88,64%	0,00%	**100,00%**
Operating room																	
	Cardiology	0,62%	0,62%	1,85%	24,07%	0,00%	0,62%	0,00%	0,00%	0,00%	0,00%	0,62%	0,00%	0,00%	71,60%	0,00%	**100,00%**
	Surgery	0,70%	1,80%	0,61%	19,30%	0,05%	0,02%	0,15%	0,06%	0,07%	0,00%	0,07%	0,02%	0,02%	77,11%	0,00%	**100,00%**
	Gastroenterology	0,00%	0,00%	0,00%	0,00%	9,52%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	90,48%	0,00%	**100,00%**
	Gynecology	0,26%	0,62%	0,15%	0,21%	0,00%	12,92%	0,05%	0,05%	0,31%	0,00%	0,88%	0,36%	0,05%	84,14%	0,00%	**100,00%**
	Internal Medicine	0,00%	2,78%	0,00%	5,56%	2,78%	5,56%	25,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	58,33%	0,00%	**100,00%**
	Pediatrics	0,00%	0,00%	0,00%	15,38%	0,00%	0,00%	7,69%	38,46%	0,00%	0,00%	0,00%	0,00%	0,00%	38,46%	0,00%	**100,00%**
	Pulmonology	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	50,00%	0,00%	0,00%	0,00%	0,00%	50,00%	0,00%	**100,00%**
	Neurology	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	33,33%	0,00%	0,00%	0,00%	66,67%	0,00%	**100,00%**
	Other	0,01%	0,15%	0,11%	0,06%	0,01%	0,01%	0,14%	0,19%	0,24%	0,26%	6,50%	0,01%	0,00%	92,31%	0,00%	**100,00%**
	Urology	0,33%	1,10%	0,28%	0,11%	0,00%	0,06%	0,11%	0,00%	0,39%	0,39%	0,44%	8,25%	0,22%	88,34%	0,00%	**100,00%**
	Obstetrics	0,06%	0,18%	0,00%	0,18%	0,00%	0,00%	0,12%	0,00%	0,00%	0,71%	0,06%	1,12%	17,15%	80,44%	0,00%	**100,00%**
Outpatient clinics																	
	Cardiology	0,02%	0,28%	20,09%	0,42%	0,05%	0,07%	0,70%	0,05%	0,63%	0,05%	0,08%	0,03%	0,00%	77,54%	0,00%	**100,00%**
	Surgery	0,20%	0,16%	0,42%	16,87%	0,16%	0,13%	0,45%	0,13%	0,22%	0,13%	0,49%	0,12%	0,04%	80,48%	0,00%	**100,00%**
	Gastroenterology	0,03%	0,17%	0,07%	0,35%	5,52%	0,14%	0,35%	0,03%	0,10%	0,03%	0,03%	0,03%	0,03%	93,09%	0,00%	**100,00%**
	Gynecology	0,00%	0,18%	0,36%	0,36%	0,00%	5,51%	0,36%	0,00%	0,00%	0,00%	0,00%	0,18%	0,71%	92,36%	0,00%	**100,00%**
	Internal Medicine	0,17%	0,37%	0,57%	0,55%	1,20%	1,29%	18,16%	0,04%	0,26%	0,23%	0,17%	0,09%	0,04%	76,88%	0,00%	**100,00%**
	Pediatrics	0,02%	0,02%	0,02%	0,00%	0,00%	0,02%	1,59%	22,19%	0,06%	0,00%	0,02%	0,35%	0,82%	74,88%	0,00%	**100,00%**
	Pulmonology	0,11%	0,55%	0,98%	0,25%	0,00%	0,30%	1,23%	1,64%	23,04%	0,08%	0,25%	0,00%	0,00%	71,58%	0,00%	**100,00%**
	Neurology	0,11%	0,25%	0,18%	0,25%	0,07%	0,36%	0,50%	0,64%	0,85%	20,78%	0,21%	0,04%	0,00%	75,77%	0,00%	**100,00%**
	Other	0,07%	0,07%	0,15%	0,17%	0,00%	0,00%	0,32%	0,18%	0,18%	0,43%	9,93%	0,00%	0,00%	88,50%	0,00%	**100,00%**
	Urology	0,18%	0,18%	0,09%	0,26%	0,18%	0,09%	0,26%	0,09%	0,00%	0,35%	0,79%	13,27%	0,18%	84,09%	0,00%	**100,00%**
	Obstetrics	0,00%	0,02%	0,03%	0,03%	0,00%	0,00%	0,03%	0,02%	0,00%	0,28%	0,02%	0,70%	8,88%	89,98%	0,00%	**100,00%**
Waiting list																	
	Cardiology	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**
	Surgery	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**
	Gastroenterology	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**
	Gynecology	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**
	Internal Medicine	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**
	Pediatrics	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**
	Pulmonology	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**
	Neurology	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**
	Other	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**
	Urology	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**
	Obstetrics	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	**100,00%**

Figure 5.12: Average over 50 realizations of the expected weekly transition probabilities of transfers of inpatients in the period 2010. The transition probabilities are from to probabilities, thus the origins are the lines, the destinations are the columns. Note that the probabilities are in %, the percentages represent a probability between 0 and 1.

in the outpatients clinics. Figure B.1 also contains the aggregate number for the state 'discharge' and 'other'. We notice that the averages for the four subspecialisms of surgery are really low, compared to the average of the state 'discharge'. Also the average number of transitions of the state 'order' is much higher than the average number of transitions of the subspecialisms of surgery.

In Figure B.2 we see the aggregate number of weekly transitions for the subdivision into specialisms. We see that averages per specialisms are about as high as for the subdivision in (sub)specialisms of surgery. However, Figure B.2 concerns the aggregated weekly transitions, whereas Figure B.1 concerns the aggregated monthly transitions. The increased number of transitions per equal time period, is due to decreasing the length of the time interval. For the specialisms surgery the average number of monthly transitions of the five subspecialisms together equals 82.75. If the time period is reduced to one week, the average number of transitions of surgery is 64.43, or equivalent to more or less, 260 transitions a month.

Moreover, we can see that the share of the patients who are discharged within the state time period, is reduced. For the subdivision into subspecialisms of surgery and the state time period of one month, the share of patients who are discharged within the state time, is equal to 93%. In the subdivision into specialisms and a state time period of one week, this share decreases to $73,75\%$. It is not convenient to make the time length of interval smaller than one week. The data will become too much blurred by the influence of weekends, as in principal no elective patients are admitted to the hospital during the weekend.

5.2.4 Markov property, homogeneity and limiting probabilities

In this section we discuss results whether the Markov property, the homogeneity properties and, limiting probabilities for Markov chains, hold. For the Markov property and homogeneity, we use Equation 3.16. Using Equation 3.18 we investigate the limiting probabilities. Although we do not investigate for all realizations the Markov and homogeneity property and the existence of a limiting distribution, the investigated realizations suggest that the properties hold for the two different subdivisions. We thus can conclude that we can model the transfers of patients from one (sub)specialism to another as a Markov chain. This is explained in the next two paragraphs. Figures B.3 and Figure B.4 in the Appendix provide an example in which we test Markov property, homogeneity property and limiting probabilities.

Investigating all possibilities concerning homogeneity and Markov property, yields an abundance of computations of Equation 3.16. For 12 different transition probabilities of transfers of inpatients all realizations are investigated: all do meet the criterion of Equation 3.16 and 3.18.

For the transfers of outpatients, the realizations of 11 different transition probabilities

are investigated. Again, all do satisfy the condition of Equation 3.16 and 3.18. So we can conclude that the Markov property, homogeneity and limiting distribution holds for the subdivision in subspecialsms of surgery and one state 'other' for the remaining part of the hospital, in which the time period of one state is equal to one month. Figure 5.13 provides an overview of the number of realizations that meets the criterion of Equation 3.16.

	Inpatients		Outpatients	
year	2010	2011	2010	2011
difference				
exceeds 10%	12	7	11	11
5%-10%	27	26	14	13
less than 5%	258	264	191	192
total	297	297	216	216

Figure 5.13: Overview of homogeneity property for the monthly transition probabilities of the subdivision in subspecialisms of surgery. For each estimation of a certain transition probability there are 12 realizations. The numbers in the first two rows of the table indicates the occurrence that of a series of realizations of one transition probability, there is at least one realization in the category which differs more than 10% or 5-10% respectively of its average. The third row reflects the series of realizations of one transition probability in which all realizations differ less than 5% of the average.

For the subdivision into 11 specialisms and the time period of one week, we also investigate the Markov property, homogeneity and limiting distribution. Figure 5.14 provides an overview of the number of realizations that meets the different criteria. As the differences between the different realizations and the average are small, this is also a good indication that the limiting distribution exists in this case.

	Inpatients 2011	
	modified	equation 3.6
difference		
exceeds 10%	19	66
5%-10%	25	3
less than 5%	671	646
total	715	715

Figure 5.14: Overview of homogeneity property for the weekly transition probabilities of the subdivision in 11 specialisms. For each estimation of a certain transition probability there are 50 realizations. The numbers in the first two rows of the table indicate the occurrence that of a series of realizations of one transition probability, there is at least one realization in the category which differs more than 10% or 5-10% respectively of its average. The third row reflects the series of realizations of one transition probability in which all realizations differ less than 5% of the average. The first column is the modified version of Equation 3.16 in which the 10 highest and lowest realizations are excluded, the second is an evaluation of Equation 3.16, including all realizations.

5.3 Average service times

The average service times are computed for different operations and admissions (one day and more than one day).

We compute the average operation times for 479 different operations. We find 232 operations having an average operating time which amount to more than one hour, we find 15 treatments with an operating time of more than 3 hours and only three treatments with an average operating time of more than 4 hours. The number of operations which have an operation time longer than one hour, also contains the number of operations which on average are longer than three and four hours. The number of operations that is longer than three hours also contains the operations which are longer than 4 hours.

In total we compute the average admission times for 980 types of treatments. We find for the admissions to the department nursing wards that 0 treatments, have an average which is 30 days or more, 60 treatments have an average which is 10 days or more, 181 treatments with an average of 5 days or more and 299 treatments with an average of 3 days or more. Again the admissions which are three days or longer, also contain the 5 and 10-day admissions. The number of admissions which is five days or longer also contains the admissions which are on average longer than 10 days.

The fact that 0 of the clinical treatments have an average service time longer than 30 days and that there are 60 treatments longer than 10 days, 181 treatments longer than 5 days and 299 longer than 3 days, justifies the choice for a one week time interval, in the Markov chain.

The average service time and the standard deviation are given in Figures C.1-C.8 of the appendix. Also the number of operations/admissions is included.

5.4 Comparision of the model

We compare our model and the 4 year average model[13] with regard to accuracy and costs. We back-test both models for a period of 20 weeks in 2011. In Section 5.4.1 we explain that our model predicts the patient volumes more accurate than the 4 year average model. Our model predicts patient volumes such that it yields lower total costs for additional/unused staff and nursing beds. In case of the average scenario, the advantage in costs in favor of our model is approximately 2.3 million euro. We explain this in Section 5.4.2.

[13]Recall that the 4 year average model is introduced for comparing the holistic model with another model. The 4 year average model uses the average of the arrivals of the same period each year.

5.4.1 Back-testing

For 117 of 220 estimates, our model provides a more accurate estimate than the 4 year average model or that is in 53 % of the cases. Moreover, in 86 of the 220 cases our model estimates a patient volume which differs only a maximum of 10 patients of the true value, against 74 of 220 cases for the 4 year average model. In 14% of the cases our model is better with respect to the maximum difference of 10 patients. In 85 of 220 cases, the 4 year average model results in a prediction, which differs at least 25 patients of the true value. For our model this is only in 78 of 220 the cases, or this is 8% better.

Figure D.1 provides the differences between the 4 year average model and the actual data and between the outcomes of our model and the actual data of week 5 to 24 of 2011. We notice for the specialisms gastroenterology, gynecology, internal medicine, neurology, pediatrics and surgery that the outcomes of our model are often more accurate than the estimation by the four year average model.

We back-test our model for the arrivals of inpatients at the various specialisms between specialisms for 20 weeks of 2011. We use the transition probability matrix for the transfers of inpatients between specialisms, which is given in Figure 5.12 and arrival figures of 2007-2010 to estimate the arrivals for 2011. For estimating arrivals at the combinations of operating theaters and specialisms and combinations of nursing wards and specialisms, we use the best fit of the ARIMA-models for these series of arrivals. We apply Equation 3.24 in order to compute the patient volumes at the various specialisms. Finally, we compare these outcomes of a certain week to the outcomes of the 4 year average model.

5.4.2 Comparison of costs

Using arbitrarily cost estimates for the use of outpatient clinic space, nursing beds and staff, and estimations for week 5 till week 24 of 2011, our model results in a cost advantage of €2,340,000.− compared to the 4 year average model. Also, again we find evidence that our model is better for planning purposes than the 4 year average.

We use arbitrarily costs estimates per ten patients per week in order to compare the two models. We assume that the costs for additional nursing beds and staff in the department nursing wards, are €60,000.−. These additional costs arise if we overestimate patient capacity. For an underestimation the costs of unused staff and nursing beds we use the same estimate of €60,000.−. For simplicity purposes, we expect that there is no difference in costs between an over- and underestimation.

Figure 5.15 contains a histogram with two scenarios. For both scenarios we assume that the capacity of a nursing ward is ten patients. The first scenario we call the worst case scenario. This is the situation in which none of the planned capacity is used in case of an overestimation. In case of an underestimation, we need the maximum of ten additional beds. The second scenario is called the average scenario. In this case, we

assume half of the planned capacity is used in case of an overestimation. In case of an underestimation only half of the maximum of additional beds, thus five beds, are needed. The classes are on the horizontal axis, the costs are on the vertical axis. The blue bars indicate the total costs of our model for the average scenario and the green bars for the worst case scenario. The red bars indicate the total costs for the average scenario for the 4 year average model, while the orange bars indicate the worst case scenario.

We compose 29 classes. The lowest class is an overestimation of 110-120 patients, or equivalent to the total costs of €360,000.− per week in the average scenario and €720,000.− in the worst case scenario. The highest class is an underestimation of 150-160 patients, or equivalent to the costs of €480.000,− per week in the average scenario and €960,000.− in the worst case scenario. Figure 5.15 provides the total costs of an under- and overestimation in patient volumes. The figure contains the total costs for 10 of 11 specialisms[14] per class of ten under- or overestimated patients.

Figure D.2 provides the total costs per class of 10 patients for our model and the 4 year average model. Applying the described cost estimation method, we predict that the extra costs for unused or additional staff for our model amounts to €14,640,000.− and for the four-year average model to €12,300,000.− in case of the average scenario. This is an advantage of €2,340,000− in favor of our model. In the worst case scenario the advantage amounts to €4,680,000.−.

Finally, Figure 5.16 gives the frequencies of each of the 11 classes of 10 patients. The blue bars indicate our model, the red bars indicate the 4 year average model. We see that our model estimates in 23% of the cases, the required number of staff and nursing beds, while the 4 year average model only estimates in 13.5% of the cases, the required number of staff and nursing beds. Moreover, note that our model estimates in 57% of the cases patient volumes, which differs 10 patients at the very most from the true values. For the 4 year average model this is only 45.5%. Our model underestimates the patient volumes per specialism less often than the 4 year average model does (34% of the cases for our model, against 75% of the cases for the 4 year average model). Our model overestimates the patient volumes more often than the 4 year average model (43% of the 200 cases for our model, against 11.5% of the cases for the 4 year average model).

[14]The specialism 'other' is excluded. Since the specialism 'other' is composed of several small specialisms and costs are allocated to specific specialisms, it has no meaning to compute the additional/unused costs for this group of specialisms.

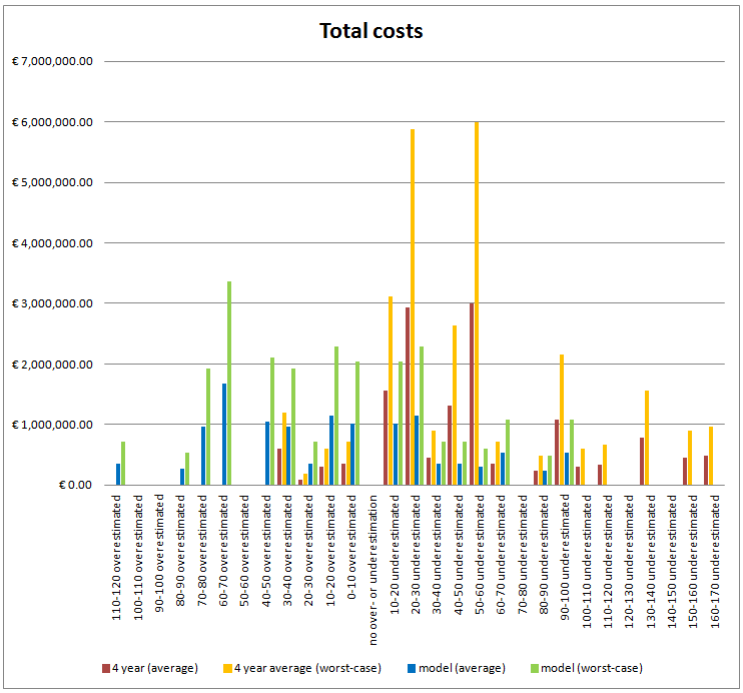


Figure 5.15: Histogram of the total costs of the holistic and the 4 year average model for the two scenarios for additional or unused nursing beds and staff for 10 specialisms in week 5 to week 24 of 2011.

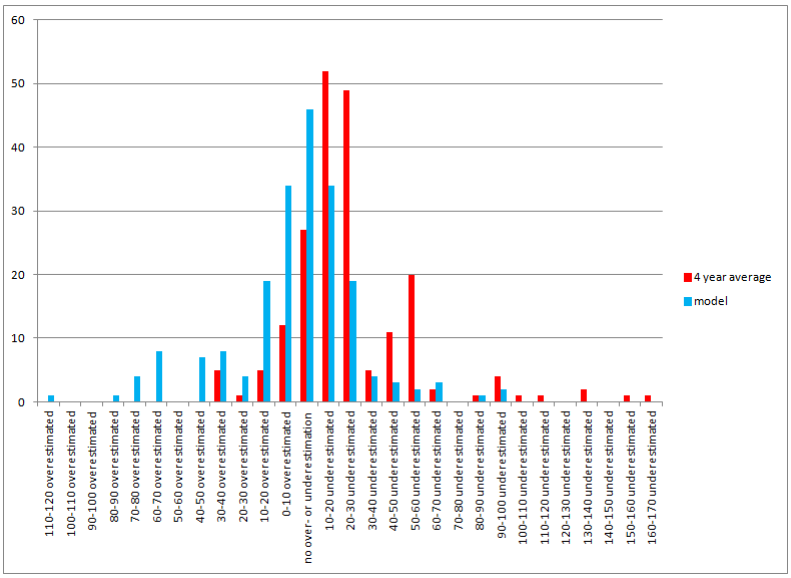


Figure 5.16: Overview of frequencies per class of 10 patients for the holistic model and the 4 year average model.

Chapter 6

Academic conclusions

In this chapter we present the conclusions of the research and pay special attention to the academic outcomes of the study. In Chapter 8 we discuss the applicability of the research with respect to ZGT and do recommendations. ZGT is interested in estimating patient volumes and occupancy rates of (sub)specialisms at the outpatient clinics, operating theaters and nursing wards, at least one month ahead. First we discuss the performance of the model. Next, we elaborate on the academic relevance of the research. We thus first conclude on the last of the four research questions, listed in Section 1.2. Finally, we provide answers to the first three research questions. The model we developed, consists of three components: estimating patient arrivals at departments, the transfers of patients between (sub)specialisms in the departments and the average service times. The first two components are necessary to compute the expected patient volumes. All components are necessary for computing the occupancy rate. Each of the first three research questions deals with one of the components.

6.1 Performance of the model

At this moment, ZGT has no model to estimate patient volumes and occupancy rates at (sub)specialisms in the three departments. The holistic model we develop, is suitable for estimating patient volumes and occupancy rates at (sub)specialisms at least one month ahead, in the departments outpatient clinics, operating theaters and nursing wards. The estimated patient volumes and occupancy rates are a useful tool for allocating nursing beds and staff. The model we develop can predict four months ahead.[1] Moreover, the model which we present, gives ZGT insight into patient flows between (sub)specialisms in the three departments.

With respect to the transfer of inpatients, the transition probability matrix provides the insight that more than 70 % of the patients who enter a certain specialism, do not

[1] In Section 5.4 we provide an example in which we forecast for 20 weeks the patient volumes at specialisms in the nursing wards.

transfer to another specialism and are discharged within one week. Predicting the arrivals of inpatients accurately, is thus the most essential part if one would like to estimate the patient volumes at specialisms in the nursing wards in the near future. These estimations can be used for allocating staff and nursing beds. Due to limitations in the data warehouse of ZGT, we can not draw the same conclusion for the transfer of outpatients with certainty. However, computations suggest that the same conclusions hold for the transfers of outpatients. We recommend that ZGT for outpatients also keeps track of all referrals within one patient path. We present ARIMA-models for 11 specialisms with which we can predict patient volumes in the outpatient clinics, operating theaters and nursing wards.

We back-test our model for 20 weeks in 2011 by estimating the expected weekly patient volumes at the nursing wards for 11 specialisms and comparing them with the actual values. Approximately 40% of the weekly patient volumes estimates, differ less than 10 patients in comparison with the actual data. About 25% of the estimations are in the range of a difference between 10 and 20 patients in comparison with the actual data. As said, ZGT uses common sense to allocate staff and nursing beds. Since these estimations are not entirely comparable, we also construct a simple measure and compare our model to this measure. This measure uses the 4 year average arrivals. In 53% of the cases, our model estimates the arrivals better than the 4 year average model. Moreover, our model predicts 14% more cases than the 4 year average model, in which the difference between the estimate and the actual data is only 10 patients or less. The 4 year average model estimates 8% more cases than our model, in which the difference is more than 25 patients compared to the actual data.

Finally, we make a cost comparison of the two models. We calculate costs of wrongly planned nursing beds and staff per group of ten patients per week in case of an over- and underestimation by our model. Next, we compare these costs to the cost estimates of the 4 year average model. For this purpose we use arbitrarily cost estimates of €1,200.− per patient per nursing day. In a scenario in which five of the ten planned beds are really used, the comparison shows a potential costs saving of 2.3 million euro for a period of 20 weeks in favor of our model. In the case of a worst case estimation, this is even higher: a cost reduction of approximately 4.6 million euro in 20 weeks. We also assume that the capacity is available for five days a week and that no transfers between specialisms are allowed. We are well aware that we use several assumptions which should be validated with real world and this will bring down the calculated cost estimate.

6.2 Academic relevance of the model

We are interested whether we can model patient paths and flows through a hospital using a holistic model of three pillars: ARIMA-models, Markov chains and statistical computation of average service times. Our research shows that the combination of the three pillars is a good method for predicting patient volumes and occupancy rates at

(sub)specialisms in the near future. Predicting patient volumes and occupancy rates in this manner is a new concept. As described above, the model predicts patient volumes at nursing wards quite accurately. The fact that we combine the three components into one model and obtain accurate estimates, is a valuable scientific result.

In particular, little research has be done with respect to applicability of Markov theory in health care. The model we develop, demonstrates that Markov chains can be used for modeling patient transfers between outpatient clinics and operating theaters and between operating theaters and nursing wards. Statistical analysis suggests that the homogeneity property and Markov property is satisfied and that the limiting distribution exists of the Markov chains we develop in this paper. This is also a valuable result.

Also with regard to patient arrivals, the choice for an ARIMA-model is a good one, as statistical analysis shows that we can predict patient volumes accurately. The maximum MSE for all developed ARIMA-models is 1.76. This means that the sum of the bias squared (difference between true and error) and the variance of the error are relatively small. Again, statistical tests provide statistical evidence that we may model patient arrivals by using ARIMA-models.

6.3 Research questions

The next subsection will answer the first three research questions defined in Section 1.2.

6.3.1 Expected number of patient arrivals at departments

For the three departments outpatient clinics, operating theaters and nursing wards, we propose relatively simple models which use a maximum of four time steps back. We develop for 11 specialisms ARIMA-models, which estimate the weekly arrivals several weeks ahead. We find no evidence of seasonal patterns in the data. The results are given in Figures A.1-A.5. Moreover, given the constraints of the maximum number of four autoregressive and four moving average terms, the proposed ARIMA-models predict the weekly patient volume well.

We see that the ARIMA-models predict increases or decreases of arrivals well. However, since ARIMA uses historical data, the ARIMA-models predict these increases or decreases about one or two weeks later than they occur in reality. This might be due to the fact that we do not incorporate sufficient autoregressive and moving average terms in our model. We do not incorporate additional terms, as the Akaike criterion indicates that introducing more terms, does not yield a better fit. Moreover, we are restricted due to limitations in the software packages Matlab and Eviews.[2] However, we recommend to do further research in the effect of incorporating additional autoregressive and moving

[2]Matlab can sometimes not compute the inverse matrix, which is used for computing the Akaike criterion. In Eviews all models have to be inputted manually.

average terms in the ARIMA-models. Extreme outliers are difficult to predict. This is due to the nature of the fitting algorithm we use. Ordinary least square fitting uses least squares, which are vulnerable for huge deviations from the mean. As the maximum MSE is 1.76 over all computed ARIMA series, the sum of the variance in the errors and the bias is also small for all computed series. This demonstrates that the difference in arrivals between the true value and error is small. Also the closer MSE is to zero, the better the fit: a MSE of zero indicates a perfect fit.

Finally, statistical tests show that the arrival data of all arrival series satisfy the condition of stationarity if the data are first differenced. We use the Akaike criterion to identify the best fit. The lowest Akaike criterion indicates the best fit. For each series of arrivals we compute 25 different ARIMA-models. We note that the Akaike criterion is not much decreasing as we introduce more autoregressive or moving average terms. As a rule, one tries to keep the ARIMA-models as simple as possible or that is trying to get a model with the least possible number of autoregressive and moving average terms. As the Akaike criterion is not much decreasing as we introduce more terms, we can thus conclude that the number of autoregressive and moving average terms used in our ARIMA-models, are sufficient. Finally, from the fits with the lowest Akaike criterion for each combination of departments and specialisms, almost all models do satisfy the normality and autocorrelation condition.

6.3.2 Transfer of outpatients and inpatients

For the transfers of outpatients and inpatients we develop transition probabilities that a patient transfers from one (sub)specialism to another. For the outpatients we develop monthly transition probabilities for the transfers between outpatient clinics of subspecialisms of surgery and the remainder of the hospital using data of 2010-2011. The results are given in Figure 5.10.

For the inpatients we develop two transition matrices. The first is with regard to the intra-specialism monthly transfers of the subspecialisms of surgery and of the remainder the hospital. We use data of 2010-2011. The results are given in Figure 5.11. The second matrix deals with the transition probabilities of the weekly transfers of inpatients between 11 specialisms, using data of 2010. These results are given in Figure 5.12.

The size of the (sub)specialisms and the time length of the interval are important. The subdivision in large specialisms yields better figures for estimating the transition probabilities than the subdivision in small (sub)specialisms of surgery. The size should not be too small: the occurrence of a transition should not be too rare within the state time. For the subdivision into subspecialisms of surgery there are a lot of time intervals in which no or very little transitions occur. This is less the case for the subdivision into specialisms.

The time length of one week yields better figures for estimating the transition probabilities than the one month interval. The length of the interval should not be too large:

as the interval becomes too large, the state 'discharge' absorbs most of the transfers. For the one month interval more than 90 % of the patients is discharged within one month. If we reduce the period to one week this decreases to approximately 70 %. A further reduction of the time interval is not recommended as the effect of weekends will trouble the numbers for computing the transition probabilities.

Finally, statistical tests suggests that homogeneity and Markov property of the proposed Markov chains hold. Moreover, it suggests the existence of a limiting distribution, which can be used for determining the long-run transition probabilities.

6.3.3 Service time of patients

The average service times are used to compute the occupancy rate at specialisms. We compute the average service times of operations and admissions. All results are given in Figures C.1-C.8. 299 treatments of 980 in the nursing wards are on average longer than five days. There are only 60 treatments with an average nursing time longer than 10 days and none with an average longer than 30 days. As the majority of the average service times of the treatments is less than seven days, the average service times also confirm that the time period of our Markov chains of one week is better than a time period of one month.

We provide a model how to compute the occupancy rate at the combination of specialisms and departments. This involves using the average service times over all treatments of a certain (sub)specialism. We do not actually compute the occupancy rates. We do this as there is no actual reference material with which we can compare our outcomes. Moreover, just taking the average over all treatments might yield a huge over- or underestimation, as some particular complex treatments have much longer service time than the majority of the other treatments. The best solution would be that we could predict patient arrivals on basis of the treatments they receive. However, as volumes for many treatments are very low, the estimation becomes very difficult and unreliable. We recommend to do further research how to incorporate the service times in the model.

Chapter 7

Discussion, limitations and recommendations

In this chapter we discuss the three techniques used in each of the pillars of our model. We elaborate on why we divide the hospital in the three departments, outpatient clinics, operating theaters and nursing wards. Also, we discuss whether the results can be applied to other health care organizations. Next, we consider the limitations of our research. Finally, we provide recommendations for further research.

7.1 Discussion

First we discuss the implications of the three modeling techniques, ARIMA theory, Markov theory and the computation of means using statistics, which we use for each pillar in our model. Next, we discuss the division into three departments and at the end we elaborate on the applicability to other health care organizations.

7.1.1 Model implications

ARIMA theory

ARIMA theory is widely used in Finance and Economics for forecasting purposes. ARIMA-models however, face some drawbacks. First, the fact that models use historical data, leads to a later detection of increases and decreases than in reality occurs. The increases or decreases can only be detected if the values of previous time periods used for the estimation, are already increasing or decreasing. The more autoregressive terms are included,[1] the earlier an increase or decrease will be noticed, however the complexity of the model will increase. As a rule for determining an ARIMA-model, we use the rule that the simpler the model, the better. That is, we try to estimate an ARIMA-model which

[1] The autoregressive terms are used, to implement values of the time series at earlier time steps. The more autoregressive terms are incorporated in the model, the more time points are taken into account, in order to forecast the next time step value.

forecasts accurately but includes the least autoregressive and moving average terms as possible. Also, the Akaike criterion confirms that incorporating more autoregressive or moving average terms in the ARIMA-model does not yield a better fit, as the Akaike criterion is not much decreasing if we do so.[2]

Moreover, for estimating an ARIMA-model, the method of ordinary least squares, is used. The method will not interpolate the huge outliers of a set of data points, when fitting an ARIMA series.

Also, there is no test that can tell you if the found fit, is an ARIMA-model which can forecast future values of a series accurately. The Akaike criterion can only provide a decisive answer what the best fit is among several ARIMA-models for the same data set. However, whether this fit is a good fit at all for the set of data points, is not answered. For ARIMA theory, there is no underlying theory which describes the selection of the best model for a given data set (Meyler, Kenny, & Quinn, 1998).

In this research, we use weekly figures from 2007-2011[3] for estimating the arrivals at the departments, outpatient clinics, operating theaters and nursing wards for 11 specialisms. The more data points are available, the better one can estimate an ARIMA-model. That is one reason why we choose our model to provide estimates of patient volumes in weeks, rather than in months. Reliable data before 2007 are not available in ZGT.

The computation of the MSE indicates, if comparing the true values with the estimated values that the differences are relatively small. A comparison with true values and the fitted values, confirm the image that outliers in the data arrivals are not predicted by the ARIMA-model. Moreover, increases and decreases are detected one week or two weeks later than in reality. However, compared with other methods for determining the arrivals at the departments, the ARIMA-models can give a good and accurate indication of the arrivals. If, for instance we had used queuing theory, a fixed arrival distribution is assumed per combination of department and (sub)specialism. The power of ARIMA-models is that they can cope with fluctuations in arrivals over time. These fluctuations can be predicted by ARIMA-models as they take into account values of previous periods. The input distribution in queuing theory, does not support this feature.

[2] In this research we choose among 25 different fits for one series of arrivals, the best fit for our ARIMA-model. We allow the maximum number of autoregressive to be four and the maximum number of moving average terms also be four (also the case of zero terms is considered, so that we obtain 25 different fits). The Akake criterion indicates that adding more terms do not yield a better result. However adding much more terms (example five of each more) might yield a better result as we can rely on more historical data for predicting the arrivals at the next time step. We do not research this in this paper, due to limitations in the software and the rule that we would like to keep the ARIMA-models as simple as possible. We suggest this for further research.

[3] For operating theaters only data from 2008-2011.

Markov theory

As stated before, relatively little research has been done in the applicability of Markov theory in health care. No framework exists for modeling health care processes as a Markov chain. In fact, no analytical proof or test is known to provide a decisive answer whether some data possesses the mathematical properties required to model a Markov chain. There are some studies in health care, which use Markov theory, although they do not discuss how to investigate whether the Markov and homogeneity property holds and how to investigate the existence of a limiting distribution for the Markov chains for a certain data set.

We provide methods which test the homogeneity and Markov property of a Markov chain. Also we give a method how to test whether the limiting distribution of a Markov chain exists. We do however not provide an analytical proof. We recommend to do further research for finding an analytical proof for the homogeneity and Markov property and the existence of a limiting distribution if modeling a Markov chain on a set of data.

We demonstrate that Markov theory is an adequate manner for modeling transfers of patients between (sub)specialisms in the departments outpatients clinics, operating theaters and nursing wards. Also we demonstrate that the transfers of outpatients and inpatients can be modeled, using Markov theory. The tests we conducted for the homogeneity and Markov properties suggest that these properties hold. The same holds for the existence of a limiting distribution. The tests we conduct suggest the existence of a limiting distribution of the proposed Markov chains.

Overall, we choose Markov theory for modeling the transfers of outpatients and inpatients between (sub)specialisms, because it is an elegant way of computing transition probabilities. The transition probabilities provide an overview what the probability is that a patient transfers from a certain (sub)specialism to another (sub)specialism in a certain time period. Other theories as queuing theory, can only provide these probabilities for the stationary or limiting situation.

Computing of average service times

The two model components, ARIMA theory and Markov theory, are necessary for computing the future patient volumes at least one month ahead at a (sub)specialism in one of the departments, outpatients clinics, operating theaters or nursing wards. The model component, average service time, should be added to obtain the occupancy rate at the (sub)specialisms.

The model we propose uses the average service time over all treatments for one certain (sub)specialism. As some treatments are very complex, their service times might deviate much from the bulk of treatments for this specialism. This might influence the average service time of this specialism and thus the occupancy rate significantly. More

research on the implementation of the service times in the model is recommended.

7.1.2 Division of hospital

In this model we divide the hospital into three departments, namely the outpatients clinics, the operating theaters and the nursing wards. We consider two Markov chains, namely the transfers of outpatients and inpatients.[4] For Markov theory we could have combined these chains into one, however instead, we choose to work with two Markov chains. This due to the data limitations within ZGT. The data characteristics for the three departments, outpatient clinics, operating theaters and nursing wards, are different.

Moreover, the division in the three departments is convenient as it coincides with the departments, outpatient clinics, operating theaters and nursing wards, for which we would like to estimate the number of arrivals.

Finally, due to data limitations we can not determine with certainty if a transfer of a single outpatient belongs to his/her patient path. ZGT does not register the visits of one patient path under one registration number. We assume that the transfers which occur in the same or the adjacent time period, belong to the same patient path. However, this is of course not necessarily the case. We require this assumption, since we otherwise can not model transfers of outpatients at all. For the transfers of inpatients, this story does not hold: for an admission to nursing wards there is a single registration number, which is used for all transfers during the admission. We recommend that ZGT also should use one registration number for all visits to the outpatient clinics for one patient path, or even better one registration number for all visits during a patient path.

7.1.3 Model comparison

Currently, ZGT uses common sense and experience of employees to estimate the number of staff and nursing beds. The estimates are based on historical production figures, the agendas of specialists and planned appointments. ZGT allocates per specialism operation time and a number of beds for a period of several months ahead. For the operating times these estimations can be fine-tuned during meetings of tactical planning. For allocating nursing beds and staff in nursing wards, such meetings do not exist. The estimates ZGT uses, do not indicate the occupancy rates during the period, neither the estimated production. It only indicates the available resources, as operation time and staff for a certain specialism for a period of several months.

[4] The first Markov chain considers the transfer of outpatients of a specific (sub)specialism from one outpatient clinic to another outpatient clinic, to the department operating theater, to the department nursing wards or to discharge. The second Markov chain considers, the transfers of inpatients of a specific (sub)specialism from one nursing ward to another nursing ward, the intensive care or discharge. Moreover, the last Markov chain distinguishes between the origin of the patients: outpatient clinics, operating theaters or nursing wards.

As there is no model in ZGT which provides an indication of (estimated) patient volumes or occupancy rate at a certain (sub)specialism in a certain department, we can not compare the performance of our model to the current model of ZGT.

We introduce another measure, the 4 year average, in order to compare our model to another model. Probably, only partly the 4 year average, replicates the current estimation procedure of ZGT. We recommend to test our model in a hospital in which more advanced (estimated) patient volumes and occupancy rates estimation models are available.

7.1.4 Cost comparison

For computing the costs of over- and underestimating patient volumes per week, we distinguish two different scenarios. In both scenarios, we assume that a planned bed is available for five days. There will be no coordination between the different specialisms. The actual cost reduction will be somewhat lower than the estimated difference of 2.3 million euro between our model and the 4 year average model. It is likely that the over- and undercapacity does not appear for the whole week, but only for parts of this week. Moreover, presumably management interventions yield a reduction in over- and undercapacity by coordinating the several specialisms during the week. This leads to a more efficient use of the staff/outpatient clinic space/nursing beds of all specialisms.

Finally, the cost estimate of €6,000.− per patient per week is obtained by using the average costs for all hospitals for one nursing day. By order of NZa, Prismant computed the average price for one nursing day, which is €1,267.− in 2008 (NZa, 2008), so for five days this is approximately €6,000.−. This price reflects all costs made.

7.1.5 Applicability to other health care organizations

We expect that the research can be applied well in other hospitals in the Netherlands. This is due to the structure of Dutch hospitals. Also, most hospitals store sufficient data.

Other hospitals in the Netherlands have similar structures to ZGT. All hospitals are divided in the departments, outpatient clinics, operating theaters and nursing wards.

Most hospitals store a lot of data about patients. The hospitals should store the admission times of patients at the outpatient clinics, operating theaters and nursing wards for determining ARIMA-models, which can forecast patient arrivals at these departments. As long as hospitals do have a good registration of the transfers a single patient undergoes in a patient path, we can compute the transition probabilities for the transfer from one (sub)specialism to another in a department in a certain time period. Finally, the hospitals should store the individual service times per patient, per treatment and per specialism.

7.2 Limitations

In this section we discuss the data limitations of this research.

7.2.1 Data limitations

As already is discussed in Section 7.1.2, data limitations require to divide the hospital in three departments: outpatient clinics, operating theaters and nursing wards. The data characteristics are different for the three departments.

Moreover, a single registration number for visits belonging to one patient path does not exist. This makes it difficult to reconstruct the patient path for outpatients. For inpatients this does not hold, as the admission number is an unique number for on admission and is used by both specialisms if a patient is transferred from one to the other. Linking the operating theaters department to the department nursing wards, is not a problem. For most operations, the date of the operation coincides with the first day of the admission.[5]

7.2.2 Reliability of the data

One can question whether the data used in this research is reliable. Probably the data possesses inaccuracies or errors, as most data is manually inputed by the medical staff in programs as Chipsoft. However, as the data we use are financial figures, we may assume that there are correct to a very large extent. The financial data is used by ZGT for doing expenses claims at insurances companies.

7.3 Recommendations for further research

This section provides recommendations for further research.

7.3.1 Incorporation of service times

We recommend to do further research how to adequately incorporate service times of patients, in order to compute the occupancy rate at a combination of a department and (sub)specialism. The proposed model uses average service times for estimating the expected occupancy rate at a specific combination of a department and a (sub)specialism. As discussed in Section 7.1.1, complex treatments can influence the average service time over all treatments for a (sub)specialism significantly. This influences the estimation of the occupancy rate at the various combinations of department and (sub)specialism.

[5] Or the operating data is very close to the first day of the admission. In fact we allow two days between the date of the operation and the first day of the admission.

7.3.2 Fitting ARIMA-models using more autoregressive and moving average terms

We recommend to do further research in adding more autoregressive and moving average terms in the ARIMA-models used for estimating patient arrivals. As argued, the estimations are not entirely accurate, but demonstrate some delay compared to the true values. Adding more autoregressive and moving average terms might yield a better estimation. In our study we allow the maximum of autoregressive terms to be four and the maximum number of moving average terms also to be four. This is due to limitations in the software we use and the fact that we want to keep the ARIMA-models as simple as possible. It might be interesting to research whether the allowance of much more autoregressive and moving average terms, yields much better fits.

7.3.3 Recomputing the transition probabilities for the transfer of outpatients

We recommend to recompute the transition probabilities for the transfer of outpatients if there is one unique registration number for a patient path of a single patient. If there exists one unique registration number for the different visits during one patient path of a single patient, we can reconstruct with certainty the correct transition probabilities of transfers of patients. As discussed in Section 7.1.2 this no problem for the transfer of inpatients. For outpatients there is no registration number and we can not with certainty reconstruct a patient path.

7.3.4 Markov chains in health care

We recommend to do further research to the applicability of Markov chains in health care. As discussed in 7.1.1 little research has been done with this respect. Also we recommend to find a proof/procedure how to check whether data and a proposed Markov chain, do satisfy the mathematical conditions of a Markov chain.

7.3.5 Coding the model

We recommend to code the model for more validation purposes. Manually the three components are evaluated. The back-testing procedure provides a performance indication of the model for 20 weeks in 2011. However, we do not provide a programming code for our holistic model. In order to implement the model, we recommend to code the model. Also, this makes the validation of the model for a period extended than 20 weeks, easier.

Chapter 8

Applicability for ZGT and recommendations

The content of this paper is at some points rather theoretically. The purpose of this chapter is to elaborate on the applicability of the research with regard to ZGT. We explain the logic behind the model and elaborate on the possibility to implement the model. Moreover, we do recommendations to ZGT with respect to estimating patient volumes and occupancy rates.

8.1 Relevance: a changing society

Increasing life expectancy, co-morbidity, political and social pressure have urged the health care industry to become more cost-conscious. High qualitative health care is considered to be important in the Netherlands, however concerns about the continuously increasing costs have risen. The general opinion is that health care should be organized more (cost) efficiently. The health care process is complex: the demand for care is uncertain. Moreover, resources, as staff and nursing beds, used in the health care industry, are scarce. One would like to fine-tune demand and supply in hospitals, as ZGT, as efficiently as possible. Aim is to reduce the occurrence of over- and undercapacity as much as possible. To make planning more efficient, planners have to estimate better the future patient volumes and/or occupancy rates in the hospital.

8.2 Estimating patient volumes and occupancy rates

There are many ways to model expected patient volumes and occupancy rates. We propose a simple and intuitive model providing a helicopter view of patient flows through ZGT. The model computes the expected patient volumes and occupancy rates at different combinations of specialisms and departments: outpatient clinics, operating theaters and nursing wards, at least one month ahead. Moreover, the model provides transfer probabilities what the next specialism will be, given the current specialism of the pa-

tient. Thus, if a patient enters the hospital we can subsequently estimate what the next treatment in the patient path will be, until the patient will finally be discharged.

Currently, no prediction model for estimating patient volumes and occupancy rates exists within ZGT. We propose two different methods to compute the patient volumes and occupancy rates. The first is a holistic model, which takes the transfers of patients between specialisms into account. The second only uses four year averages for computing future demands. In this report the focus is on the first model. The model combines techniques of different disciplines, as Finance, Econometrics and Probability theory in order to estimate patient volumes and occupancy rates.

The holistic model consists of three components. The model allows us to estimate patient volumes and occupancy rates. It uses transfer probabilities in order to estimate what the next step in a patient path will be. These estimations occur on the level of a combination of department[1] and specialism.[2] As the incidence for the demand for care is uncertain, we use many aspects of Probability theory in the holistic model. The model is depicted in Figure 8.1.

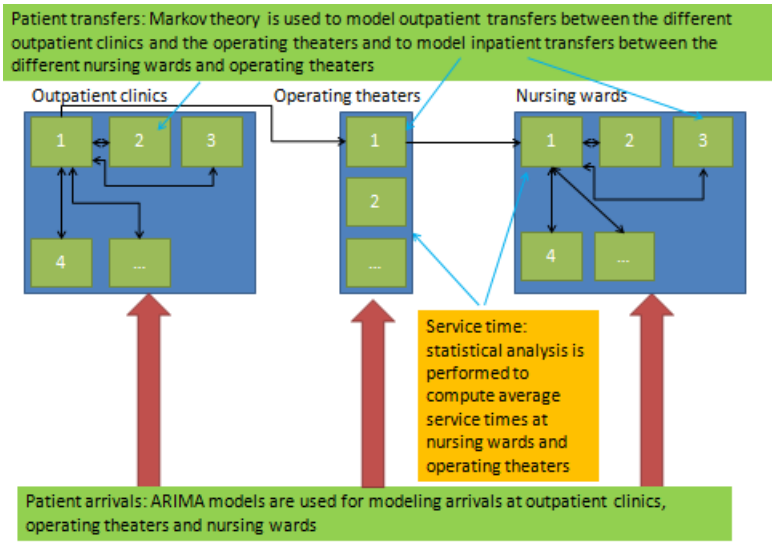


Figure 8.1: A graphical representation of the subdivision of the hospital ZGT in the three departments. The numbers at the green boxes in the departments represents the specialisms. In the figure we indicate where we apply the three components.

The transfer probabilities are modeled by a Markov chain. Markov chains are used in order to model transfers from one state to another. It assumes that the next time step

[1] These departments are the outpatient clinics, operating theaters and nursing wards.
[2] E.g. cardiology or surgery.

only depends on the previous time step and not on its history. We estimate the transition probabilities of weekly transfer of inpatients between 11 specialisms. The results are in Figure 5.12. 10 of the 11 specialisms coincides with some of the established RVEs[3] after the reorganization of 2012. The advantages of this approach is that we can define as much transfers as possible. It only requires the storage of one step in a patient path. Moreover, if we assume that the composition of the specialisms and departments will not change over time, we do not have to adjust the transition probabilities. Finally, we can compute the behavior of patients in the long run.

Markov chains are useful for modeling the transfers of patients within the hospital. However, we should also model the arrivals of the patients. For this purpose we use ARIMA-models. These models are for instance used in Finance in order to predict what the price of shares will be in the future. The results for the weekly arrivals of 11 specialisms are in Figures A.1-A.5. Advantage of ARIMA-models is that it can take into account fluctuations over time as it will follow a trend. Patient arrivals also possess fluctuations over time. The first two components are required in order to compute the expected number of patients at a combination of department and specialism.

Finally, the last component of the model is the computation of the average service time of treatments and admissions. This component is required so that we can compute the expected occupancy rates. Occupancy rates are computed by the number of patients times the indication how long these patients will stay.

8.3 Opportunities and recommendations

Results in this paper show that the holistic model can lead to a potential cost saving. The potential cost saving can be achieved if the demand for care can be estimated accurately. The model proposed, estimates patient volumes at different combinations of departments and specialisms at least one month ahead. Compared to the four year average model the estimations of the proposed model are more accurate. Moreover, the model provides insight into the patient flows within ZGT. Results demonstrate that approximately 70% of the patients enter and leave the hospital within one week at the same specialism.

The outcome of the model could support the planning process within the hospital. Currently, planning of operating theaters is managed in tactical planning. As far as we know, for the planning of outpatient clinics and nursing wards, the planning process is less sophisticated. The outcomes of our model can be used to predict patient volumes at specialisms of these three departments at least one month ahead. The more accurate the prediction, the more efficient staff and medical equipment can be used. Of two proposed models, the holistic model is the most accurate in its predictions of the patient volumes.

[3]RVE, Resultaat Verantwoordelijke Eenheid, English Profit Responsible Unit, see Figure 1.3 for the new structure of ZGT.

We recommend for the two departments, outpatient clinics and nursing wards to set up planning meetings, similar to the meetings of tactical planning, in which the planning and realizations of several months is discussed. In this meetings the outcome of our model, future patient volumes can be used for determining the usage of staff and medical equipment. For the department operating theaters, the outcome of our model can be used to support the planning decision making process of tactical planning.

Recommendations for ZGT

Having researched the patient flow through the three departments, outpatient clinics, operating theaters and nursing wards, we make the following recommendations to ZGT:

1. Predict patient volumes at specialisms in the department nursing wards using the model. The outcomes can be used to allocate staff and nursing beds at least one month ahead.

2. Use the outcomes of our model with regard to the arrivals at specialisms in the department operating theaters in order to support the decisions made in meetings of tactical planning to allocate operating times to specific specialisms.

3. Set up similar meetings for planning, as tactical planning, in the departments outpatient clinics and nursing wards.

4. The use of a uniform system to register details of visits/treatments of patients in the three departments, outpatient clinics, operating theaters and nursing wards.

5. The use of one unique registration number for the visits/treatments which belong to the patient path of a single patient. This improves the outcomes of the model, as we can drop certain modeling assumptions and as a result estimate the transition probabilities of the transfers of outpatients more reliably.[4]

8.4 Implementation and usage

The holistic model we propose is only a pilot model. The components for computing the patient volumes are the output of different software programs. In order to make the model applicable, it is recommended to integrate the different components of the model in one program. Implementing the model requires some additional research and effort. One can choose two different approaches. The Finance and Information Department of ZGT can use the theory provided in this paper and build this model. This requires additional time of the current staff members. However, time consuming, this will lead to the required knowledge of staff for future releases. Another possibility is letting an informatics student code the model. This could be the basis for a master or bachelor thesis.

[4] We assume that the visits of one single outpatient in one or the adjacent time period belong to one patient path. If there is one registration number for the visits belonging to one patient path we can with certainty reconstruct a patient path.

Estimation of patient volumes and occupancy rates holds the following:

- Estimate the patient arrivals at the various combinations of the departments and specialisms. One can use the ARIMA models in Figures A.1-A.5.
- Next, multiply the estimated arrivals with the transition probability matrix. That is for instance if we have the weekly arrivals at the nursing wards and one would like to compute the transfers of inpatients between specialisms in the nursing wards, multiplying the arrivals with the transfer matrix in Figure 5.12.
- Finally, for computing the occupancy rate, use the average services times provided in Figures C.1-C.8.

After the model is implemented, the model can be used for predicting patient volumes. This requires data input. Monthly data admissions figures of the different specialisms should be uploaded to the model in order to keep the predictions accurately. One can update and estimate the patient volume of different specialisms at least one month ahead. Next, to other planning material, these figures can be used for determining an efficient allocation decisions of staff to the different specialisms. The model has the opportunity to predict patient volumes at least one month ahead.

8.5 Summary

To conclude, the results demonstrate that the holistic model provides promising results in predicting patient volumes at different specialisms. We have established a model which can estimate the transition probabilities of a transfer of in- and outpatients from one (sub)specialism to another (sub)specialism in a certain time period. In particular, we established the transition probabilities for inpatients and arrival rates for 10 specialisms which coincides with RVEs. Moreover, 70% of the patients entering the hospital at a given specialism will also leave the hospital at this specialism within one week. So in essence, the most important task is to determine the arrival process of patients at the various departments. In this paper we provide a method for continuously updating the expected arrivals at the various specialisms. However, as this study is only a pilot, the model proposed can not be implemented immediately.

Bibliography

References

Abdel-Aal, R., & Mangoud, A. (1998). Modeling and forecasting monthly patient volume at a primary health care clinic using univariate time-series analysis. *Computer Methods and Programs in Biomedicines*, 235–247.

Akkerman, R., & Knip, M. (2004). Reallocation of beds to reduce waiting time for cardiac surgery. *Health Care Management Science*, 119–126.

Albers, W., & Nijdam, W. (2007). *Wiskundige statistiek.* Enschede: Universiteit Twente.

Alexander, C. (2001). *Market models: A guide to financial data analysis.* Chichester: John Wiley and sons Ltd.

Bickenbach, F., & Bode, E. (2003). Evaluating the markov property in the sudies of economic convergence. *International regional science review*, 363-392.

CBS. (2010). *Persbericht: Groei van de uitgaven aan de zorg blijft hoog* (report). Centraal Bureau voor de Statistiek.

Creemers, S., & Lambrecht, M. (2007). Modelling a healthcare system as a queueing network: the case of a Belgian hospital.

Eggink, E., Oudijk, D., & Woittiez, I. (2010). *Persbericht: Groei van de uitgaven aan de zorg blijft hoog* (report). Zorgen voor zorg.

Engle, R. F., & Russel, J. R. (1998). Autoregressive conditional duration: A new model for irregularly spaced transaction data. *Econometrica*, 1127-1162.

Hull, J. C. (2009). *Options, futures and other derivatives.* London: Pearson Prentice Hall.

Kao, E. P., & Tung, G. G. (1980). Forecasting demands for inpatient services in a large public health care delivery system. *Socio-Economic Planning Sciences*, 97–106.

Leite, C., et al. (2010). Modeling of medical care with stochastic petri nets. *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, 1336-1339.

Lin, W. (1989). Modeling and forecasting hospital patient movements: Univariate and multiple time series approaches. *International Journal of Forecasting*, 195–208.

Maruster, L., van der Aalst, W., Weijters, T., van den Bosch, A., & Daelemans. (2001). Automated discovery of workflow models from hospital datal.

Meyler, A., Kenny, G., & Quinn, T. (1998). *Forecasts Irish infliation using arima models* (Tech. Rep.). Economic Analysis, research and publications department, Central

Bank of Ireland.

NZa. (2008). *Financiële statistiek* (report). Prismant.

Perez, A., Chan, & Dennis, W. (2004). Predicting the length of stay of patients admitted for intensive care using a first step analysis. *Health care management science*, 127–138.

Ross, S. M. (2007). *Introduction to probability models*. Oxford: Academic press.

Schwartzman, G. (1970). The patient arrival process in hospitals, statistical analysis. *Health services research*, 320-329.

Utley, M., et al. (2003). Analytical methods for calculating the capacity required to operate an effective booked admissions policy for elective inpatient services. *Health care managemant science*, 97-104.

VWS. (2012, feb). *Tekort zorgpersoneel tegengaan.* Retrieved from http://www.rijksoverheid.nl/onderwerpen/werken-in-de-zorg/tekort-zorgp%ersoneel-tegengaan

Winkler, G. (1995). *Image analysis, ramdom fields and Markov Chain Monte Carlo Methods*. Heidelberg: Springer.

Yaffee, R. A., & McGee, M. (2000). *Introduction to time series analysis and forecasting with applications of sas® and spss®*. Hobroken: Academic Press.

ZGT. (2010). *Jaardocument* (report). Ziekenhuisgroep Twente.

Appendix A

Time series analysis data

This appendix contains the results for the ARIMA-models for 11 specialisms, required for predicting weekly patient arrivals. The data we use, is from the period 2007-2011.[1] The figures below provide the coefficients of ARMA terms. Notice that for all series we take the first difference to obtain stationarity. The column 'ADF[2]' indicates whether the data is stationary at significance level $\alpha = 5\%$. A rejection of the null hypothesis is indicated by 0, an acceptation by 1. Next, we show results whether the residuals are assumed to have a normal distribution. This is provided in column 'Jarque-Bera'. For this test, we used different confidence levels. The number in this column indicates at which significance level we accept the null hypothesis. Finally, we also provide whether the series is autocorrelated, this is denoted in the column 'Ljung-Box'. In this column a zero denotes the acceptation of the null hypothesis at a significance level of $\alpha = 5\%$. Most data is obtained, using the Matlab software package, however as some Matlab could not compute some inverse matrices for checking routines, we also used Eviews. The fits computed by Eviews, are marked yellow.

Figures A.1-A.5 show the results for the best ARIMA fits for each series of arrivals.[3] The results of the Augmented Dickey-Fuller test, Jarque-Bera test and Ljung-Box test respectively are also in these figures. We list the results for 11 specialisms for the departments outpatient clinics (first and repeated visits), the operating theaters and nursing wards (one day admission (heavy or light) or more than day).

[1] For the department operating theaters, the data is from 2008-2011.

[2] ADF, Augmented Dickey-Fuller.

[3] The best fit is determined by the Akaike criterion, the lowest Akaike criterion indicates the best fit. For all series the Akaike criterion are computed. These can be found in Figures A.6-A.8.

specialism	Constant	AR 1	AR 2	AR 3	AR 4	MA 1	MA 2	MA 3	MA 4	Variance	Likelihood	ADF	Jarque Bera	Ljung Box	Scenario number	OK?
Cardiology	0,06	-0,23	0,11	0,76	0,00	-0,55	-0,41	-0,82	0,78	0,00	-1340,76	1	0,01	0	20	yes
Surgery	-0,25	-0,79	-0,79	0,19	0,00	-0,01	0,01	-1,00	0,00	2589,44	-1415,98	1	non significant	0	19	no
Gastroenterology	0,10	0,74	0,21	-0,46	-0,11	-1,53	0,27	0,73	-0,42	4246,07	-1163,59	1	0,05	0	25	yes
Gynecology	0,07	-0,08	-0,20	-0,87	0,25	-0,70	0,00	0,70	-1,00	578,50	-1262,67	1	0,05	0	25	yes
Internal Medicine	0,00	0,53	0,56	-0,69	0,00	-1,32	-0,16	1,00	-0,52	1326,54	-1315,26	1	0,001	0	20	yes
Pediatrics	0,04	-0,91	0,30	0,70	0,00	0,26	-1,05	-0,67	0,46	1918,81	-1159,82	1	0,05	0	20	yes
Pulmonology	0,02	0,76	0,00	0,00	0,00	-1,60	0,60	0,00	0,00	614,48	-1184,74	1	0,05	0	8	yes
Neurology	0,21	-1,12	-0,23	0,44	0,00	0,32	-0,74	-0,85	0,26	686,27	-1286,39	1	0,001	0	20	yes
Other	0,48	0,67	0,41	-0,69	0,00	-1,43	0,04	1,00	-0,61	1526,09	-1765,89	1	non significant	0	20	no
Urology	0,13	-0,95	-0,86	-0,07	0,04	0,03	-0,02	-0,98				1	0,1	0	20	yes
Obstetrics	-0,03	-0,03	0,04	-0,81	0,00	-0,98	0,08	0,92	-0,91	67623,15	-910,12	1	0,05	0	20	yes

Figure A.1: ARIMA coefficients, ADF, Jarque-Bera and Ljung-Box results for the number of first outpatient visits.

specialism	Constant	AR 1	AR 2	AR 3	AR 4	MA 1	MA 2	MA 3	MA 4	Variance	Likelihood	ADF	Jarque Bera	Ljung Box	Scenario number	OK?
Cardiology	0,13	-0,33	0,08	0,73	0,13	-0,59	-0,36	-0,80	0,75	77,75	-1465,64	1	0,0001	0	25	yes
Surgery	0,78	-0,07	-0,67	0,05	0,26	-0,83	0,87	-0,96	0,00	6460,74	-1594,93	1	non significant	0	24	no
Gastroenterology	0,22	0,00	0,00	0,00	0,00	-0,88	0,00	0,00	0,00	19549,92	-1365,07	1	non significant	0	2	no
Gynecology	0,04	-0,10	0,35	0,00	0,00	-0,53	-0,47	0,00	0,00	2830,62	-1397,42	1	non significant	0	13	no
Internal Medicine	0,24	0,49	0,11	-0,65	0,00	-1,43	0,39	0,67	-0,64	3638,03	-1540,97	1	non significant	0	20	no
Pediatrics	0,04	0,25	0,12	0,08	0,16	-1,00	0,00	0,00	0,00	11886,77	-1319,81	1	0,001	0	22	yes
Pulmonology	0,05	0,75	0,03	0,00	0,00	-1,71	0,71	0,00	0,00	1997,85	-1332,17	1	0,05	0	18	yes
Neurology	0,50	0,29	-0,76	0,00	0,00	-1,20	1,13	-0,84	0,00	2298,42	-1353,35	1	non significant	0	14	no
Other	0,71	0,54	0,19	0,00	0,00	-1,29	0,29	0,00	0,00	2684,26	-1911,65	1	non significant	0	13	no
Urology	0,54	-0,14	-0,91	-0,12	0,00	-1,00	1,00	-1,00	0,00	213598,94	-1444,17	1	0,05	0	19	yes
Obstetrics	-0,11	-0,22	-0,92	-0,25	0,00	-0,75	0,99	-0,77	0,00	5316,31	-1195,49	1	0,05	0	19	yes

Figure A.2: ARIMA coefficients, ADF, Jarque-Bera and Ljung-Box results for the number of repeated outpatient visits.

specialism	Constant	AR 1	AR 2	AR 3	AR 4	MA 1	MA 2	MA 3	MA 4	Variance	Likelihood	ADF	Jarque Bera	Ljung Box	Scenario number	OK?
Surgery	-0,22	-0,55	-0,16	0,66	0,00	-0,04	-0,31	-0,93	0,28	0,00	-973,38	1	non significant	0	20	no
Gynecology	-0,10	-1,23	-0,90	0,10	0,11	0,54	-0,11	-0,99	-0,23	775,49	-744,17	1	0,025	0	25	yes
Other	-1,54	-1,30	-0,07	0,45	0,00	0,71	-0,92	-0,82	0,17	85,31	-1370,86	1	non significant	0	20	no
Urology	-0,02	-0,01	-0,40	-0,43	0,33	-0,64	0,42	-0,17	-0,61	38068,90	-738,46	1	0,05	1	25	no
Midwifery	-0,10	-0,82	0,00	0,00	0,00	-0,01	-0,79	0,00	0,00	87,96	-826,50	1	0,05	0	8	yes
Cardiology	-0,01	0,20	-0,95	0,00	0,00	-1,16	1,22	-0,92	0,00	182,95	-404,27	1	0,05	0	14	yes
Surgery	-0,03	0,63	0,65	-0,68	0,00	-1,67	0,14	1,00	-0,46	3,06	-936,28	1	non significant	0	20	no
Gastroenterology	0,00	-0,21	-0,80	0,00	0,00	-0,74	0,54	-0,80	0,00	572,73	-423,28	1	non significant	0	14	no
Gynecology	-0,07	-1,09	-0,96	0,00	0,00	0,24	0,00	-0,89	0,00	3,64	-591,23	1	0,05	0	14	yes
Other	-0,22	-0,06	0,06	0,69	-0,35	-0,46	-0,32	-0,84	0,68	18,68	-1128,24	1	non significant	0	25	no
Obstetrics	0,10	-1,42	-0,77	0,00	0,00	0,66	-0,40	-0,66	-0,17	3707,44	-589,71	1	non significant	0	15	no

Figure A.3: ARIMA coefficients, ADF, Jarque-Bera and Ljung-Box results for the number of operations.

Specialism (light)	Constant	AR 1	AR 2	AR 3	AR 4	MA 1	MA 2	MA 3	MA 4	Variance	Likelihood	ADF	Jarque Bera	Ljung Box	Scenario number	OK?
Cardiology	0,04	1,10	-0,57	-0,24	0,26	-1,94	1,50	-0,34	-0,22	85,22	-796,11	1	0,05	0	25	yes
Surgery	0,18	0,21	0,02	-0,83	0,20	-0,98	0,12	0,88	-0,87	31,67	-1086,35	1	non significant	0	25	no
Gastroenterology	0,38	-1,19	-0,63	0,22	0,00	0,51	-0,37	-0,94	0,00	333,93	-953,01	1	0,001	0	19	yes
Gynecology	0,00	0,21	0,17	0,00	0,00	-1,00	0,00	0,00	0,00	113,62	-808,66	1	0,05	0	12	yes
Internal Medicine	0,08	-0,22	0,74	0,00	0,00	-0,63	-1,02	0,65	0,04	34,84	-932,54	1	0,05	0	15	yes
Pediatrics	0,01	0,20	0,00	0,00	0,00	-0,90	0,00	0,00	0,00	104,76	-832,03	1	0,001	0	7	yes
Pulmonology	0,08	-0,70	-0,61	0,36	0,16	-0,10	0,10	-1,00	0,00	41,43	-760,82	1	non significant	0	24	no
Neurology	0,11	-0,23	-0,23	-0,95	0,00	-0,80	0,12	0,69	-0,89	24,39	-842,51	1	0,05	0	20	yes
Other	0,02	1,12	0,08	-0,17	-0,08	-2,00	1,00	0,00	0,00	47,65	-1275,02	1	non significant	0	23	no
Urology	0,05	-0,31	-0,65	-0,71	0,00	-0,66	0,41	0,01	-0,70	1425,20	-754,63	1	0,05	0	20	yes
Obstetrics	-0,01	0,71	0,00	0,00	0,00	-1,47	0,47	0,00	0,00	24,51	-975,71	1	non significant	0	8	no
Specialism (heavy)																
Surgery	0,00	0,68	0,00	0,00	0,00	-1,44	0,44	0,00	0,00	131,01	-857,13	1	0,001	0	8	yes
Gynecology	-0,01	-0,44	-0,52	-0,89	0,10	-0,34	0,04	0,45	-0,93	50,22	-536,75	1	non significant	0	25	no
Other	0,03	0,24	0,00	0,00	0,00	-0,96	0,00	0,00	0,00	4,54	-1225,38	1	0,001	0	7	yes
Urology	0,00	-1,11	-0,67	-0,43	0,00	-0,26	-0,74	0,00	0,00	937,20	-765,46	1	0,001	0	18	yes
Other	0,23	0,01	-0,56	0,39	0,19	-0,46	0,47	-0,85	0,00	24,75	-1060,51	1	non significant	0	24	no

Figure A.4: ARIMA coefficients, ADF, Jarque-Bera and Ljung-Box results for the number of one-day nursing admission, subdivided in light and heavy.

specialism	Constant	AR 1	AR 2	AR 3	AR 4	MA 1	MA 2	MA 3	MA 4	Variance	Likelihood	ADF	Jarque Bera	Ljung Box	Scenario number	OK?
Cardiology	-0,02	0,34	0,56			-1,22	-0,29	0,25	0,25			1	0,05	0	23	yes
Surgery	0,00	0,01	-0,82	0,20	0,00	-0,78	0,82	-0,97	0,00	744,42	-1093,74	1	0,01	0	19	yes
Gastroenterology	0,00	-1,04	-0,74	0,17	0,00	0,25	-0,16	-0,96	0,00	333,06	-682,96	1	0,05	0	19	yes
Gynacology	0,04	-0,20	-0,75	-0,51	0,00	-0,64	0,44	-0,07	-0,66	13,55	-851,44	1	0,05	0	20	yes
Internal Medicine	0,00	0,71	0,00	0,00	0,00	-1,60	0,60	0,00	0,00	52,74	-912,11	1	0,001	0	8	yes
Pediatrics	0,00	0,35	0,19	0,20		-0,99						1		0	9	yes
Pulmonology	-0,01	-1,01	0,00	0,71	0,29	0,16	-0,82	-0,64	0,30	76,68	-841,05	1	0,05	0	25	yes
Neurology	0,00	-1,49	-0,94	0,00	0,00	0,53	-0,53	-1,00	0,00	48,70	-783,97	1	0,05	0	14	yes
Other	0,01	0,72	0,00	0,00	0,00	-1,37	0,37	0,00	0,00	30,10	-1156,87	1	non significant	0	8	no
Urology	0,05	-0,40	-0,74	0,21	0,10	-0,41	0,41	-1,00	0,00	538,22	-829,09	1	0,05	0	24	yes
Obstetrics	0,00	0,24	0,89	-0,20	0,00	-1,04	-0,93	0,96	0,00	42,31	-912,27	1	0,05	0	19	yes

Figure A.5: ARIMA coefficients, ADF, Jarque-Bera and Ljung-Box results for the number of clinical admisions regarding more than one nursing day.

A.1 Results for Akaike criterion

The Akaike criterion is an indication for the best fit. For a series of fitted ARIMA series, the lowest Akaike criterion indicates the best fit. Figures A.6-A.11 provide the Akaike criterion, for the departments outpatient clinics (first and repeated visits), operating theaters and nursing wards (one day (heavy and light) and more than one day).

specialism	Cardiology	Surgery	Gastroenterology	Gynecology	Internal medicine	Pediatrics	Pulmonology	Neurology	Other	Obstetrics
best scenario	21	20	26	26	21	21	9	21	21	21
scenario										
1	2837,15	2977,27	2459,68	2668,63	2758,17	2428,85	2511,25	2722,14	3657,68	2002,65
2	2720,59	2853,45	2359,92	2574,26	2672,50	2355,22	2391,11	2606,13	3583,85	1848,15
3	2721,55	2848,14	2351,55	2561,53	2660,04	2350,75	2392,70	2598,42	3564,33	1849,93
4	2722,21	2849,23	2353,04	2563,40	2652,44	2352,66	2392,82	2589,23	3552,56	1851,92
5	2724,18	2850,22	2349,85	2565,39	2653,87	2354,22	2393,52	2591,10	3552,14	1851,13
6	2772,79	2926,50	2417,07	2641,53	2704,91	2392,67	2440,85	2648,23	3605,04	1936,58
7	2721,38	2847,50	2350,98	2562,58	2655,73	2341,63	2392,59	2595,41	3557,24	1849,93
8	2723,12	2849,40	2352,98	2557,40	2657,09	2350,44	2377,48	2591,83	3557,39	1851,84
9	2724,09	2851,05	2354,79	2549,76	2654,10	2350,21	2379,30	2590,57	3552,95	1853,62
10	2726,06	2852,04	2351,85	2563,41	2655,82	2351,20	2393,59	2590,84	3553,96	1849,76
11	2758,15	2908,29	2397,10	2609,56	2700,16	2373,89	2420,26	2641,80	3601,25	1896,34
12	2722,14	2849,10	2352,66	2563,51	2654,16	2341,34	2392,26	2590,81	3552,99	1851,93
13	2724,00	2851,07	2354,54	2565,32	2654,09	2350,04	2379,35	2592,46	3554,29	1853,61
14	2715,77	2851,53	2354,11	2556,09	2655,91	2338,61	2392,94	2593,07	3554,90	1849,34
15	2717,77	2853,03	2352,77	2551,17	2657,72	2348,65	2394,81	2592,75	3555,33	1847,17
16	2745,19	2906,16	2397,06	2594,68	2695,05	2366,94	2418,01	2636,68	3601,47	1880,15
17	2724,11	2851,10	2353,78	2564,63	2655,30	2340,19	2392,53	2591,95	3553,97	1851,15
18	2725,99	2854,50	2353,35	2565,80	2656,07	2342,25	2392,95	2591,69	3555,77	1849,55
19	2720,36	2845,95	2352,52	2546,00	2657,88	2339,19	2394,16	2591,77	3555,94	1845,57
20	2697,52	2850,84	2354,52	2553,14	2646,53	2335,65	2386,39	2588,77	3547,77	1836,24
21	2743,26	2903,59	2394,86	2592,72	2695,09	2357,65	2408,21	2629,60	3596,85	1880,39
22	2724,94	2849,82	2351,19	2565,83	2655,64	2341,83	2394,52	2593,84	3552,06	1851,78
23	2726,45	2848,42	2346,08	2565,45	2653,37	2343,44	2394,87	2591,88	3554,04	1848,00
24	2723,92	2848,80	2348,01	2552,59	2661,62	2338,98	2393,32	2593,85	3553,35	1849,34
25	2699,49	2849,27	2345,17	2543,33	2659,32	2337,93	2394,29	2590,52	3549,77	1837,43

Figure A.6: Akaike numbers for the 25 configurations for the department outpatient clinics (first visit).

specialism	Cardiology	Surgery	Gastroenterology	Gynecology	Internal medicine	Pediatrics	Pulmonology	Neurology	Other	Urologie	Obstetrics
best scenario	26	25	3	14	21	23	19	15	14	20	20
scenario											
1	3110,25	3368,30	2887,58	2890,23	3232,15	2766,91	2831,92	2863,58	3939,82	3114,06	2584,80
2	2959,26	3221,81	2734,14	2838,12	3101,84	2658,58	2687,04	2722,72	3838,66	2913,04	2417,11
3	2961,26	3223,49	2735,57	2825,27	3101,82	2660,05	2689,02	2724,34	3839,80	2912,01	2413,60
4	2963,23	3206,86	2736,99	2805,82	3100,05	2661,97	2690,88	2723,02	3836,69	2912,76	2412,19
5	2965,19	3208,45	2738,83	2807,44	3102,03	2663,78	2692,83	2725,01	3837,19	2914,53	2413,96
6	3039,04	3253,20	2816,49	2849,15	3159,77	2707,86	2757,50	2785,99	3867,72	3010,06	2463,74
7	2961,26	3223,30	2735,63	2808,95	3101,35	2659,99	2689,02	2724,24	3839,98	2910,81	2412,04
8	2957,46	3222,61	2737,11	2806,94	3103,05	2651,62	2689,40	2722,81	3842,85	2909,61	2412,61
9	2958,75	3208,25	2738,84	2806,07	3102,04	2652,69	2691,33	2725,02	3835,92	2911,90	2413,87
10	2966,29	3210,03	2740,79	2808,75	3104,02	2662,86	2676,34	2726,41	3837,88	2913,52	2415,86
11	3014,14	3249,36	2785,29	2848,61	3148,10	2688,93	2731,49	2772,09	3857,97	2979,05	2441,68
12	2963,22	3206,94	2737,06	2804,96	3100,06	2661,93	2690,86	2723,47	3835,05	2912,08	2411,75
13	2964,68	3207,84	2738,89	2804,83	3101,70	2661,02	2691,38	2725,46	3833,29	2911,61	2413,36
14	2956,84	3209,57	2736,41	2806,78	3103,67	2659,14	2688,20	2718,70	3834,89	2912,97	2412,38
15	2954,16	3211,57	2742,83	2808,02	3105,64	2661,08	2678,29	2725,88	3836,94	2914,68	2416,17
16	2987,35	3243,72	2768,33	2842,28	3137,90	2671,61	2717,55	2766,49	3855,88	2961,68	2431,09
17	2962,77	3207,62	2738,93	2804,91	3101,93	2663,89	2692,79	2725,28	3835,06	2914,04	2413,64
18	2966,53	3209,47	2740,86	2806,28	3103,69	2652,74	2676,33	2722,37	3835,27	2913,54	2415,29
19	2953,72	3211,65	2742,58	2807,28	3101,91	2661,10	2682,91	2720,58	3836,76	2902,33	2404,97
20	2951,11	3210,32	2740,45	2808,38	3097,94	2652,53	2678,45	2722,35	3838,59	2913,16	2418,78
21	2983,13	3240,27	2762,19	2843,10	3137,81	2668,42	2711,46	2754,23	3852,11	2958,80	2422,41
22	2959,16	3209,39	2740,93	2806,89	3103,93	2651,62	2694,26	2725,58	3835,54	2915,87	2415,40
23	2958,64	3211,24	2742,74	2808,73	3103,99	2659,84	2694,99	2727,51	3837,12	2914,91	2416,74
24	2953,68	3205,85	2743,11	2808,85	3104,75	2664,49	2684,87	2725,19	3838,31	2904,13	2406,39
25	2949,27	3211,95	2740,55	2810,38	3106,24	2664,48	2678,95	2725,75	3840,83	2913,45	2412,42

Figure A.7: Akaike numbers for the 25 configurations for the department outpatient clinics (repeated visit).

specialism	Surgery	Gynecology	Other	Urology	Obstetrics	Cardiology	Surgery2	Gastroenterology	Gynecology2	Other4	Obstetrics2
best scenario	21	26	21	26	9	15	21	15	15	26	16
scenario											
1	2039,84	1593,40	2824,23	1574,37	1773,41	939,92	2042,90	985,23	1328,15	2332,92	1292,35
2	1990,60	1516,17	2775,60	1535,23	1665,28	824,09	1904,43	871,59	1206,87	2296,58	1194,17
3	1982,84	1511,89	2763,12	1516,79	1667,27	825,61	1906,27	872,35	1208,43	2282,35	1195,66
4	1974,24	1513,50	2760,93	1497,26	1668,43	827,39	1904,92	874,26	1209,86	2276,88	1197,66
5	1968,85	1513,73	2761,96	1499,24	1669,78	826,73	1904,47	876,25	1211,00	2278,83	1199,36
6	2000,46	1557,68	2794,38	1537,70	1724,55	892,59	1959,26	941,00	1273,06	2309,52	1245,26
7	1975,44	1511,39	2758,91	1506,53	1667,27	825,65	1906,22	872,18	1208,48	2277,58	1195,66
8	1977,24	1513,32	2759,53	1507,52	1661,00	827,48	1896,28	865,42	1204,19	2279,43	1193,50
9	1972,40	1515,25	2761,36	1499,21	1662,34	829,13	1896,14	866,83	1204,44	2278,85	1195,39
10	1970,74	1515,61	2763,54	1500,07	1664,33	827,73	1898,04	868,16	1211,55	2279,70	1196,07
11	1995,80	1539,94	2788,75	1539,65	1693,92	857,28	1955,13	918,33	1238,92	2307,88	1225,92
12	1997,28	1513,02	2759,86	1504,87	1668,38	827,52	1904,45	874,12	1209,48	2279,15	1197,66
13	1973,12	1515,01	2761,51	1499,68	1662,02	829,19	1895,75	867,29	1210,62	2280,42	1195,34
14	1974,38	1509,94	2758,17	1499,67	1661,65	820,55	1897,80	858,56	1194,47	2280,01	1196,87
15	1972,49	1507,98	2765,54	1501,42	1663,65	829,72	1899,91	862,93	1201,54	2280,47	1193,42
16	1997,79	1537,90	2787,87	1532,64	1686,39	847,78	1938,54	909,12	1226,29	2303,27	1224,47
17	1973,52	1514,31	2761,68	1496,11	1669,87	825,78	1902,24	876,11	1210,85	2279,16	1199,63
18	1973,00	1515,91	2764,05	1497,78	1663,97	824,84	1897,45	869,21	1212,50	2278,44	1195,70
19	1971,15	1507,32	2758,08	1499,66	1663,65	826,29	1896,66	862,92	1202,22	2282,66	1194,26
20	1962,76	1509,26	2757,72	1498,15	1665,60	827,14	1888,55	861,90	1197,93	2281,20	1194,94
21	1995,87	1538,90	2786,72	1533,63	1682,37	839,59	1939,48	904,40	1224,04	2296,29	1202,23
22	1968,48	1515,82	2762,45	1497,64	1671,77	825,44	1904,01	878,07	1212,40	2281,03	1197,52
23	1972,23	1517,05	2760,38	1499,37	1665,96	826,41	1899,40	871,20	1213,56	2278,81	1194,00
24	1971,88	1508,19	2763,70	1498,94	1665,56	827,94	1906,05	862,47	1198,09	2281,04	1194,82
25	1963,73	1506,34	2761,93	1494,92	1667,24	824,29	1889,86	863,67	1199,88	2274,48	1196,72

Figure A.8: Akaike numbers for the 25 configurations the department operating theaters.

specialism	Cardiology	Surgery	Gastroenterology	Gynecology	Internal medicine	Pediatrics	Pulmonology	Neurology	Other	Urologie	Obstetrics
best scenario	26	26	20	13	16	8	25	21	24	21	9
scenario											
1	1741,25	2301,43	2029,22	1744,48	2029,39	1770,45	1678,65	1902,29	2680,71	1676,22	2066,81
2	1618,43	2201,94	1929,49	1648,69	1898,95	1674,52	1562,83	1714,29	2591,74	1531,54	1989,05
3	1620,38	2198,26	1922,67	1637,35	1900,88	1670,82	1562,69	1713,52	2587,88	1533,40	1987,42
4	1622,01	2200,05	1923,30	1627,10	1902,88	1671,71	1557,27	1714,06	2579,70	1533,23	1988,16
5	1623,44	2201,85	1924,85	1626,56	1903,49	1673,70	1557,80	1715,71	2576,19	1534,41	1989,27
6	1673,11	2256,73	1988,36	1680,86	1962,58	1723,67	1608,91	1796,21	2617,87	1595,16	2023,41
7	1620,37	2197,84	1921,67	1631,60	1900,86	1670,06	1560,95	1713,06	2581,96	1533,38	1983,53
8	1614,34	2198,57	1923,63	1628,50	1884,17	1671,83	1552,49	1705,78	2570,26	1535,36	1959,42
9	1622,98	2199,96	1925,24	1626,13	1885,94	1673,42	1553,32	1706,71	2571,00	1535,03	1961,13
10	1624,97	2197,25	1926,65	1625,60	1887,87	1675,16	1552,02	1708,51	2572,53	1536,27	1978,45
11	1656,71	2233,74	1965,04	1673,97	1942,44	1708,12	1595,82	1774,68	2607,07	1572,91	2005,35
12	1622,02	2199,78	1923,40	1625,32	1902,86	1671,64	1554,30	1713,60	2574,69	1531,75	1981,08
13	1623,01	2195,36	1924,60	1627,22	1885,99	1673,16	1553,33	1705,77	2572,26	1531,51	1973,59
14	1624,53	2197,28	1927,12	1625,62	1884,06	1675,14	1558,24	1707,37	2566,86	1534,70	1963,42
15	1626,49	2199,22	1928,04	1630,36	1879,09	1676,13	1546,38	1709,33	2578,18	1536,54	1985,13
16	1638,18	2221,03	1950,11	1673,38	1916,01	1697,49	1593,56	1754,15	2607,07	1558,52	1992,17
17	1623,20	2200,71	1924,58	1626,94	1902,71	1673,63	1555,99	1715,31	2576,23	1532,06	1994,04
18	1624,95	2201,50	1925,92	1628,73	1887,79	1675,15	1551,01	1707,70	2577,33	1533,81	1973,63
19	1619,10	2202,15	1920,03	1627,15	1886,18	1674,40	1541,71	1709,34	2568,46	1531,08	1988,34
20	1619,44	2203,75	1923,69	1629,85	1881,92	1678,13	1542,14	1701,03	2571,29	1525,26	1962,15
21	1629,09	2221,91	1950,23	1669,92	1910,79	1694,20	1583,55	1746,37	2607,39	1558,43	1994,05
22	1616,17	2201,52	1925,33	1626,11	1898,45	1675,47	1557,93	1716,54	2577,40	1530,72	1966,78
23	1626,87	2198,04	1924,28	1627,49	1888,61	1676,91	1552,67	1709,52	2564,04	1531,84	1964,94
24	1612,31	2199,99	1926,00	1629,92	1887,96	1676,18	1537,64	1711,34	2579,13	1530,83	1961,51
25	1610,23	2190,70	1925,69	1633,30	1883,90	1670,73	1542,65	1713,32	2573,02	1531,68	1972,09

Figure A.9: Akaike numbers for the 25 configurations for the department nursing wards (one day (light)).

specialism	Surgery	Gynecology	Other	Urologie	Other2
best scenario	9	26	8	19	25
scenario					
1	1831,07	1222,37	2563,67	1845,28	2201,26
2	1735,44	1107,92	2465,91	1626,17	2160,06
3	1727,47	1106,33	2458,63	1592,73	2153,44
4	1727,20	1107,19	2457,42	1589,92	2150,64
5	1726,44	1107,93	2459,34	1587,73	2150,77
6	1786,82	1178,73	2518,18	1766,74	2178,46
7	1724,04	1106,62	2456,77	1607,67	2149,56
8	1722,26	1099,89	2458,30	1579,37	2150,21
9	1724,01	1101,25	2459,33	1571,72	2150,35
10	1724,98	1103,20	2461,33	1563,32	2152,05
11	1762,45	1143,04	2507,06	1697,57	2170,59
12	1724,60	1107,93	2457,96	1574,40	2150,51
13	1724,17	1100,58	2459,59	1575,94	2151,53
14	1723,92	1103,95	2461,24	1573,28	2142,13
15	1725,70	1103,83	2463,17	1552,21	2148,03
16	1754,24	1140,32	2492,33	1615,83	2154,02
17	1723,41	1108,49	2459,67	1566,50	2156,02
18	1725,71	1102,58	2461,24	1542,92	2153,35
19	1726,51	1104,84	2462,29	1544,72	2140,46
20	1724,86	1100,69	2460,65	1546,72	2137,76
21	1750,80	1131,84	2486,85	1610,19	2156,02
22	1724,78	1107,32	2458,93	1563,19	2145,83
23	1724,52	1102,72	2460,12	1543,92	2148,23
24	1728,64	1106,56	2462,69	1545,84	2137,01
25	1726,85	1091,51	2461,89	1546,73	2138,82

Figure A.10: Akaike numbers for the 25 configurations for the department nursing wards (one day (heavy)).

specialism	Surgery	Gastroenterology	Gynecology	Internal medicine	Pulmonology	Neurology	Other	Urologie	Obstetrics
best scenario	20	20	21	9	26	15	9	25	20
scenario									
1	2332,97	1520,08	1862,02	1965,75	1847,28	1743,77	2409,07	1802,85	1968,89
2	2231,00	1398,58	1732,67	1847,60	1709,82	1584,97	2341,88	1683,06	1859,93
3	2224,22	1397,19	1727,50	1846,81	1710,56	1586,31	2334,85	1678,05	1856,16
4	2218,46	1397,05	1729,00	1847,15	1712,50	1586,66	2331,35	1674,58	1858,15
5	2218,31	1397,67	1730,57	1849,12	1713,72	1588,59	2329,67	1676,02	1857,84
6	2273,67	1456,88	1821,16	1906,59	1764,58	1665,81	2365,94	1741,41	1922,61
7	2220,76	1396,49	1728,61	1846,13	1710,50	1586,17	2329,23	1676,20	1855,77
8	2211,42	1390,08	1729,21	1832,22	1711,72	1587,30	2321,75	1677,43	1856,75
9	2213,40	1389,79	1732,25	1839,73	1713,65	1586,68	2323,65	1675,62	1856,61
10	2217,03	1389,44	1732,41	1840,24	1706,79	1588,65	2325,64	1677,62	1857,48
11	2265,55	1439,01	1793,62	1893,16	1733,42	1644,08	2355,89	1734,07	1892,18
12	2218,37	1396,29	1729,73	1846,76	1712,50	1586,04	2324,13	1675,39	1857,72
13	2212,47	1398,00	1732,18	1839,42	1713,56	1586,61	2323,72	1675,68	1856,19
14	2210,67	1384,50	1731,72	1834,04	1713,06	1579,95	2322,73	1677,51	1838,58
15	2202,74	1391,99	1735,91	1835,98	1714,69	1581,95	2324,67	1679,34	1858,64
16	2266,20	1437,03	1789,66	1882,84	1722,49	1616,69	2354,52	1719,46	1886,26
17	2220,06	1398,23	1731,73	1848,39	1713,83	1587,91	2324,66	1676,04	1856,97
18	2218,56	1389,10	1732,67	1840,65	1715,30	1588,45	2324,64	1677,48	1857,15
19	2201,49	1379,93	1733,72	1835,70	1705,90	1580,97	2324,71	1679,48	1838,54
20	2203,49	1393,33	1718,88	1833,39	1708,97	1582,94	2325,91	1679,88	1846,21
21	2259,24	1434,14	1768,20	1878,87	1723,90	1613,83	2353,57	1717,01	1874,94
22	2216,08	1398,45	1729,95	1850,38	1706,41	1583,63	2326,53	1677,60	1858,97
23	2205,16	1400,84	1731,43	1842,61	1710,13	1585,50	2326,94	1679,40	1858,63
24	2203,11	1381,90	1732,04	1837,69	1704,90	1583,22	2324,92	1674,19	1846,12
25	2205,72	1391,29	1732,94	1833,90	1700,09	1584,99	2326,89	1683,64	1860,64

Figure A.11: Akaike numbers for the 25 configurations for the department nursing wards (more than one day).

A.2 Seasonality

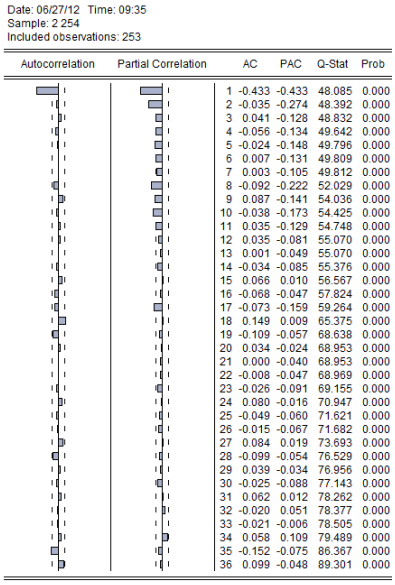
This section deals with checking the data on seasonality. In the paper we provide plots with the actual data, the fitted ARIMA-model and its residuals for the arrivals at the department outpatient clinics (first visits) of the the specialism surgery. This appendix contains the accompanying plots (Figures A.12-A.15) of the autocorrelation (ACF) and partial autocorrelation functions (PCF).

The bars indicate the extent of autocorrelation at the lags. The lags at which the bars lay behind the vertical dash, are the lags at which the test statistic identifies that the series possesses autocorrelation at a significance level $\alpha = 5\%$.[4]

Moreover, this Appendix contains the comparison whether the data possesses seasonality components of the arrivals at the department nursing wards (more than one day), for the specialism cardiology. The results are in Figures A.16-A.19. Also a comparison for the arrivals at the department nursing wards (more than one day) for the specialism surgery are provided. The results are in Figures A.23-A.26. Finally, a comparison for the arrivals at the department nursing wards (one day) for the specialisms surgery is given. The results are in Figures A.23-A.26.

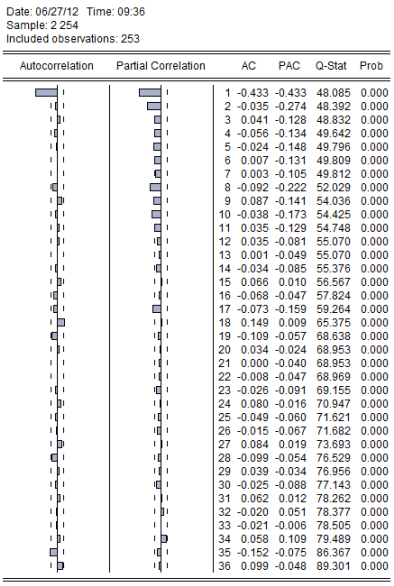
We provide plots of the $(0,0,0)$-, $(0,1,0)$-, $(0,0,0)X(0,1,0)12$- and $(0,0,0)X(0,1,0)50$-ARIMA-models and its residuals. Also for $(0,1,0)$-, $(0,0,0)X(0,1,0)12$- and $(0,0,0)X(0,1,0)50$-ARIMA-models, we provide the plot of the autocorrelation functions (ACF) and partial correlation functions (PCF). We only expect autocorrelation at the lag at which we suspect the season pattern. We see that for $(0,0,0)X(0,1,0)12$- and $(0,0,0)X(0,1,0)50$-ARIMA-models there is still autocorrelation at lags other than lag 12 and 50.

[4] The Q test statistic is the output of a Box-Pierce test.


Date: 06/27/12 Time: 09:35
Sample: 2 254
Included observations: 253

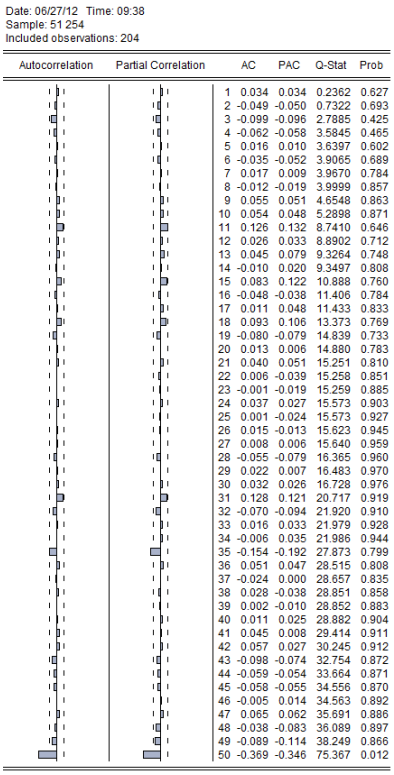
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.433	-0.433	48.085	0.000
		2	-0.035	-0.274	48.392	0.000
		3	0.041	-0.128	48.832	0.000
		4	-0.056	-0.134	49.642	0.000
		5	-0.024	-0.148	49.796	0.000
		6	0.007	-0.131	49.809	0.000
		7	0.003	-0.105	49.812	0.000
		8	-0.092	-0.222	52.029	0.000
		9	0.087	-0.141	54.036	0.000
		10	-0.038	-0.173	54.425	0.000
		11	0.035	-0.129	54.748	0.000
		12	0.035	-0.081	55.070	0.000
		13	0.001	-0.049	55.070	0.000
		14	-0.034	-0.085	55.376	0.000
		15	0.066	0.010	56.567	0.000
		16	-0.068	-0.047	57.824	0.000
		17	-0.073	-0.159	59.264	0.000
		18	0.149	0.009	65.375	0.000
		19	-0.109	-0.057	68.638	0.000
		20	0.034	-0.024	68.953	0.000
		21	0.000	-0.040	68.953	0.000
		22	-0.008	-0.047	68.969	0.000
		23	-0.026	-0.091	69.155	0.000
		24	0.080	-0.016	70.947	0.000
		25	-0.049	-0.060	71.621	0.000
		26	-0.015	-0.067	71.682	0.000
		27	0.084	0.019	73.693	0.000
		28	-0.099	-0.054	76.529	0.000
		29	0.039	-0.034	76.956	0.000
		30	-0.025	-0.088	77.143	0.000
		31	0.062	0.012	78.262	0.000
		32	-0.020	0.051	78.377	0.000
		33	-0.021	-0.006	78.505	0.000
		34	0.058	0.109	79.489	0.000
		35	-0.152	-0.075	86.367	0.000
		36	0.099	-0.048	89.301	0.000

Figure A.12: Autocorrelation function and partial correlation function plot of $(0,1,0)X(0,0,0)$ ARIMA-model of arrivals at the department outpatient clinics (first visits) for the specialism surgery. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.


Date: 06/27/12 Time: 09:36
Sample: 2 254
Included observations: 253

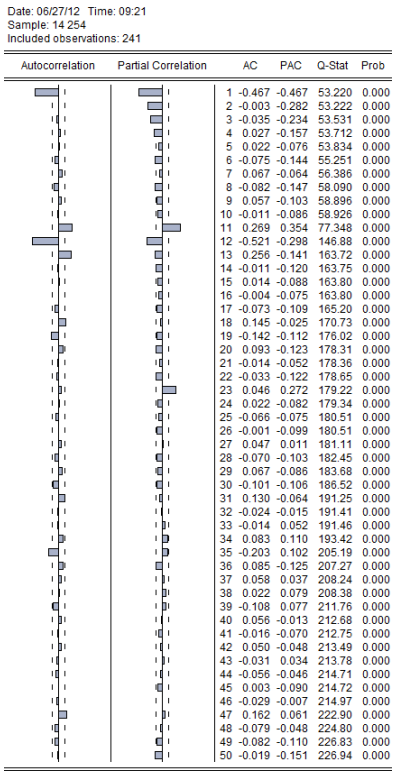
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.433	-0.433	48.085	0.000
		2	-0.035	-0.274	48.392	0.000
		3	0.041	-0.128	48.832	0.000
		4	-0.056	-0.134	49.642	0.000
		5	-0.024	-0.148	49.796	0.000
		6	0.007	-0.131	49.809	0.000
		7	0.003	-0.105	49.812	0.000
		8	-0.092	-0.222	52.029	0.000
		9	0.087	-0.141	54.036	0.000
		10	-0.038	-0.173	54.425	0.000
		11	0.035	-0.129	54.748	0.000
		12	0.035	-0.081	55.070	0.000
		13	0.001	-0.049	55.070	0.000
		14	-0.034	-0.085	55.376	0.000
		15	0.066	0.010	56.567	0.000
		16	-0.068	-0.047	57.824	0.000
		17	-0.073	-0.159	59.264	0.000
		18	0.149	0.009	65.375	0.000
		19	-0.109	-0.057	68.638	0.000
		20	0.034	-0.024	68.953	0.000
		21	0.000	-0.040	68.953	0.000
		22	-0.008	-0.047	68.969	0.000
		23	-0.026	-0.091	69.155	0.000
		24	0.080	-0.016	70.947	0.000
		25	-0.049	-0.060	71.621	0.000
		26	-0.015	-0.067	71.682	0.000
		27	0.084	0.019	73.693	0.000
		28	-0.099	-0.054	76.529	0.000
		29	0.039	-0.034	76.956	0.000
		30	-0.025	-0.088	77.143	0.000
		31	0.062	0.012	78.262	0.000
		32	-0.020	0.051	78.377	0.000
		33	-0.021	-0.006	78.505	0.000
		34	0.058	0.109	79.489	0.000
		35	-0.152	-0.075	86.367	0.000
		36	0.099	-0.048	89.301	0.000

Figure A.13: Autocorrelation function and partial correlation function plot of $(0,0,0)X(0,1,0)12$ ARIMA-model of arrivals at the department outpatient clinics (first visits) for the specialism surgery. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.



	AC	PAC	Q-Stat	Prob
1	0.034	0.034	0.2362	0.627
2	-0.049	-0.050	0.7322	0.693
3	-0.099	-0.096	2.7885	0.425
4	-0.062	-0.058	3.5845	0.465
5	0.016	0.010	3.6397	0.602
6	-0.035	-0.052	3.9065	0.689
7	0.017	0.009	3.9670	0.784
8	-0.012	-0.019	3.9999	0.857
9	0.055	0.051	4.6548	0.863
10	0.054	0.048	5.2898	0.871
11	0.126	0.132	8.7410	0.646
12	0.026	0.033	8.8902	0.712
13	0.045	0.079	9.3264	0.748
14	-0.010	0.020	9.3497	0.808
15	0.083	0.122	10.888	0.760
16	-0.048	-0.038	11.406	0.784
17	0.011	0.048	11.433	0.833
18	0.093	0.106	13.373	0.769
19	-0.080	-0.079	14.839	0.733
20	0.013	0.006	14.880	0.783
21	0.040	0.051	15.251	0.810
22	0.006	-0.039	15.258	0.851
23	-0.001	-0.019	15.259	0.885
24	0.037	0.027	15.573	0.903
25	0.001	-0.024	15.573	0.927
26	0.015	-0.013	15.623	0.945
27	0.008	0.006	15.640	0.959
28	-0.055	-0.079	16.365	0.960
29	0.022	0.007	16.483	0.970
30	0.032	0.026	16.728	0.976
31	0.128	0.121	20.717	0.919
32	-0.070	-0.094	21.920	0.910
33	0.016	0.033	21.979	0.928
34	-0.006	0.035	21.986	0.944
35	-0.154	-0.192	27.873	0.799
36	0.051	0.047	28.515	0.808
37	-0.024	0.000	28.657	0.835
38	0.028	-0.038	28.851	0.858
39	0.002	-0.010	28.852	0.883
40	0.011	0.025	28.882	0.904
41	0.045	0.008	29.414	0.911
42	0.057	0.027	30.245	0.912
43	-0.098	-0.074	32.754	0.872
44	-0.059	-0.054	33.664	0.871
45	-0.058	-0.055	34.556	0.870
46	-0.005	0.014	34.563	0.892
47	0.065	0.062	35.691	0.886
48	-0.038	-0.083	36.089	0.897
49	-0.089	-0.114	38.249	0.866
50	-0.369	-0.346	75.367	0.012

Figure A.14: Autocorrelation function and partial correlation function plot of $(0,0,0)X(0,1,0)50$ ARIMA-model of arrivals at the department outpatient clinics (first visits) for the specialism surgery. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.



	AC	PAC	Q-Stat	Prob
1	-0.467	-0.467	53.220	0.000
2	-0.003	-0.282	53.222	0.000
3	-0.035	-0.234	53.531	0.000
4	0.027	-0.157	53.712	0.000
5	0.022	-0.076	53.834	0.000
6	-0.075	-0.144	55.251	0.000
7	0.067	-0.064	56.386	0.000
8	-0.082	-0.147	58.090	0.000
9	0.057	-0.103	58.896	0.000
10	-0.011	-0.086	58.926	0.000
11	0.269	0.354	77.348	0.000
12	-0.521	-0.298	146.88	0.000
13	0.256	-0.141	163.72	0.000
14	-0.011	-0.120	163.75	0.000
15	0.014	-0.088	163.80	0.000
16	-0.004	-0.075	163.80	0.000
17	-0.073	-0.109	165.20	0.000
18	0.145	-0.025	170.73	0.000
19	-0.142	-0.112	176.02	0.000
20	0.093	-0.123	178.31	0.000
21	-0.014	-0.052	178.36	0.000
22	-0.033	-0.122	178.65	0.000
23	0.046	0.272	179.22	0.000
24	0.022	-0.082	179.34	0.000
25	-0.066	-0.075	180.51	0.000
26	-0.001	-0.099	180.51	0.000
27	0.047	0.011	181.11	0.000
28	-0.070	-0.103	182.45	0.000
29	0.067	-0.086	183.68	0.000
30	-0.101	-0.106	186.52	0.000
31	0.130	-0.064	191.25	0.000
32	-0.024	-0.015	191.41	0.000
33	-0.014	0.052	191.46	0.000
34	0.083	0.110	193.42	0.000
35	-0.203	0.102	205.19	0.000
36	0.085	-0.125	207.27	0.000
37	0.058	0.037	208.24	0.000
38	0.022	0.079	208.38	0.000
39	-0.108	0.077	211.76	0.000
40	0.056	-0.013	212.68	0.000
41	-0.016	-0.070	212.75	0.000
42	0.050	-0.048	213.49	0.000
43	-0.031	0.034	213.78	0.000
44	-0.056	-0.046	214.71	0.000
45	0.003	-0.090	214.72	0.000
46	-0.029	-0.007	214.97	0.000
47	0.162	0.061	222.90	0.000
48	-0.079	-0.048	224.80	0.000
49	-0.082	-0.110	226.83	0.000
50	-0.019	-0.151	226.94	0.000

Figure A.15: Autocorrelation function and partial correlation function plot of $(0,0,0)X(0,1,0)12$ ARIMA-model of arrivals at the department outpatient clinics (first visits) for the specialism surgery. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.

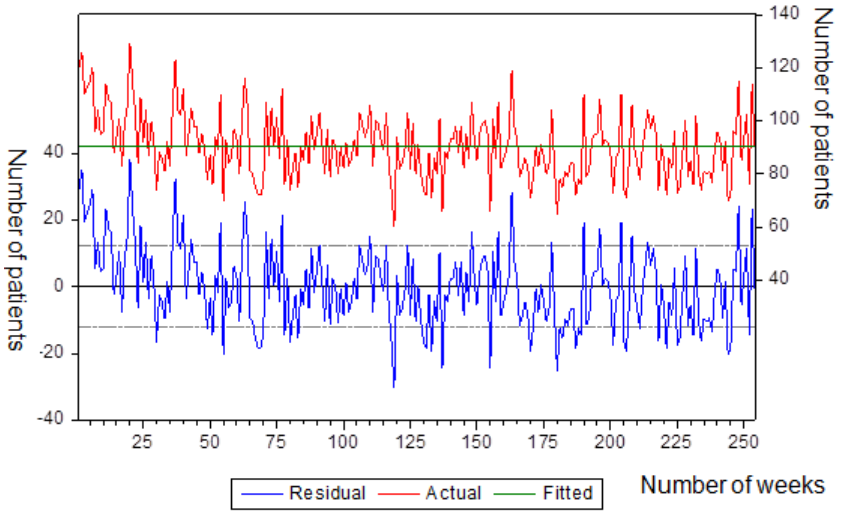


Figure A.16: Plot of $(0, 0, 0)$-ARIMA-model of arrivals at the department nursing wards (more than one day) for cardiology. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

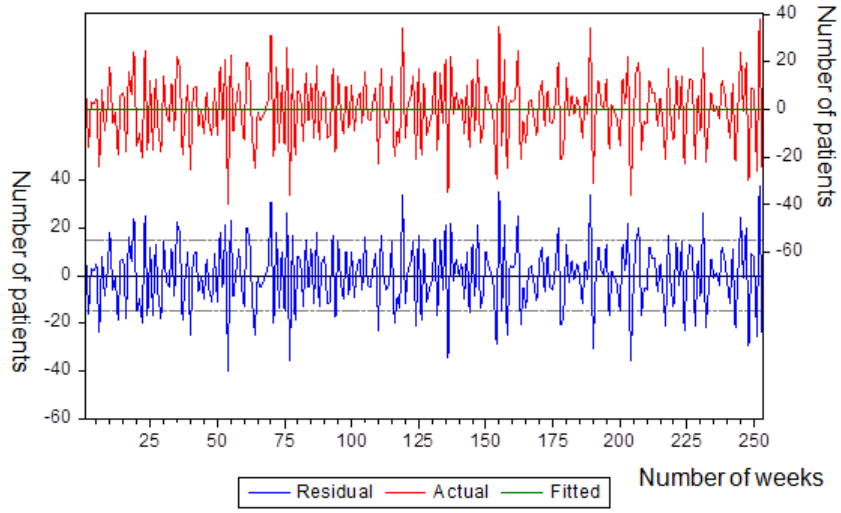


Figure A.17: Plot of $(0, 1, 0)$-ARIMA-model of arrivals at the department nursing wards (more than one day) for cardiology. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

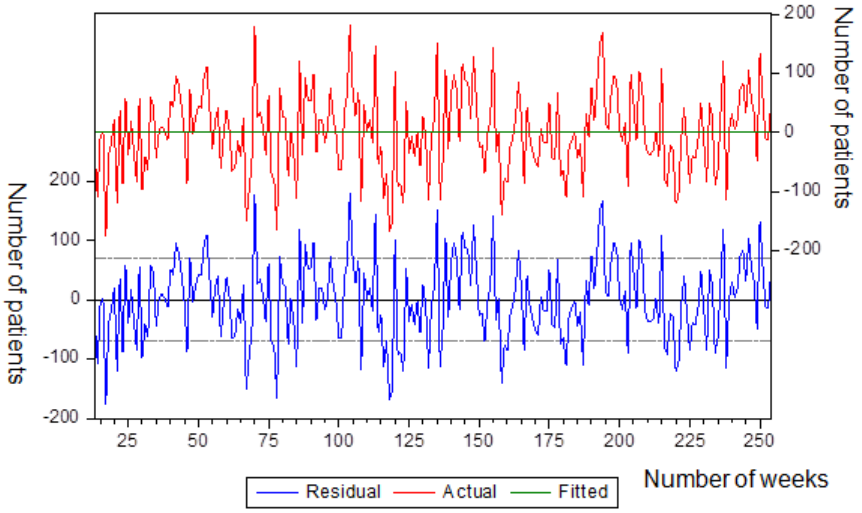


Figure A.18: Plot of $(0,0,0)X(0,1,0)12$-ARIMA-model of arrivals at the department nursing wards (more than one day) for cardiology. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

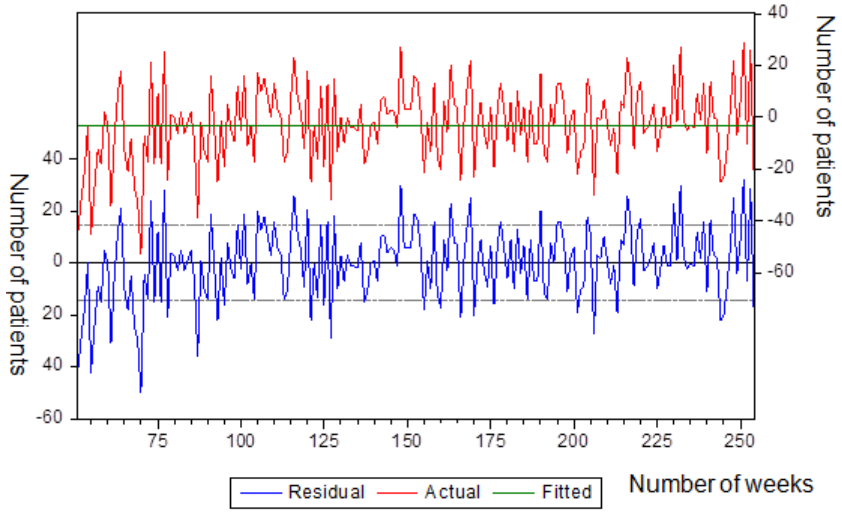
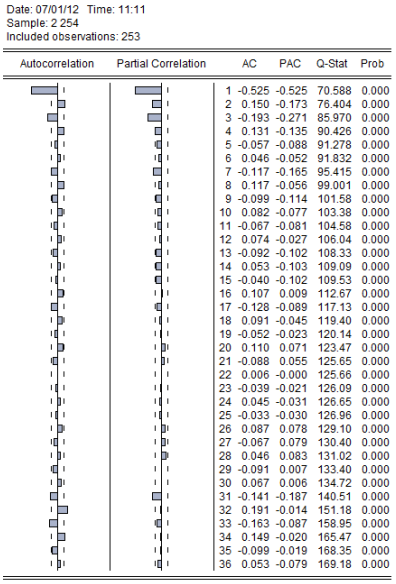
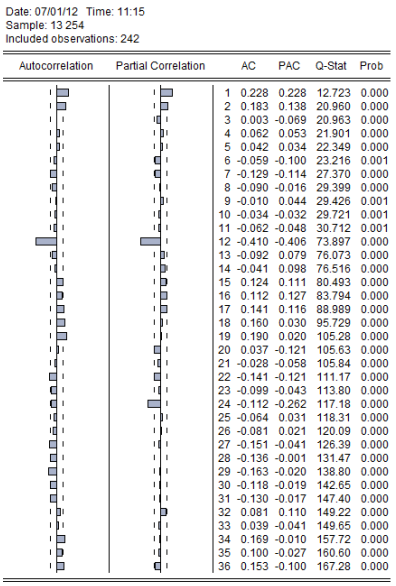


Figure A.19: Residual plot of $(0,0,0)X(0,1,0)50$-ARIMA-model of arrivals at the department nursing wards (more than one day) for cardiology. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.



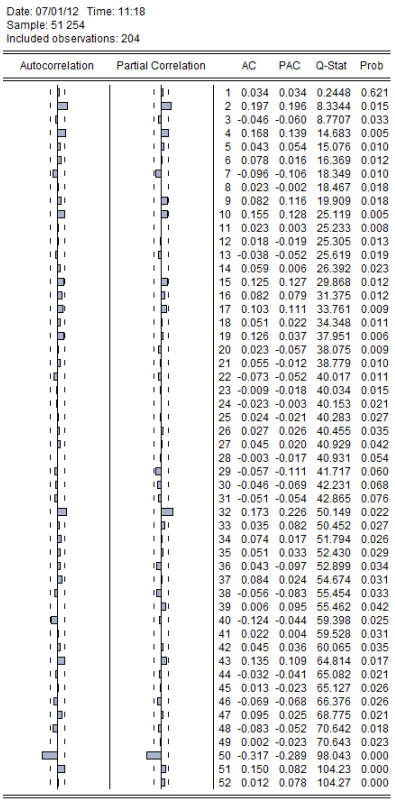
	AC	PAC	Q-Stat	Prob
1	-0.525	-0.525	70.588	0.000
2	0.150	-0.173	76.404	0.000
3	-0.193	-0.271	85.970	0.000
4	0.131	-0.135	90.426	0.000
5	-0.057	-0.088	91.278	0.000
6	0.046	-0.052	91.832	0.000
7	-0.117	-0.165	95.415	0.000
8	0.117	-0.056	99.001	0.000
9	-0.099	-0.114	101.58	0.000
10	0.082	-0.077	103.38	0.000
11	-0.067	-0.081	104.58	0.000
12	0.074	-0.027	106.04	0.000
13	-0.092	-0.102	108.33	0.000
14	0.053	-0.103	109.09	0.000
15	-0.040	-0.102	109.53	0.000
16	0.107	0.009	112.67	0.000
17	-0.128	-0.089	117.13	0.000
18	0.091	-0.045	119.40	0.000
19	-0.052	-0.023	120.14	0.000
20	0.110	0.071	123.47	0.000
21	-0.088	0.055	125.65	0.000
22	0.006	-0.000	125.66	0.000
23	-0.039	-0.021	126.09	0.000
24	0.045	-0.031	126.65	0.000
25	-0.033	-0.030	126.96	0.000
26	0.087	0.078	129.10	0.000
27	-0.067	0.079	130.40	0.000
28	0.046	0.083	131.02	0.000
29	-0.091	0.007	133.40	0.000
30	0.067	0.006	134.72	0.000
31	-0.141	-0.187	140.51	0.000
32	0.191	-0.014	151.18	0.000
33	-0.163	-0.087	158.95	0.000
34	0.149	-0.020	165.47	0.000
35	-0.099	-0.019	168.35	0.000
36	0.053	-0.079	169.18	0.000

Figure A.20: Autocorrelation function and partial correlation function plot of $(0, 1, 0)$-ARIMA-model of arrivals at the department nursing wards (more than one day) for cardiology. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.



	AC	PAC	Q-Stat	Prob
1	0.228	0.228	12.723	0.000
2	0.183	0.138	20.960	0.000
3	0.003	-0.069	20.963	0.000
4	0.062	0.053	21.901	0.000
5	0.042	0.034	22.349	0.000
6	-0.059	-0.100	23.216	0.001
7	-0.129	-0.114	27.370	0.000
8	-0.090	-0.016	29.399	0.000
9	-0.010	0.044	29.426	0.001
10	-0.034	-0.032	29.721	0.001
11	-0.062	-0.048	30.712	0.001
12	-0.410	-0.406	73.897	0.000
13	-0.092	0.079	76.073	0.000
14	-0.041	0.098	76.516	0.000
15	0.124	0.111	80.493	0.000
16	0.112	0.127	83.794	0.000
17	0.141	0.116	88.989	0.000
18	0.160	0.030	95.729	0.000
19	0.190	0.020	105.28	0.000
20	0.037	-0.121	105.63	0.000
21	-0.028	-0.058	105.84	0.000
22	-0.141	-0.121	111.17	0.000
23	-0.099	-0.043	113.80	0.000
24	-0.112	-0.262	117.18	0.000
25	-0.064	0.031	118.31	0.000
26	-0.081	0.021	120.09	0.000
27	-0.151	-0.041	126.39	0.000
28	-0.136	-0.001	131.47	0.000
29	-0.163	-0.020	138.80	0.000
30	-0.118	-0.019	142.65	0.000
31	-0.130	-0.017	147.40	0.000
32	0.081	0.110	149.22	0.000
33	0.039	-0.041	149.65	0.000
34	0.169	-0.010	157.72	0.000
35	0.100	-0.027	160.60	0.000
36	0.153	-0.100	167.28	0.000

Figure A.21: Autocorrelation function and partial correlation functionplot of of $(0, 0, 0)X(0, 1, 0)12$-ARIMA-model of arrivals at the department nursing wards (more than one day) for cardiology. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.



	AC	PAC	Q-Stat	Prob
1	0.034	0.034	0.2448	0.621
2	0.197	0.196	8.3344	0.015
3	-0.046	-0.060	8.7707	0.033
4	0.168	0.139	14.683	0.005
5	0.043	0.054	15.076	0.010
6	0.078	0.016	16.369	0.012
7	-0.096	-0.106	18.349	0.010
8	0.023	-0.002	18.467	0.018
9	0.082	0.116	19.909	0.018
10	0.155	0.128	25.119	0.005
11	0.023	0.003	25.233	0.008
12	0.018	-0.019	25.305	0.013
13	-0.038	-0.052	25.619	0.019
14	0.059	0.006	26.392	0.023
15	0.125	0.127	29.868	0.012
16	0.082	0.079	31.375	0.012
17	0.103	0.111	33.761	0.009
18	0.051	0.022	34.348	0.011
19	0.126	0.037	37.951	0.006
20	0.023	-0.057	38.075	0.009
21	0.055	-0.012	38.779	0.010
22	-0.073	-0.052	40.017	0.011
23	-0.009	-0.018	40.034	0.015
24	-0.023	-0.003	40.153	0.021
25	0.024	-0.021	40.283	0.027
26	0.027	0.026	40.455	0.035
27	0.045	0.020	40.929	0.042
28	-0.003	-0.017	40.931	0.054
29	-0.057	-0.111	41.717	0.060
30	-0.046	-0.069	42.231	0.068
31	-0.051	-0.054	42.865	0.076
32	0.173	0.226	50.149	0.022
33	0.035	0.082	50.452	0.027
34	0.074	0.017	51.794	0.026
35	0.051	0.033	52.430	0.029
36	0.043	-0.097	52.899	0.034
37	0.084	0.024	54.674	0.031
38	-0.056	-0.083	55.454	0.033
39	0.006	0.095	55.462	0.042
40	-0.124	-0.044	59.398	0.025
41	0.022	0.004	59.528	0.031
42	0.045	0.036	60.065	0.035
43	0.135	0.109	64.814	0.017
44	-0.032	-0.041	65.082	0.021
45	0.013	-0.023	65.127	0.026
46	-0.069	-0.068	66.376	0.026
47	0.095	0.025	68.775	0.021
48	-0.083	-0.052	70.642	0.018
49	0.002	-0.023	70.643	0.023
50	-0.317	-0.289	98.043	0.000
51	0.150	0.082	104.23	0.000
52	0.012	0.078	104.27	0.000

Figure A.22: Autocorrelation function and partial correlation function plot of $(0,0,0)X(0,1,0)50$-ARIMA-model of arrivals at the department nursing wards (more than one day) for cardiology. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.

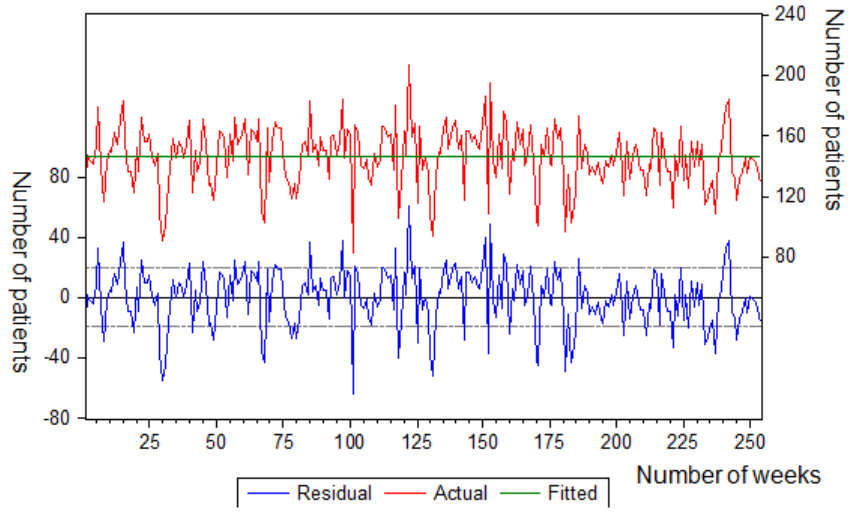


Figure A.23: Plot of $(0, 0, 0)$-ARIMA-model of arrivals at the department nursing wards (more than one day) for surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

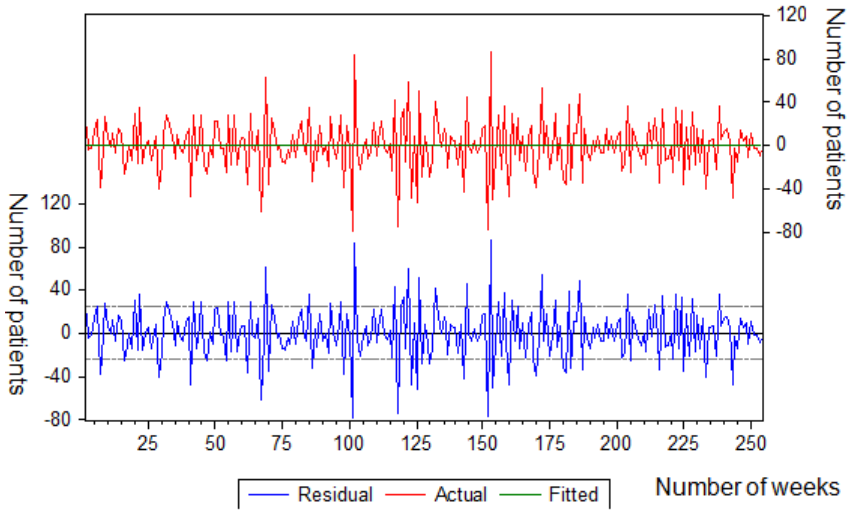


Figure A.24: Plot of $(0, 1, 0)$-ARIMA-model of arrivals at the department nursing wards (more than one day) for surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

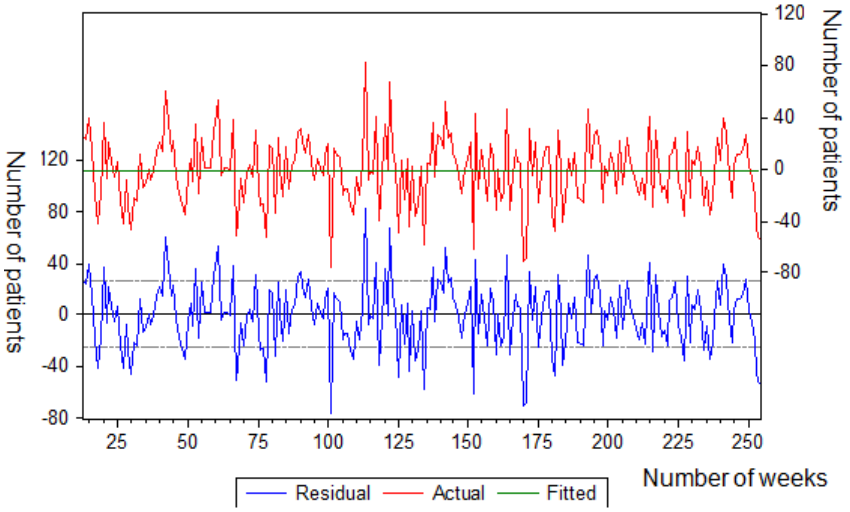


Figure A.25: Plot of $(0,0,0)X(0,1,0)12$-ARIMA-model of arrivals at the department nursing wards (more than one day) for surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

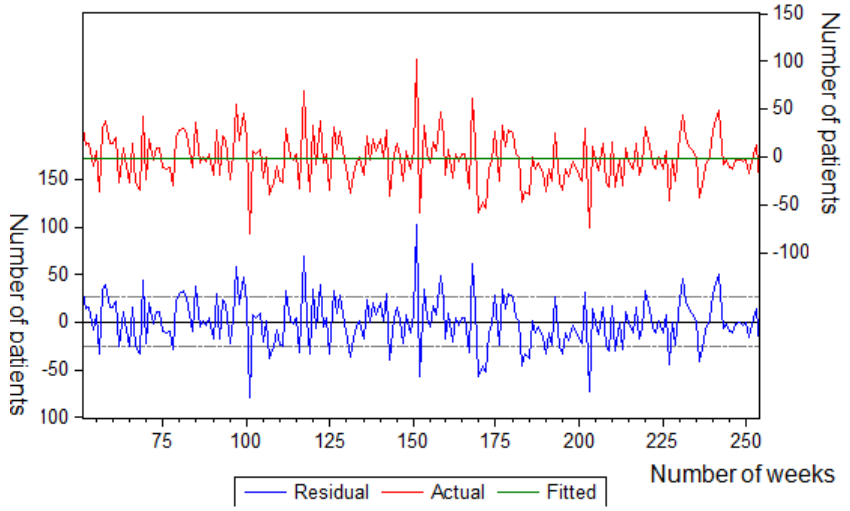
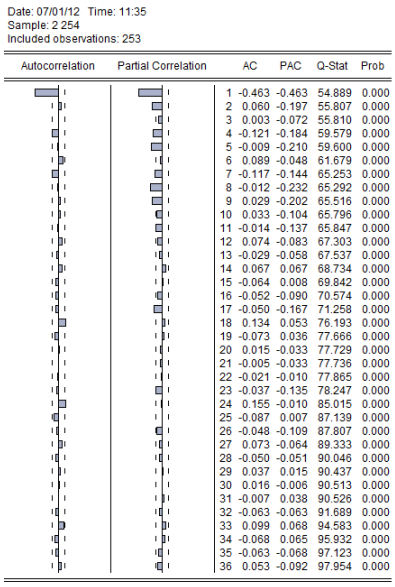
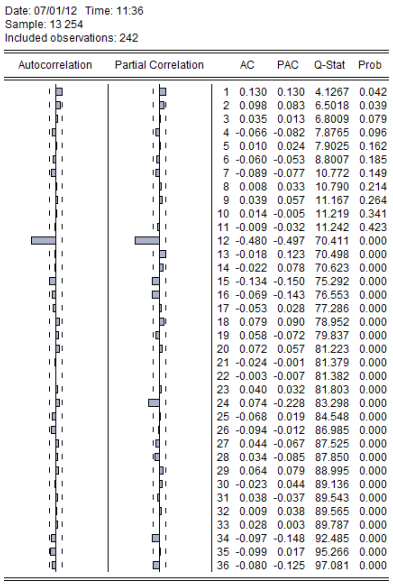


Figure A.26: Plot of $(0,0,0)X(0,1,0)50$-ARIMA-model of arrivals at the department nursing wards (more than one day) for surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.



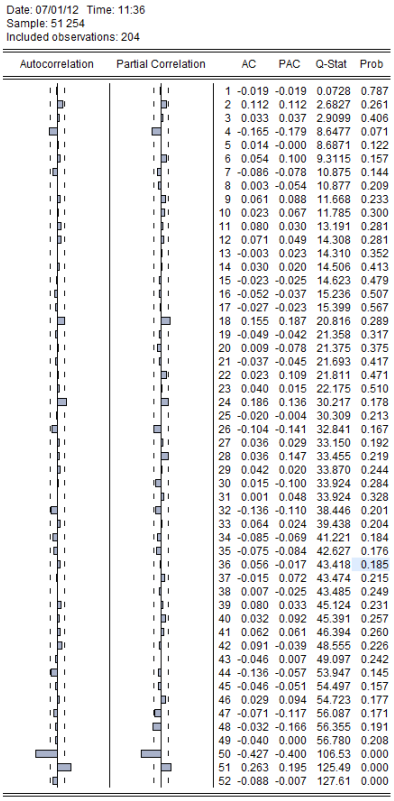
	AC	PAC	Q-Stat	Prob
1	-0.463	-0.463	54.889	0.000
2	0.060	-0.197	55.807	0.000
3	0.003	-0.072	55.810	0.000
4	-0.121	-0.184	59.579	0.000
5	-0.009	-0.210	59.600	0.000
6	0.089	-0.048	61.679	0.000
7	-0.117	-0.144	65.253	0.000
8	-0.012	-0.232	65.292	0.000
9	0.029	-0.202	65.516	0.000
10	0.033	-0.104	65.796	0.000
11	-0.014	-0.137	65.847	0.000
12	0.074	-0.083	67.303	0.000
13	-0.029	-0.058	67.537	0.000
14	0.067	0.067	68.734	0.000
15	-0.064	0.008	69.842	0.000
16	-0.052	-0.090	70.574	0.000
17	-0.050	-0.167	71.258	0.000
18	0.134	0.053	76.193	0.000
19	-0.073	0.036	77.666	0.000
20	0.015	-0.033	77.729	0.000
21	-0.005	-0.033	77.736	0.000
22	-0.021	-0.010	77.865	0.000
23	-0.037	-0.135	78.247	0.000
24	0.155	-0.010	85.015	0.000
25	-0.087	0.007	87.139	0.000
26	-0.048	-0.109	87.807	0.000
27	0.073	-0.064	89.333	0.000
28	-0.050	-0.051	90.046	0.000
29	0.037	0.015	90.437	0.000
30	0.016	-0.006	90.513	0.000
31	-0.007	0.038	90.526	0.000
32	-0.063	-0.063	91.689	0.000
33	0.099	0.068	94.583	0.000
34	-0.068	0.065	95.932	0.000
35	-0.063	-0.068	97.123	0.000
36	0.053	-0.092	97.954	0.000

Figure A.27: Autocorrelation function and partial correlation function plot of $(0, 1, 0)$-ARIMA-model of arrivalsat the department nursing wards (more than one day) for surgery. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.



	AC	PAC	Q-Stat	Prob
1	0.130	0.130	4.1267	0.042
2	0.098	0.083	6.5018	0.039
3	0.035	0.013	6.8009	0.079
4	-0.066	-0.082	7.8765	0.096
5	0.010	0.024	7.9025	0.162
6	-0.060	-0.053	8.8007	0.185
7	-0.089	-0.077	10.772	0.149
8	0.008	0.033	10.790	0.214
9	0.039	0.057	11.167	0.264
10	0.014	-0.005	11.219	0.341
11	-0.009	-0.032	11.242	0.423
12	-0.480	-0.497	70.411	0.000
13	-0.018	0.123	70.498	0.000
14	-0.022	0.078	70.623	0.000
15	-0.134	-0.150	75.292	0.000
16	-0.069	-0.143	76.553	0.000
17	-0.053	0.028	77.286	0.000
18	0.079	0.090	78.952	0.000
19	0.058	-0.072	79.837	0.000
20	0.072	0.057	81.223	0.000
21	-0.024	-0.001	81.379	0.000
22	-0.003	-0.007	81.382	0.000
23	0.040	0.032	81.803	0.000
24	0.074	-0.228	83.298	0.000
25	-0.068	0.019	84.548	0.000
26	-0.094	-0.012	86.985	0.000
27	0.044	-0.067	87.525	0.000
28	0.034	-0.085	87.850	0.000
29	0.064	0.079	88.995	0.000
30	-0.023	0.044	89.136	0.000
31	0.038	-0.037	89.543	0.000
32	0.009	0.038	89.565	0.000
33	0.028	0.003	89.787	0.000
34	-0.097	-0.148	92.485	0.000
35	-0.099	0.017	95.266	0.000
36	-0.080	-0.125	97.081	0.000

Figure A.28: Autocorrelation function and partial correlation function plot of of $(0, 0, 0)X(0, 1, 0)12$-ARIMA-model of arrivals at the department nursing wards (more than one day) for surgery. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.



	AC	PAC	Q-Stat	Prob
1	-0.019	-0.019	0.0728	0.787
2	0.112	0.112	2.6827	0.261
3	0.033	0.037	2.9099	0.406
4	-0.165	-0.179	8.6477	0.071
5	0.014	-0.000	8.6871	0.122
6	0.054	0.100	9.3115	0.157
7	-0.086	-0.078	10.875	0.144
8	0.003	-0.054	10.877	0.209
9	0.061	0.088	11.668	0.233
10	0.023	0.067	11.785	0.300
11	0.080	0.030	13.191	0.281
12	0.071	0.049	14.308	0.281
13	-0.003	0.023	14.310	0.352
14	0.030	0.020	14.506	0.413
15	-0.023	-0.025	14.623	0.479
16	-0.052	-0.037	15.236	0.507
17	-0.027	-0.023	15.399	0.567
18	0.155	0.187	20.816	0.289
19	-0.049	-0.042	21.358	0.317
20	0.009	-0.078	21.375	0.375
21	-0.037	-0.045	21.693	0.417
22	0.023	0.109	21.811	0.471
23	0.040	0.015	22.175	0.510
24	0.186	0.136	30.217	0.178
25	-0.020	-0.004	30.309	0.213
26	-0.104	-0.141	32.841	0.167
27	0.036	0.029	33.150	0.192
28	0.036	0.147	33.455	0.219
29	0.042	0.020	33.870	0.244
30	0.015	-0.100	33.924	0.284
31	0.001	0.048	33.924	0.328
32	-0.136	-0.110	38.446	0.201
33	0.064	0.024	39.438	0.204
34	-0.085	-0.069	41.221	0.184
35	-0.075	-0.084	42.627	0.176
36	0.056	-0.017	43.418	0.185
37	-0.015	0.072	43.474	0.215
38	0.007	-0.025	43.485	0.249
39	0.080	0.033	45.124	0.231
40	0.032	0.092	45.391	0.257
41	0.062	0.061	46.394	0.260
42	0.091	-0.039	48.555	0.226
43	-0.046	0.007	49.097	0.242
44	-0.136	-0.057	53.947	0.145
45	-0.046	-0.051	54.497	0.157
46	0.029	0.094	54.723	0.177
47	-0.071	-0.117	56.087	0.171
48	-0.032	-0.166	56.355	0.191
49	-0.040	0.000	56.780	0.208
50	-0.427	-0.400	106.53	0.000
51	0.263	0.195	125.49	0.000
52	-0.088	-0.007	127.61	0.000

Figure A.29: Autocorrelation function and partial correlation function plot of $(0,0,0)X(0,1,0)50$-ARIMA-model of arrivals at the department nursing wards (more than one day) for surgery. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.

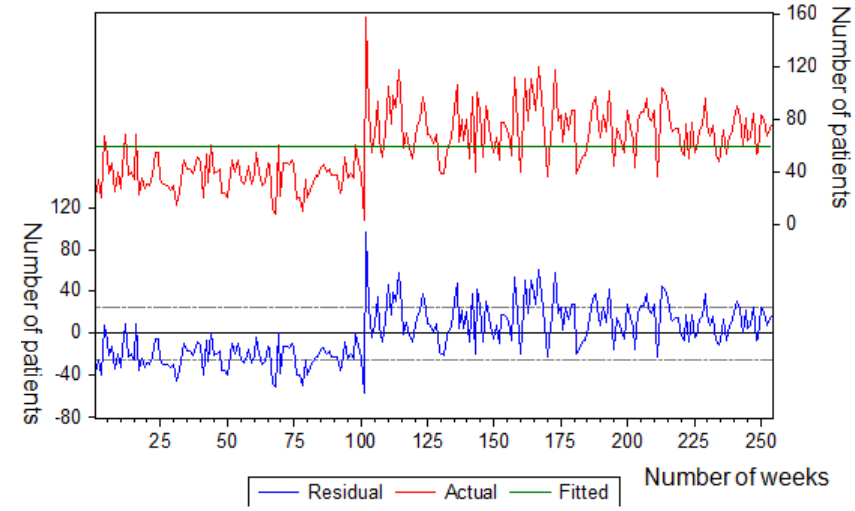


Figure A.30: Plot of $(0, 0, 0)$-ARIMA-model of arrivals at the department nursing wards (one day) for surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

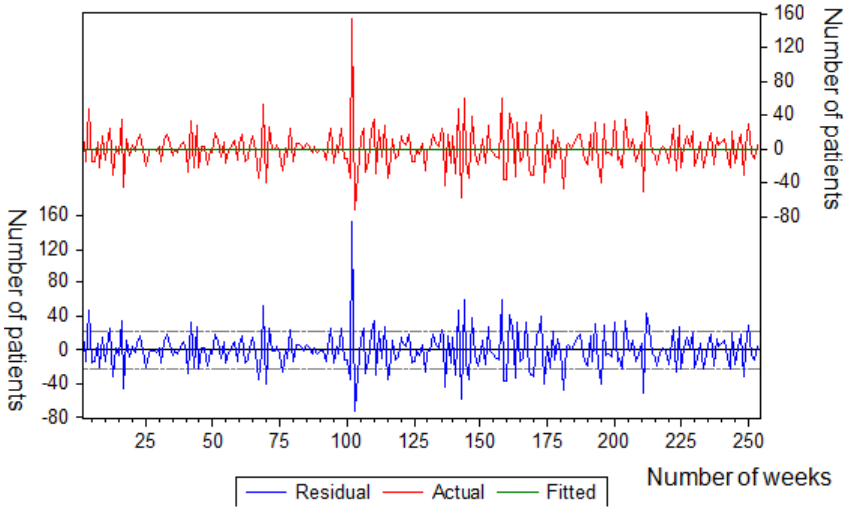


Figure A.31: Plot of $(0, 1, 0)$-ARIMA-model of arrivals at the department nursing wards (one day) for surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

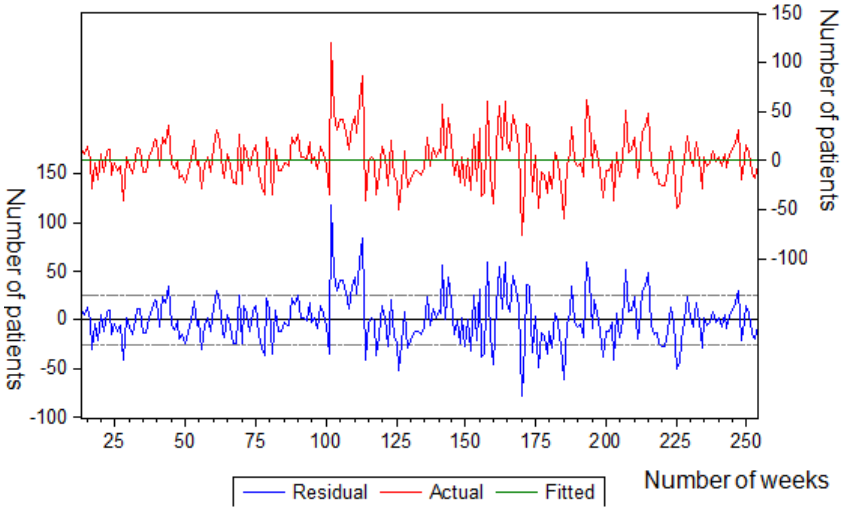


Figure A.32: Plot of $(0,0,0)X(0,1,0)12$-ARIMA-model of arrivals at the department nursing wards (one day) for surgery. The red line indicates the actual data, the green line the estimated ARIMA-model and the blue lines depicts the residuals.

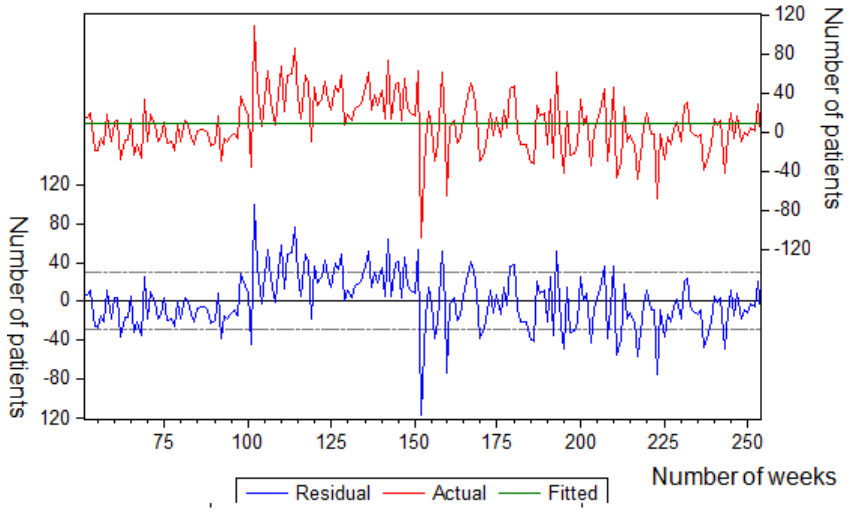
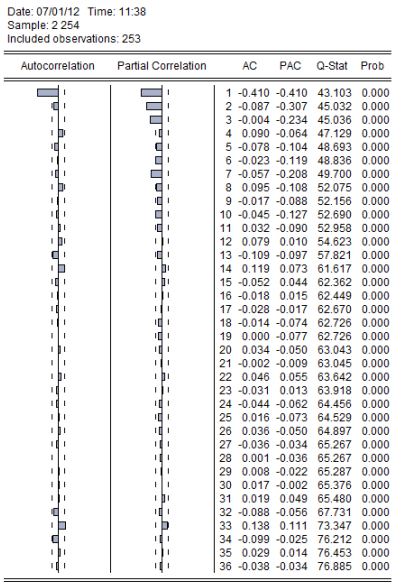


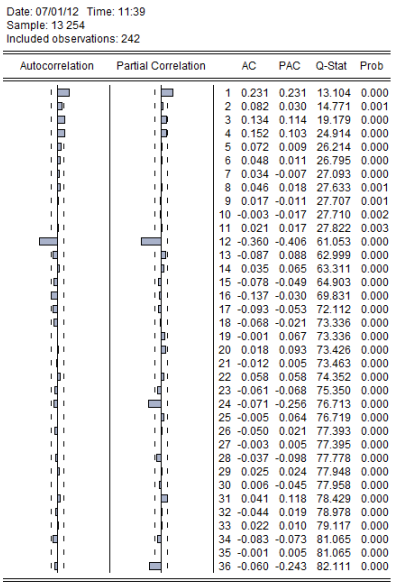
Figure A.33: Plot of $(0,0,0)X(0,1,0)50$-ARIMA-model of arrivals at the department nursing wards (one day) for surgery. The red line indicates the actual data, green the estimated ARIMA-model and blue are the residuals.



Date: 07/01/12 Time: 11:38
Sample: 2 254
Included observations: 253

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.410	-0.410	43.103	0.000
		2	-0.087	-0.307	45.032	0.000
		3	-0.004	-0.234	45.036	0.000
		4	0.090	-0.064	47.129	0.000
		5	-0.079	-0.104	48.693	0.000
		6	-0.023	-0.119	48.836	0.000
		7	-0.057	-0.208	49.700	0.000
		8	0.095	-0.108	52.075	0.000
		9	-0.017	-0.088	52.156	0.000
		10	-0.045	-0.127	52.690	0.000
		11	0.032	-0.090	52.958	0.000
		12	0.079	0.010	54.623	0.000
		13	-0.109	-0.097	57.821	0.000
		14	0.119	0.073	61.617	0.000
		15	-0.052	0.044	62.362	0.000
		16	-0.018	0.015	62.449	0.000
		17	-0.028	-0.017	62.670	0.000
		18	-0.014	-0.074	62.726	0.000
		19	0.000	-0.077	62.726	0.000
		20	0.034	-0.050	63.043	0.000
		21	-0.002	-0.009	63.045	0.000
		22	0.046	0.055	63.642	0.000
		23	-0.031	0.013	63.918	0.000
		24	-0.044	-0.062	64.456	0.000
		25	0.016	-0.073	64.529	0.000
		26	0.036	-0.050	64.897	0.000
		27	-0.036	-0.034	65.267	0.000
		28	0.001	-0.036	65.267	0.000
		29	0.008	-0.022	65.287	0.000
		30	0.017	-0.002	65.376	0.000
		31	0.019	0.049	65.480	0.000
		32	-0.088	-0.056	67.731	0.000
		33	0.138	0.111	73.347	0.000
		34	-0.099	-0.025	76.212	0.000
		35	0.029	0.014	76.453	0.000
		36	-0.038	-0.034	76.885	0.000

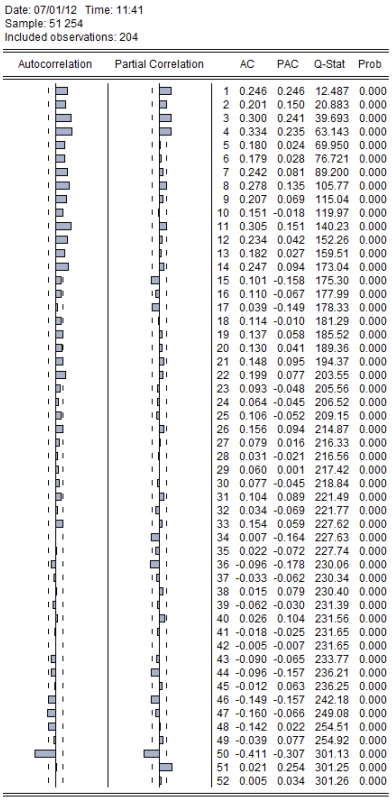
Figure A.34: Autocorrelation function and partial correlation function plot of $(0, 1, 0)$-ARIMA-model of arrivals at the department nursing wards (one day) for surgery. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.



Date: 07/01/12 Time: 11:39
Sample: 13 254
Included observations: 242

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.231	0.231	13.104	0.000
		2	0.082	0.030	14.771	0.001
		3	0.134	0.114	19.179	0.000
		4	0.152	0.103	24.914	0.000
		5	0.072	0.009	26.214	0.000
		6	0.048	0.011	26.795	0.000
		7	0.034	-0.007	27.093	0.000
		8	0.046	0.018	27.633	0.001
		9	0.017	-0.011	27.707	0.001
		10	-0.003	-0.017	27.710	0.002
		11	0.021	0.017	27.822	0.003
		12	-0.360	-0.406	61.053	0.000
		13	-0.087	0.088	62.999	0.000
		14	0.035	0.065	63.311	0.000
		15	-0.078	-0.049	64.903	0.000
		16	-0.137	-0.030	69.831	0.000
		17	-0.093	-0.053	72.112	0.000
		18	-0.068	-0.021	73.336	0.000
		19	-0.001	0.067	73.336	0.000
		20	0.018	0.093	73.426	0.000
		21	-0.012	0.005	73.463	0.000
		22	0.058	0.058	74.352	0.000
		23	-0.061	-0.068	75.350	0.000
		24	-0.071	-0.256	76.713	0.000
		25	-0.005	0.064	76.719	0.000
		26	-0.050	0.021	77.393	0.000
		27	-0.003	0.005	77.395	0.000
		28	-0.037	-0.098	77.778	0.000
		29	0.025	0.024	77.948	0.000
		30	0.006	-0.045	77.958	0.000
		31	0.041	0.118	78.429	0.000
		32	-0.044	0.019	78.978	0.000
		33	0.022	0.010	79.117	0.000
		34	-0.083	-0.073	81.065	0.000
		35	-0.001	0.005	81.065	0.000
		36	-0.060	-0.243	82.111	0.000

Figure A.35: Autocorrelation function and partial correlation function plot of $(0, 0, 0)X(0, 1, 0)12$-ARIMA-model of arrivals at the department nursing wards (one day) for surgery. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.



		AC	PAC	Q-Stat	Prob
1		0.246	0.246	12.487	0.000
2		0.201	0.150	20.883	0.000
3		0.300	0.241	39.693	0.000
4		0.334	0.235	63.143	0.000
5		0.180	0.024	69.950	0.000
6		0.179	0.028	76.721	0.000
7		0.242	0.081	89.200	0.000
8		0.278	0.135	105.77	0.000
9		0.207	0.069	115.04	0.000
10		0.151	-0.018	119.97	0.000
11		0.305	0.151	140.23	0.000
12		0.234	0.042	152.26	0.000
13		0.182	0.027	159.51	0.000
14		0.247	0.094	173.04	0.000
15		0.101	-0.158	175.30	0.000
16		0.110	-0.067	177.99	0.000
17		0.039	-0.149	178.33	0.000
18		0.114	-0.010	181.29	0.000
19		0.137	0.058	185.52	0.000
20		0.130	0.041	189.36	0.000
21		0.148	0.095	194.37	0.000
22		0.199	0.077	203.55	0.000
23		0.093	-0.048	205.56	0.000
24		0.064	-0.045	206.52	0.000
25		0.106	-0.052	209.15	0.000
26		0.156	0.094	214.87	0.000
27		0.079	0.016	216.33	0.000
28		0.031	-0.021	216.56	0.000
29		0.060	0.001	217.42	0.000
30		0.077	-0.045	218.84	0.000
31		0.104	0.089	221.49	0.000
32		0.034	-0.069	221.77	0.000
33		0.154	0.059	227.62	0.000
34		0.007	-0.164	227.63	0.000
35		0.022	-0.072	227.74	0.000
36		-0.096	-0.178	230.06	0.000
37		-0.033	-0.062	230.34	0.000
38		0.015	0.079	230.40	0.000
39		-0.062	-0.030	231.39	0.000
40		0.026	0.104	231.56	0.000
41		-0.018	-0.025	231.65	0.000
42		-0.005	-0.007	231.65	0.000
43		-0.090	-0.065	233.77	0.000
44		-0.096	-0.157	236.21	0.000
45		-0.012	0.063	236.25	0.000
46		-0.149	-0.157	242.18	0.000
47		-0.160	-0.066	249.08	0.000
48		-0.142	0.022	254.51	0.000
49		-0.039	0.077	254.92	0.000
50		-0.411	-0.307	301.13	0.000
51		0.021	0.254	301.25	0.000
52		0.005	0.034	301.26	0.000

Figure A.36: Autocorrelation function and partial correlation function plot of $(0,0,0)X(0,1,0)50$-ARIMA-model of arrivals at the department nursing wards (one day) surgery. The bars indicate the extent of correlation, bars behind the vertical dash indicate significant correlation.

A.3 Mean squared error for time series analysis

This part of the appendix contains figures with the mean squared errors (MSE) of the ARIMA-models for estimating the arrivals at 11 specialims. The figures contain for all 25 possible fits the MSE. The MSE is defined as the sum of the variance of the residuals and the bias squared. A MSE of 0 indicates a perfect fit. The closer the number is to zero, the smaller the difference between the estimates and the actual values. Figures A.37-A.42 contain the MSE for the departments outpatient clinics (first and repeated visit), operating theaters and nursing wards (one day (heavy and light) and more than one day).

scenario	Cardiology	Surgery	Gastroenterology	Gynecology	Internal medicine	Pediatrics	Pulmonology	Neurology	Other	Obstetrics
1	0,5099	0,5841	0,5515	0,4533	0,4743	0,4517	0,3828	0,4238	1,0771	1,1313
2	0,5763	0,6233	0,5893	0,5428	0,5034	0,5045	0,4851	0,5104	1,0871	1,1334
3	0,5606	0,6125	0,5794	0,5185	0,4957	0,5021	0,4827	0,5014	1,0864	1,1334
4	0,5611	0,6117	0,5802	0,5192	0,4952	0,5043	0,4829	0,5050	1,0864	1,1335
5	0,5516	0,6197	0,5800	0,5170	0,4942	0,5043	0,4815	0,4962	1,0838	1,1328
6	0,5448	0,5985	0,5567	0,4659	0,5022	0,4555	0,4007	0,4679	1,1441	1,1312
7	0,5667	0,6273	0,5919	0,5399	0,5217	0,5031	0,5014	0,5233	1,1005	1,1335
8	0,5523	0,6294	0,6526	0,5594	0,5181	0,6399	0,5520	0,5418	1,1276	1,1396
9	0,6275	0,6237	0,6367	0,5408	0,5130	0,6464	0,5286	0,5259	1,0956	1,1411
10	0,5690	0,6246	0,6093	0,5897	0,5054	0,5032	0,4547	0,5170	1,2507	1,1330
11	0,5504	0,6088	0,5626	0,4830	0,5008	0,4596	0,4045	0,4683	1,1452	1,1323
12	0,5639	0,6289	0,5894	0,5421	0,5235	0,5116	0,4986	0,5269	1,0949	1,1336
13	0,5906	0,6151	0,5760	0,5061	0,5129	0,6359	0,5416	0,4965	1,0908	1,1402
14	0,8631	0,8232	0,6199	0,5693	0,5520	0,6278	0,4969	0,5739	1,1100	1,1475
15	0,6778	0,6641	0,6148	0,5687	0,5881	0,5454	0,4876	0,5185	1,2593	1,1444
16	0,5763	0,6214	0,5619	0,5006	0,5105	0,4625	0,4117	0,4804	1,1632	1,1311
17	0,5666	0,6287	0,5917	0,5385	0,5285	0,5155	0,4952	0,5311	1,1158	1,1349
18	0,7076	0,7108	0,6006	0,5515	0,5290	0,5101	0,4696	0,6398	1,1690	1,1355
19	0,6515	0,7243	0,7470	0,6155	0,5785	0,5243	0,4697	0,5415	1,3807	1,1500
20	0,6807	0,7532	0,6068	0,6734	0,6899	0,5655	0,4874	0,7054	1,3785	1,1171
21	0,5868	0,6299	0,5614	0,5077	0,5146	0,4656	0,4204	0,4928	1,1841	1,1308
22	0,5536	0,6226	0,5933	0,5383	0,5273	0,5154	0,4952	0,5310	1,1073	1,1349
23	0,6656	0,7146	0,6160	0,6915	0,5929	0,5140	0,4677	0,6042	1,1224	1,1412
24	0,6094	0,7169	0,6580	0,5754	0,6197	0,5775	0,5382	0,5642	1,2261	1,1495
25	0,7118	0,7632	0,6548	0,5684	0,6353	0,5691	0,4933	0,7101	1,3773	1,1174

Figure A.37: MSE for the department outpatient clinics (first visits).

scenario	Cardiology	Surgery	Gastroenterology	Gynecology	Internal medicine	Pediatrics	Pulmonology	Neurology	Other	Urologie	Obstetrics
1	0,6578	0,7856	0,8350	0,5987	0,7000	0,6843	0,5034	0,5186	1,4458	1,4038	0,6342
2	0,6881	0,8082	0,8370	0,6333	0,7161	0,7004	0,5719	0,5600	1,4508	1,4043	0,6615
3	0,6865	0,8106	0,8437	0,6276	0,7146	0,7005	0,5686	0,5570	1,4520	1,4043	0,6556
4	0,6904	0,8101	0,8406	0,6290	0,7146	0,7002	0,5703	0,5630	1,4521	1,4050	0,6547
5	0,6947	0,8101	0,8417	0,6288	0,7157	0,7008	0,5705	0,5606	1,4514	1,4044	0,6557
6	0,7069	0,8993	0,8495	0,6210	0,7651	0,6854	0,5360	0,5427	1,5544	1,4076	0,6376
7	0,6882	0,8035	0,8465	0,6288	0,7115	0,7001	0,5738	0,5639	1,4493	1,4044	0,6642
8	0,7286	1,0131	0,8478	0,6435	0,7330	0,7339	0,7786	0,6400	1,6482	1,4066	0,7076
9	0,6865	0,8670	0,8429	0,6269	0,7480	0,7340	0,6445	0,6422	1,5604	1,4060	0,7014
10	0,7039	0,9369	0,8669	0,7247	0,7084	0,7902	0,5921	0,7110	1,5875	1,4075	0,6681
11	0,7184	0,8965	0,8598	0,6207	0,7706	0,6918	0,5418	0,5479	1,5567	1,4112	0,6446
12	0,6881	0,8381	0,8477	0,6293	0,7150	0,7000	0,5759	0,5777	1,4763	1,4044	0,6617
13	0,8056	0,9055	0,8471	0,6418	0,7151	0,7146	0,6444	0,6212	1,5237	1,4116	0,6983
14	0,7811	0,8481	0,9550	0,6355	0,7423	0,7350	0,7752	0,6631	1,5077	1,4075	0,6930
15	0,8345	0,8473	0,8898	0,6917	0,7437	0,8017	0,6023	0,6925	1,7228	1,4130	0,7012
16	0,7659	0,9199	0,8627	0,6316	0,8027	0,6901	0,5624	0,5605	1,5950	1,3990	0,6434
17	0,6719	0,8562	0,8478	0,6371	0,7197	0,7003	0,5735	0,5814	1,4478	1,4051	0,6617
18	0,8000	0,8806	0,8620	0,6910	0,7602	0,7453	0,7133	0,6608	1,5086	1,4131	0,6778
19	0,7995	1,1370	0,9129	0,6836	0,8684	0,7288	0,7455	0,6848	1,7581	1,4166	0,7074
20	0,7797	0,9955	0,8994	0,7674	0,8484	0,7562	0,6079	0,6607	1,3846	1,3781	0,7214
21	0,7862	0,9438	0,8653	0,6347	0,8140	0,6908	0,5757	0,5756	1,6281	1,3937	0,6425
22	0,6751	0,8578	0,8479	0,6373	0,7275	0,7019	0,5659	0,5873	1,4461	1,4053	0,6608
23	0,6821	0,8856	0,8469	0,7385	0,8476	0,7180	0,5910	0,5726	1,7150	1,4154	0,7180
24	0,8592	0,8923	0,9258	0,7182	0,8253	0,7544	0,6935	0,6288	1,6612	1,4165	0,7070
25	0,8178	1,0035	0,8848	0,6729	0,8479	0,8112	0,6334	0,6617	1,3501	1,3804	0,7209

Figure A.38: MSE for the department outpatient clinics (repeated visits).

scenario	Surgery	Gynecology	Other	Urologie	Obstetrics	Cardiology	Surgery2	Gastroenterology	Gynecology3	Other4	Obstetrics5
1	0,600	0,354	0,989	0,993	0,303	0,280	0,388	0,390	0,170	0,547	0,551
2	0,614	0,405	0,991	0,996	0,375	0,391	0,431	0,439	0,297	0,567	0,551
3	0,610	0,391	0,993	0,996	0,369	0,394	0,425	0,443	0,300	0,566	0,551
4	0,610	0,386	0,992	0,996	0,369	0,391	0,426	0,442	0,290	0,566	0,551
5	0,607	0,392	0,992	0,998	0,375	0,395	0,426	0,444	0,288	0,563	0,551
6	0,602	0,356	1,029	0,992	0,311	0,280	0,439	0,390	0,174	0,573	0,552
7	0,609	0,410	1,006	0,996	0,376	0,391	0,434	0,438	0,350	0,556	0,551
8	0,610	0,430	1,034	0,994	0,367	0,362	0,507	0,431	0,369	0,583	0,552
9	0,610	0,426	1,035	0,993	0,369	0,358	0,504	0,431	0,306	0,560	0,552
10	0,614	0,388	1,059	0,992	0,436	0,361	0,507	0,506	0,292	0,624	0,552
11	0,602	0,357	1,039	0,992	0,319	0,280	0,439	0,390	0,178	0,576	0,551
12	0,648	0,410	1,000	0,996	0,375	0,391	0,439	0,436	0,351	0,554	0,551
13	0,611	0,437	1,066	0,991	0,368	0,360	0,500	0,412	0,297	0,558	0,552
14	0,620	0,567	1,418	0,996	0,529	0,363	0,522	0,435	0,353	0,607	0,553
15	0,635	0,404	1,063	0,995	0,457	0,390	0,480	0,443	0,338	0,642	0,552
16	0,601	0,357	1,064	0,991	0,331	0,280	0,460	0,390	0,187	0,596	0,552
17	0,610	0,410	1,007	0,994	0,378	0,391	0,451	0,438	0,348	0,566	0,551
18	0,619	0,391	1,075	0,991	0,447	0,358	0,500	0,412	0,340	0,623	0,552
19	0,633	0,400	1,147	0,997	0,462	0,425	0,483	0,451	0,389	0,666	0,551
20	0,638	0,459	1,309	0,983	0,562	0,518	0,575	0,431	0,325	0,572	0,553
21	0,603	0,356	1,079	0,991	0,338	0,281	0,466	0,390	0,192	0,612	0,552
22	0,609	0,409	1,002	0,994	0,382	0,391	0,451	0,440	0,347	0,565	0,551
23	0,618	0,474	1,173	0,991	0,435	0,359	0,502	0,413	0,337	0,639	0,552
24	0,649	0,448	1,354	0,994	0,454	0,407	0,547	0,434	0,322	0,593	0,551
25	0,588	0,459	1,257	1,009	0,460	0,539	0,577	0,431	0,396	0,514	0,552

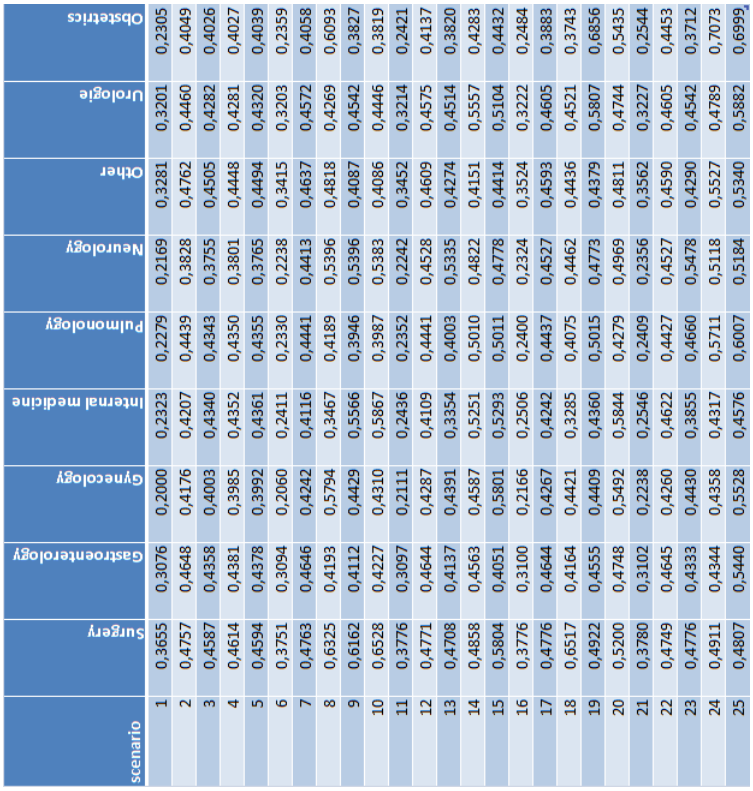
Figure A.39: MSE for the department operating theaters.

scenario	Cardiology	Surgery	Gastroenterology	Gynecology	Internal medicine	Pediatrics	Pulmonology	Neurology	Other	Obstetrics
1	0,2325	0,2995	0,3065	0,2332	0,2312	0,2393	0,1936	0,2133	0,4284	0,4264
2	0,4219	0,4347	0,4525	0,4200	0,4110	0,4276	0,4368	0,4030	0,5052	0,4780
3	0,3977	0,4188	0,4357	0,4167	0,3912	0,4161	0,4572	0,3958	0,5030	0,4731
4	0,3967	0,4154	0,4405	0,4167	0,3883	0,4286	0,4617	0,4063	0,5042	0,4757
5	0,3974	0,4157	0,4325	0,4175	0,3879	0,4208	0,4632	0,4005	0,5020	0,4804
6	0,2370	0,3128	0,3102	0,2342	0,2474	0,2413	0,1997	0,2320	0,4512	0,4249
7	0,4362	0,4578	0,4656	0,4194	0,4263	0,4500	0,4306	0,4460	0,4974	0,5118
8	0,5284	0,4503	0,5216	0,5655	0,4524	0,5511	0,4403	0,5642	0,5101	0,5970
9	0,5493	0,4297	0,5109	0,4233	0,4142	0,5640	0,4381	0,5660	0,5142	0,5918
10	0,4228	0,4728	0,4474	0,4187	0,4129	0,4125	0,4301	0,5842	0,5117	0,5174
11	0,2391	0,3201	0,3143	0,2359	0,2512	0,2430	0,2002	0,2327	0,4533	0,4241
12	0,4369	0,4582	0,4656	0,4196	0,4289	0,4574	0,4350	0,4480	0,5001	0,5157
13	0,4219	0,4436	0,4556	0,4192	0,4078	0,5329	0,4363	0,5650	0,5658	0,5113
14	0,4332	0,4368	0,6879	0,5044	0,4478	0,5469	0,4425	0,7070	0,5777	0,5554
15	0,4415	0,4730	0,3916	0,5215	0,4520	0,4440	0,4391	0,4311	0,5360	0,5389
16	0,2434	0,3348	0,3186	0,2369	0,2654	0,2458	0,2026	0,2424	0,4607	0,4240
17	0,4435	0,4565	0,4653	0,4043	0,4305	0,4574	0,4334	0,4486	0,4994	0,4294
18	0,5300	0,4253	0,4915	0,4189	0,4092	0,4442	0,4327	0,4278	0,5942	0,5120
19	0,5898	0,5025	0,6658	0,4296	0,4275	0,4514	0,4410	0,7183	0,5814	0,5112
20	0,5846	0,4960	0,4559	0,4127	0,4691	0,4929	0,5171	0,5855	0,5552	0,5537
21	0,2464	0,3378	0,3199	0,2379	0,2722	0,2473	0,2055	0,2493	0,4648	0,4240
22	0,4444	0,4563	0,4654	0,4520	0,4270	0,4573	0,4363	0,4475	0,5018	0,5204
23	0,4276	0,4275	0,5099	0,4162	0,4109	0,4441	0,4341	0,6738	0,5410	0,5172
24	0,4524	0,4115	0,4359	0,4150	0,4288	0,4530	0,4404	0,4989	0,5119	0,5301
25	0,5560	0,5187	0,3947	0,4049	0,4221	0,4481	0,4323	0,5872	0,5741	0,5391

Figure A.40: MSE the department nursing wards (one day (light).

scenario	Surgery	Gynecology	Other	Urologie
1	0,2453	0,2536	0,1873	0,3832
2	0,4060	0,4322	0,4207	0,4992
3	0,4079	0,4081	0,3929	0,5814
4	0,4021	0,4088	0,3881	0,5566
5	0,4031	0,4071	0,3891	0,5675
6	0,2549	0,2550	0,1869	0,4058
7	0,4521	0,4373	0,4351	0,4899
8	0,5489	0,4302	0,4735	0,6337
9	0,5492	0,4335	0,3617	0,5126
10	0,5445	0,4358	0,3695	0,5260
11	0,2601	0,2565	0,1871	0,4113
12	0,4505	0,4339	0,4370	0,4875
13	0,5476	0,4328	0,4401	0,5668
14	0,4811	0,4484	0,3622	0,6006
15	0,4894	0,4146	0,3806	0,5158
16	0,2703	0,2600	0,1875	0,4315
17	0,4582	0,4396	0,4356	0,4853
18	0,4651	0,4256	0,3702	0,4610
19	0,5284	0,4116	0,5326	0,5572
20	0,4692	0,4535	0,7205	0,5644
21	0,2710	0,2620	0,1880	0,4419
22	0,4509	0,4289	0,4440	0,4881
23	0,4527	0,6079	0,5240	0,4730
24	0,4722	0,4022	0,6391	0,5521
25	0,4682	0,4662	0,7126	0,5694

Figure A.41: MSE the department nursing wards (one day (heavy).



scenario	Surgery	Gastroenterology	Gynecology	Internal medicine	Pulmonology	Neurology	Other	Urologie	Obstetrics
1	0,3655	0,3076	0,2000	0,2323	0,2279	0,2169	0,3281	0,3201	0,2305
2	0,4757	0,4648	0,4176	0,4207	0,4439	0,3828	0,4762	0,4460	0,4049
3	0,4587	0,4358	0,4003	0,4340	0,4343	0,3755	0,4505	0,4282	0,4026
4	0,4614	0,4381	0,3985	0,4352	0,4350	0,3801	0,4448	0,4281	0,4027
5	0,4594	0,4378	0,3992	0,4361	0,4355	0,3765	0,4494	0,4320	0,4039
6	0,3751	0,3094	0,2060	0,2411	0,2330	0,2238	0,3415	0,3203	0,2359
7	0,4763	0,4646	0,4242	0,4116	0,4441	0,4413	0,4637	0,4572	0,4058
8	0,6325	0,4193	0,5794	0,3467	0,4189	0,5396	0,4818	0,4269	0,6093
9	0,6162	0,4112	0,4429	0,5566	0,3946	0,5396	0,4087	0,4542	0,3827
10	0,6528	0,4227	0,4310	0,5867	0,3987	0,5383	0,4086	0,4446	0,3819
11	0,3776	0,3097	0,2111	0,2436	0,2352	0,2242	0,3452	0,3214	0,2421
12	0,4771	0,4644	0,4287	0,4109	0,4441	0,4528	0,4609	0,4575	0,4137
13	0,4708	0,4137	0,4391	0,3354	0,4003	0,5335	0,4274	0,4514	0,3820
14	0,4858	0,4563	0,4587	0,5251	0,5010	0,4822	0,4151	0,5557	0,4283
15	0,5804	0,4051	0,5801	0,5293	0,5011	0,4778	0,4414	0,5104	0,4432
16	0,3776	0,3100	0,2166	0,2506	0,2400	0,2324	0,3524	0,3222	0,2484
17	0,4776	0,4644	0,4267	0,4242	0,4437	0,4527	0,4593	0,4605	0,3883
18	0,6517	0,4164	0,4421	0,3285	0,4075	0,4462	0,4436	0,4521	0,3743
19	0,4922	0,4555	0,4409	0,4360	0,5015	0,4773	0,4379	0,5807	0,6856
20	0,5200	0,4748	0,5492	0,5844	0,4279	0,4969	0,4811	0,4744	0,5435
21	0,3780	0,3102	0,2238	0,2546	0,2409	0,2356	0,3562	0,3227	0,2544
22	0,4749	0,4645	0,4260	0,4622	0,4427	0,4527	0,4590	0,4605	0,4453
23	0,4776	0,4333	0,4430	0,3855	0,4660	0,5478	0,4290	0,4542	0,3712
24	0,4911	0,4344	0,4358	0,4317	0,5711	0,5118	0,5527	0,4789	0,7073
25	0,4807	0,5440	0,5528	0,4576	0,6007	0,5184	0,5340	0,5882	0,6999

Figure A.42: MSE for the department nursing wards (more than one day).

Appendix B

Markov data

B.1 Subdivision and length of time interval

Figures B.1 and B.2 of this section contain respectively the aggregate number of weekly and monthly transitions of transfers of outpatients. The weekly transfers concern the transfers between subspecialisms of surgery, the monthly transfers are between 11 specialisms.

period	IC other	General surgery and surgery for children	Oncology, lung surgery and gastrointensinal surgery	Traumatology and ER	Vascular surgery	other	discharge	Waiting list OR surgery	Waiting list OR other	Total
jan-10	50	19	35	23	13	360	6486	1	24	7011
feb-10	49	11	40	18	23	355	5851		19	6366
mrt-10	58	4	15	4	10	99	6891		27	7108
apr-10	44	16	28	22	14	341	6256	1	43	6765
mei-10	44	16	28	22	14	341	6256	1	43	6765
jun-10	50	20	32	20	34	379	6631		16	7182
jul-10	47	16	23	29	21	246	5566	1	46	5995
aug-10	38	18	34	18	19	315	4921	1	37	5401
sep-10	48	16	40	28	26	347	6429		24	6958
okt-10	36	12	17	23	16	318	5997	1	27	6447
nov-10	41	10	31	22	17	388	6302		16	6827
dec-10	39	3	16	6	8	86	6218			6376
jan-11	42	14	24	29	23	393	6725	4	50	7304
feb-11	48	19	33	35	25	348	5969	4	50	6531
mrt-11	37	12	39	19	25	341	7021	5	18	7517
apr-11	49	12	19	19	23	307	6394	4	32	6859
mei-11	39	10	25	25	22	358	6133	5	20	6637
jun-11	51	24	34	26	25	376	5911	7	45	6499
jul-11	41	13	34	26	22	261	5998	5	32	6432
aug-11	38	5	9	3	6	66	5384	8	34	5553
sep-11	46	18	29	38	22	279	6229	6	40	6707
okt-11	47	15	35	19	24	367	5910		47	6464
nov-11	45	15	37	25	16	384	6399		14	6936
dec-11	40	13	22	20	9	246	6164			6514
mean	44,458	13,792	28,292	21,625	19,042	304,208	6168,375	3,600	32,000	6631,417
sd	5,477	5,073	8,615	8,381	6,805	95,193	464,030	2,444	12,142	493,555
modus	50	16	34	22	23	341	6256	1	24	6765

sd=standard deviation

Figure B.1: The total number of transitions for the subspecialisms of surgery per month and the average, standard deviation and modus for the period 2010-2011.

week	IC other	Cardiology	Surgery	Gastroenterology	Gynaecology	Internal medicine	Pediatrics	Pulmonology	Neurology	Other	Urology	Midwifery	Discharge	Waiting list	Total
2	14	68	121	5	12	86	60	46	36	90	11	27	1345	217	2144
3	3	48	64	5	11	60	36	42	24	55	12	13	1570	214	2163
4	8	40	64	6	9	60	37	21	26	52	11	19	1562	231	2148
5	10	35	73	8	3	59	38	49	11	43	3	18	1631	210	2192
6	6	57	60	10	7	54	36	39	10	64	9	19	1439	186	2000
7	8	50	72	8	10	55	31	33	18	54	18	16	1645	194	2213
8	10	39	76	4	7	47	29	37	20	53	13	18	1627	200	2188
9	4	43	57	4	5	51	43	35	21	39	6	22	1171	207	1713
10	8	36	44	7	4	46	23	38	13	57	10	11	1607	242	2148
11	11	43	66	2	5	56	36	26	12	43	6	17	1478	217	2018
12	6	46	72	6	10	57	33	23	13	54	8	25	1630	209	2197
13	6	33	71	7	5	55	46	32	10	37	12	25	1628	192	2165
14	6	42	69	1	13	52	34	24	12	40	11	15	1535	194	2048
15	7	30	59	10	5	38	42	25	19	44	7	21	1313	192	1813
16	7	31	84	5	11	43	33	24	19	60	8	16	1506	205	2053
17	9	35	68	7	7	40	32	29	18	50	8	17	1535	236	2091
18	4	44	49	4	3	55	21	31	10	62	8	17	1402	249	1965
19	2	33	49	4	2	47	29	28	14	34	7	20	1028	228	1527
20	2	39	52	7	3	48	25	31	17	28	7	24	1071	222	1578
21	5	25	72	7	7	39	28	21	14	50	8	22	1493	241	2035
22	7	39	83	9	7	46	25	29	12	47	7	29	1377	220	1940
23	7	35	77	5	10	49	28	25	13	43	8	25	1580	234	2146
24	4	44	88	7	12	45	52	24	18	46	8	44	1483	245	2122
25	10	37	70	7	8	45	46	17	20	44	12	21	1458	227	2022
26	7	37	78	4	9	43	42	12	16	52	23	5	1492	215	2041
27	8	41	63	3	6	43	31	26	13	65	4	25	1530	210	2070
28	10	39	72	6	5	43	36	27	16	50	8	21	1482	185	2000
29	4	28	65	10	1	50	23	20	18	34	8	16	1267	174	1720
30	3	23	58	7		34	27	15	13	44	5	15	1190	183	1619
31	15	26	70	13	2	38	16	22	19	31	5	13	1055	169	1496
32	8	22	59	12	2	39	16	22	16	31	9	20	968	175	1399
33	5	22	48	6	6	27	16	26	12	36	9	16	1007	181	1418
34	3	29	58	5	5	33	15	17	12	33	6	17	1083	193	1514
35	7	25	78	11	7	47	20	23	16	46	11	14	1357	220	1882
36	8	29	53	29	18	14	51	7	10	6	2	23	1382	252	1884
37	10	24	80	4	8	45	23	29	10	56	10	20	1451	252	2026
38	6	31	90	8	7	34	22	21	23	49	4	16	1512	257	2085
39	4	32	59	8	7	38	28	27	19	57	7	25	1518	242	2072
40	14	28	54	5	10	39	27	27	31	59	7	23	1498	249	2071
41	3	36	59	9	9	44	23	25	20	59	8	14	1380	239	1932
42	2	38	52	5	7	38	28	20	12	67	8	12	1512	236	2041
43	5	40	50	7	10	37	21	24	21	52	3	17	1520	239	2046
44	8	28	50	4	7	39	30	26	19	57	7	11	1197	225	1708
45	8	39	51	2	13	46	27	31	21	72	9	12	1466	246	2047
46	4	49	60	4	4	41	18	18	12	56	5	11	1440	249	1977
47	6	38	43	6	10	38	16	17	16	49	10	12	1436	242	1940
48	9	46	50	4	7	46	26	24	15	59	9	20	1466	224	2005
49	8	41	67	7	5	42	26	18	21	57	13	22	1478	187	1993
50	8	36	67	7	11	47	21	17	18	49	5	25	1527	153	1995
51	5	43	61	4	6	43	24	17	14	56	9	22	1510	93	1908
52	9	56	31	31	12	38	22	5	21	2	19	2	1186	50	1485
mean	6,882	37,216	64,431	7,176	7,400	45,078	29,765	25,333	16,745	48,490	8,647	18,627	1412,235	210,824	1941,235
sd	3,031	9,388	14,765	5,290	3,452	10,365	10,071	8,653	5,336	14,614	3,872	6,560	180,694	38,474	224,223
modus	8	39	72	7	7	38	36	24	12	57	8	25	1478	242	2148

sd= standard deviation

Figure B.2: The total number of transitions for 11 specialisms per week and the average, standard deviation and modus for the period 2010.

B.2 Markov property, homogeneity and limiting probabilities

Figure B.3 shows an example for the computation of the M^{n+m}-transition probabilities of transfers of outpatients. For computing these probabilities, we use the Chapman-Kolmogorov equations. In Figure B.4 there is an example for the M^{n+m}-transition probabilities of transfer of inpatients.[1]

Both examples deal with the subdivision into subspecialisms of surgery. The first example regards all realizations of the transition probabilities that an inpatient transfers from the state 'other' to the state 'discharge'. The second example deals with all realizations of the transfers of inpatients, treated by the 'other part of the hospital', to the state 'discharge'.

On top of the figure, one sees the different realizations of the monthly one step transition probabilities. Next, the 2-transition, 4-transition, 8-transition, 16-transition and 32-transition probabilities realizations, are provided.

[1] More data is available digitally.

	jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec	max norm	difference
	81,83%	85,31%	77,47%	86,83%	70,78%	80,47%	82,86%	83,64%	82,84%	83,89%	82,71%	85,93%	11,27%	not ok
two step	1	2	3	4	5	6	7	8	9	10	11	12	max norm	difference
1	66,97%	69,82%	63,40%	71,06%	57,92%	65,85%	67,81%	68,45%	67,79%	68,65%	67,68%	70,32%	9,22%	not ok
2	69,82%	72,78%	66,09%	74,08%	60,38%	68,65%	70,69%	71,36%	70,67%	71,57%	70,56%	73,31%	9,61%	not ok
3	63,40%	66,09%	60,02%	67,27%	54,83%	62,34%	64,20%	64,80%	64,17%	64,99%	64,07%	66,57%	8,73%	not ok
4	71,06%	74,08%	67,27%	75,40%	61,46%	69,87%	71,95%	72,63%	71,93%	72,84%	71,82%	74,61%	9,79%	not ok
5	57,92%	60,38%	54,83%	61,46%	50,09%	56,95%	58,65%	59,20%	58,63%	59,37%	58,54%	60,82%	7,98%	not ok
6	65,85%	68,65%	62,34%	69,87%	56,95%	64,75%	66,68%	67,30%	66,65%	67,50%	66,55%	69,14%	9,07%	not ok
7	67,81%	70,69%	64,20%	71,95%	58,65%	66,68%	68,66%	69,31%	68,64%	69,51%	68,53%	71,20%	9,34%	not ok
8	68,45%	71,36%	64,80%	72,63%	59,20%	67,30%	69,31%	69,96%	69,29%	70,17%	69,18%	71,87%	9,43%	not ok
9	67,79%	70,67%	64,17%	71,93%	58,63%	66,65%	68,64%	69,29%	68,62%	69,49%	68,51%	71,18%	9,34%	not ok
10	68,65%	71,57%	64,99%	72,84%	59,37%	67,50%	69,51%	70,17%	69,49%	70,37%	69,38%	72,08%	9,45%	not ok
11	67,68%	70,56%	64,07%	71,82%	58,54%	66,55%	68,53%	69,18%	68,51%	69,38%	68,41%	71,07%	9,32%	not ok
12	70,32%	73,31%	66,57%	74,61%	60,82%	69,14%	71,20%	71,87%	71,18%	72,08%	71,07%	73,83%	9,68%	not ok
four step	1	2	3	4	5	6	7	8	9	10	11	12	max norm	niet ok
1	44,85%	46,75%	42,46%	47,59%	38,79%	44,10%	45,41%	45,84%	45,40%	45,97%	45,33%	47,09%	6,18%	niet ok
2	48,74%	50,81%	46,14%	51,72%	42,16%	47,93%	49,36%	49,82%	49,34%	49,96%	49,26%	51,18%	6,71%	niet ok
3	40,19%	41,90%	38,05%	42,65%	34,76%	39,52%	40,70%	41,08%	40,69%	41,20%	40,62%	42,20%	5,54%	niet ok
4	50,49%	52,64%	47,80%	53,58%	43,67%	49,65%	51,13%	51,61%	51,11%	51,76%	51,03%	53,02%	6,95%	niet ok
5	33,55%	34,97%	31,76%	35,59%	29,01%	32,99%	33,97%	34,29%	33,96%	34,39%	33,90%	35,22%	4,62%	ok
6	43,36%	45,20%	41,05%	46,01%	37,50%	42,63%	43,91%	44,32%	43,89%	44,45%	43,82%	45,53%	5,97%	niet ok
7	45,98%	47,94%	43,53%	48,79%	39,77%	45,21%	46,56%	47,00%	46,55%	47,14%	46,47%	48,28%	6,33%	niet ok
8	46,85%	48,85%	44,36%	49,72%	40,52%	46,07%	47,44%	47,89%	47,43%	48,03%	47,35%	49,20%	6,45%	niet ok
9	45,95%	47,91%	43,50%	48,76%	39,74%	45,18%	46,53%	46,97%	46,51%	47,10%	46,44%	48,25%	6,33%	niet ok
10	47,12%	49,13%	44,61%	50,00%	40,76%	46,34%	47,72%	48,17%	47,70%	48,31%	47,63%	49,48%	6,49%	niet ok
11	45,81%	47,76%	43,37%	48,61%	39,62%	45,04%	46,39%	46,82%	46,37%	46,96%	46,30%	48,10%	6,31%	niet ok
12	49,44%	51,55%	46,81%	52,46%	42,76%	48,62%	50,07%	50,54%	50,05%	50,68%	49,97%	51,92%	6,81%	niet ok
average	45,31%													
8-step	1	2	3	4	5	6	7	8	9	10	11	12	max norm	niet ok
1	20,11%	20,97%	19,04%	21,34%	17,40%	19,78%	20,37%	20,56%	20,36%	20,62%	20,33%	21,12%	2,77%	ok
2	23,76%	24,77%	22,49%	25,21%	20,55%	23,36%	24,06%	24,28%	24,05%	24,35%	24,01%	24,95%	3,27%	ok
3	16,16%	16,84%	15,29%	17,14%	13,97%	15,88%	16,36%	16,51%	16,35%	16,56%	16,33%	16,96%	2,22%	ok
4	25,49%	26,58%	24,14%	27,05%	22,05%	25,07%	25,82%	26,06%	25,81%	26,13%	25,77%	26,77%	3,51%	ok
5	11,25%	11,73%	10,65%	11,94%	9,73%	11,07%	11,40%	11,50%	11,39%	11,54%	11,37%	11,82%	1,55%	ok
6	18,80%	19,60%	17,80%	19,95%	16,26%	18,49%	19,04%	19,22%	19,03%	19,27%	19,00%	19,74%	2,59%	ok
7	21,14%	22,04%	20,02%	22,44%	18,29%	20,79%	21,41%	21,61%	21,40%	21,67%	21,37%	22,20%	2,91%	ok
8	21,95%	22,89%	20,78%	23,29%	18,99%	21,59%	22,23%	22,44%	22,22%	22,50%	22,19%	23,05%	3,02%	ok
9	21,12%	22,01%	19,99%	22,41%	18,26%	20,76%	21,38%	21,58%	21,37%	21,65%	21,34%	22,17%	2,91%	ok
10	22,21%	23,15%	21,02%	23,56%	19,21%	21,84%	22,49%	22,70%	22,48%	22,76%	22,44%	23,32%	3,06%	ok
11	20,99%	21,88%	19,87%	22,27%	18,15%	20,64%	21,25%	21,45%	21,24%	21,51%	21,21%	22,04%	2,89%	ok
12	24,45%	25,49%	23,14%	25,94%	21,14%	24,04%	24,76%	24,99%	24,75%	25,06%	24,71%	25,67%	3,37%	ok
gemiddel	20,67%													
16-step	1	2	3	4	5	6	7	8	9	10	11	12	max norm	niet ok
1	4,05%	4,22%	3,83%	4,29%	3,50%	3,98%	4,10%	4,14%	4,10%	4,15%	4,09%	4,25%	0,56%	ok
2	5,64%	5,88%	5,34%	5,99%	4,88%	5,55%	5,72%	5,77%	5,71%	5,79%	5,70%	5,93%	0,78%	ok
3	2,61%	2,72%	2,47%	2,77%	2,26%	2,57%	2,64%	2,67%	2,64%	2,68%	2,64%	2,74%	0,36%	ok
4	6,50%	6,78%	6,15%	6,90%	5,62%	6,39%	6,58%	6,64%	6,58%	6,66%	6,57%	6,82%	0,90%	ok
5	1,27%	1,32%	1,20%	1,34%	1,10%	1,25%	1,28%	1,29%	1,28%	1,30%	1,28%	1,33%	0,17%	ok
6	3,53%	3,68%	3,35%	3,75%	3,06%	3,48%	3,58%	3,61%	3,58%	3,62%	3,57%	3,71%	0,49%	ok
7	4,47%	4,66%	4,23%	4,74%	3,87%	4,40%	4,53%	4,57%	4,53%	4,58%	4,52%	4,69%	0,62%	ok
8	4,82%	5,02%	4,56%	5,11%	4,17%	4,74%	4,88%	4,93%	4,88%	4,94%	4,87%	5,06%	0,66%	ok
9	4,46%	4,65%	4,22%	4,73%	3,86%	4,38%	4,52%	4,56%	4,51%	4,57%	4,51%	4,68%	0,61%	ok
10	4,93%	5,14%	4,67%	5,23%	4,27%	4,85%	4,99%	5,04%	4,99%	5,06%	4,98%	5,18%	0,68%	ok
11	4,40%	4,59%	4,17%	4,67%	3,81%	4,33%	4,46%	4,50%	4,46%	4,51%	4,45%	4,62%	0,61%	ok
12	5,98%	6,23%	5,66%	6,34%	5,17%	5,88%	6,05%	6,11%	6,05%	6,13%	6,04%	6,28%	0,82%	ok
average	4,40%													
max	6,90%													
min	1,10%													
32 step	1	2	3	4	5	6	7	8	9	10	11	12	max norm	difference
1	0,16%	0,17%	0,15%	0,17%	0,14%	0,16%	0,17%	0,17%	0,17%	0,17%	0,17%	0,17%	0,02%	ok
2	0,32%	0,33%	0,30%	0,34%	0,28%	0,31%	0,32%	0,33%	0,32%	0,33%	0,32%	0,33%	0,04%	ok
3	0,07%	0,07%	0,06%	0,07%	0,06%	0,07%	0,07%	0,07%	0,07%	0,07%	0,07%	0,07%	0,01%	ok
4	0,42%	0,44%	0,40%	0,45%	0,37%	0,42%	0,43%	0,43%	0,43%	0,43%	0,43%	0,44%	0,06%	ok
5	0,02%	0,02%	0,02%	0,02%	0,01%	0,02%	0,02%	0,02%	0,02%	0,02%	0,02%	0,02%	0,00%	ok
6	0,12%	0,13%	0,12%	0,13%	0,11%	0,12%	0,13%	0,13%	0,13%	0,13%	0,13%	0,13%	0,02%	ok
7	0,20%	0,21%	0,19%	0,21%	0,17%	0,20%	0,20%	0,20%	0,20%	0,20%	0,20%	0,21%	0,03%	ok
8	0,23%	0,24%	0,22%	0,25%	0,20%	0,23%	0,24%	0,24%	0,24%	0,24%	0,23%	0,24%	0,03%	ok
9	0,20%	0,21%	0,19%	0,21%	0,17%	0,20%	0,20%	0,20%	0,20%	0,20%	0,20%	0,21%	0,03%	ok
10	0,24%	0,25%	0,23%	0,26%	0,21%	0,24%	0,25%	0,25%	0,25%	0,25%	0,25%	0,26%	0,03%	ok
11	0,19%	0,20%	0,18%	0,21%	0,17%	0,19%	0,20%	0,20%	0,20%	0,20%	0,20%	0,20%	0,03%	ok
12	0,36%	0,37%	0,34%	0,38%	0,31%	0,35%	0,36%	0,37%	0,36%	0,37%	0,36%	0,38%	0,05%	ok
average	0,21%													
max	0,45%													
min	0,01%													

Figure B.3: An example of Markov limiting probabilities, Markov property and homogeneity for the transfer of outpatients. The Chapman-Kolmogorov equations are computed for $2, 34, 8, 16$ and 32-transition probabilities for the first month. The example concerns the transfer from the state 'other' to the state 'discharge' for outpatients who did not underwent an operation.

	jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec	max norm difference	
	98,31%	97,85%	99,04%	96,90%	99,83%	96,50%	97,69%	95,11%	96,60%	97,19%	96,36%	99,69%	2,48%	ok
two step	1	2	3	4	5	6	7	8	9	10	11	12	max norm difference	
1	96,64%	96,19%	97,36%	95,26%	98,14%	94,86%	96,03%	93,50%	94,96%	95,55%	94,73%	98,00%	2,44%	ok
2	96,19%	95,74%	96,91%	94,82%	97,68%	94,42%	95,59%	93,06%	94,52%	95,10%	94,29%	97,55%	2,43%	ok
3	97,36%	96,91%	98,08%	95,97%	98,87%	95,57%	96,75%	94,19%	95,67%	96,26%	95,44%	98,73%	2,45%	ok
4	95,26%	94,82%	95,97%	93,90%	96,74%	93,51%	94,66%	92,16%	93,60%	94,18%	93,38%	96,60%	2,40%	ok
5	98,14%	97,68%	98,87%	96,74%	99,66%	96,34%	97,52%	94,95%	96,43%	97,03%	96,20%	99,52%	2,47%	ok
6	94,86%	94,42%	95,57%	93,51%	96,34%	93,12%	94,27%	91,78%	93,22%	93,79%	92,99%	96,20%	2,39%	ok
7	96,03%	95,59%	96,75%	94,66%	97,52%	94,27%	95,43%	92,91%	94,36%	94,94%	94,14%	97,39%	2,42%	ok
8	93,50%	93,06%	94,19%	92,16%	94,95%	91,78%	92,91%	90,46%	91,87%	92,44%	91,65%	94,82%	2,36%	ok
9	94,96%	94,52%	95,67%	93,60%	96,43%	93,22%	94,36%	91,87%	93,31%	93,88%	93,08%	96,30%	2,39%	ok
10	95,55%	95,10%	96,26%	94,18%	97,03%	93,79%	94,94%	92,44%	93,88%	94,46%	93,66%	96,89%	2,41%	ok
11	94,73%	94,29%	95,44%	93,38%	96,20%	92,99%	94,14%	91,65%	93,08%	93,66%	92,86%	96,07%	2,39%	ok
12	98,00%	97,55%	98,73%	96,60%	99,52%	96,20%	97,39%	94,82%	96,30%	96,89%	96,07%	99,39%	2,47%	ok
gemiddel	95,24%													
four step	1	2	3	4	5	6	7	8	9	10	11	12	max norm difference	
1	93,39%	92,96%	94,09%	92,06%	94,84%	91,68%	92,80%	90,36%	91,77%	92,33%	91,55%	94,71%	2,35%	ok
2	92,53%	92,10%	93,21%	91,20%	93,96%	90,83%	91,94%	89,52%	90,92%	91,48%	90,70%	93,83%	2,33%	ok
3	94,79%	94,35%	95,49%	93,43%	96,26%	93,05%	94,19%	91,71%	93,14%	93,71%	92,91%	96,12%	2,39%	ok
4	90,74%	90,32%	91,42%	89,44%	92,15%	89,08%	90,17%	87,79%	89,16%	89,71%	88,95%	92,02%	2,29%	ok
5	96,31%	95,87%	97,03%	94,94%	97,81%	94,55%	95,71%	93,18%	94,64%	95,22%	94,41%	97,67%	2,43%	ok
6	89,99%	89,58%	90,66%	88,71%	91,39%	88,34%	89,43%	87,07%	88,43%	88,97%	88,22%	91,26%	2,27%	ok
7	92,22%	91,79%	92,91%	90,90%	93,65%	90,53%	91,64%	89,22%	90,62%	91,18%	90,40%	93,52%	2,33%	ok
8	87,42%	87,01%	88,07%	86,17%	88,78%	85,81%	86,87%	84,58%	85,90%	86,43%	85,69%	88,65%	2,20%	ok
9	90,17%	89,75%	90,84%	88,89%	91,57%	88,52%	89,61%	87,24%	88,61%	89,15%	88,39%	91,45%	2,27%	ok
10	91,29%	90,86%	91,97%	89,98%	92,71%	89,61%	90,71%	88,32%	89,70%	90,26%	89,49%	92,58%	2,30%	ok
11	89,74%	89,32%	90,41%	88,46%	91,13%	88,09%	89,17%	86,82%	88,18%	88,72%	87,97%	91,00%	2,26%	ok
12	96,05%	95,60%	96,76%	94,67%	97,54%	94,28%	95,44%	92,92%	94,38%	94,96%	94,15%	97,40%	2,42%	ok
gemiddel	91,38%													
8 step	1	2	3	4	5	6	7	8	9	10	11	12	max norm difference	
1	87,22%	86,81%	87,87%	85,97%	88,57%	85,62%	86,67%	84,38%	85,70%	86,23%	85,50%	88,45%	2,20%	ok
2	85,61%	85,21%	86,25%	84,39%	86,94%	84,04%	85,07%	82,83%	84,12%	84,64%	83,92%	86,82%	2,16%	ok
3	89,84%	89,43%	90,51%	88,56%	91,24%	88,19%	89,28%	86,92%	88,28%	88,83%	88,07%	91,11%	2,27%	ok
4	82,34%	81,96%	82,95%	81,16%	83,62%	80,83%	81,82%	79,66%	80,91%	81,41%	80,71%	83,50%	2,08%	ok
5	92,76%	92,33%	93,45%	91,44%	94,20%	91,06%	92,18%	89,75%	91,15%	91,71%	90,93%	94,07%	2,34%	ok
6	80,99%	80,61%	81,59%	79,83%	82,25%	79,50%	80,48%	78,36%	79,58%	80,07%	79,39%	82,13%	2,04%	ok
7	85,05%	84,65%	85,68%	83,83%	86,37%	83,49%	84,51%	82,28%	83,57%	84,08%	83,37%	86,25%	2,14%	ok
8	76,42%	76,07%	76,99%	75,33%	77,61%	75,02%	75,94%	73,94%	75,09%	75,56%	74,91%	77,50%	1,93%	ok
9	81,31%	80,94%	81,92%	80,15%	82,58%	79,82%	80,80%	78,67%	79,90%	80,39%	79,71%	82,46%	2,05%	ok
10	83,34%	82,95%	83,96%	82,15%	84,63%	81,81%	82,81%	80,63%	81,89%	82,39%	81,69%	84,51%	2,10%	ok
11	80,53%	80,16%	81,13%	79,38%	81,78%	79,05%	80,02%	77,91%	79,13%	79,62%	78,94%	81,67%	2,03%	ok
12	92,25%	91,82%	92,93%	90,93%	93,68%	90,55%	91,67%	89,25%	90,64%	91,20%	90,42%	93,55%	2,33%	ok
gemiddel	84,19%													
16 step	1	2	3	4	5	6	7	8	9	10	11	12	max norm difference	
1	76,07%	75,72%	76,64%	74,98%	77,25%	74,67%	75,59%	73,60%	74,75%	75,21%	74,57%	77,14%	1,92%	ok
2	73,29%	72,95%	73,84%	72,24%	74,43%	71,95%	72,83%	70,91%	72,02%	72,46%	71,84%	74,33%	1,85%	ok
3	80,72%	80,34%	81,32%	79,56%	81,97%	79,24%	80,21%	78,09%	79,32%	79,80%	79,12%	81,86%	2,04%	ok
4	67,80%	67,48%	68,30%	66,83%	68,85%	66,55%	67,37%	65,59%	66,62%	67,03%	66,46%	68,75%	1,71%	ok
5	86,05%	85,65%	86,69%	84,82%	87,39%	84,47%	85,51%	83,25%	84,56%	85,08%	84,35%	87,26%	2,17%	ok
6	65,59%	65,29%	66,08%	64,65%	66,61%	64,39%	65,18%	63,46%	64,45%	64,85%	64,29%	66,52%	1,65%	ok
7	72,33%	71,99%	72,87%	71,30%	73,45%	71,00%	71,88%	69,98%	71,07%	71,51%	70,90%	73,35%	1,82%	ok
8	58,40%	58,13%	58,84%	57,57%	59,31%	57,33%	58,04%	56,50%	57,39%	57,74%	57,25%	59,23%	1,47%	ok
9	66,12%	65,81%	66,61%	65,17%	67,14%	64,90%	65,70%	63,97%	64,97%	65,37%	64,81%	67,05%	1,67%	ok
10	69,45%	69,13%	69,97%	68,46%	70,53%	68,17%	69,01%	67,19%	68,24%	68,66%	68,08%	70,43%	1,75%	ok
11	64,85%	64,55%	65,33%	63,92%	65,86%	63,66%	64,44%	62,74%	63,72%	64,12%	63,57%	65,77%	1,63%	ok
12	85,09%	84,70%	85,73%	83,88%	86,42%	83,53%	84,56%	82,33%	83,62%	84,13%	83,41%	86,30%	2,15%	ok
gemiddel	71,62%													
max	87,39%													
min	56,50%													
32 step	1	2	3	4	5	6	7	8	9	10	11	12	max norm difference	
1	57,87%	57,60%	58,30%	57,04%	58,77%	56,80%	57,50%	55,99%	56,86%	57,21%	56,72%	58,68%	1,46%	ok
2	53,72%	53,47%	54,12%	52,95%	54,55%	52,73%	53,38%	51,97%	52,78%	53,11%	52,66%	54,47%	1,35%	ok
3	65,15%	64,85%	65,64%	64,22%	66,17%	63,96%	64,74%	63,04%	64,02%	64,42%	63,87%	66,07%	1,64%	ok
4	45,97%	45,75%	46,31%	45,31%	46,68%	45,12%	45,68%	44,47%	45,17%	45,45%	45,06%	46,61%	1,16%	ok
5	74,05%	73,70%	74,60%	72,99%	75,20%	72,69%	73,58%	71,64%	72,76%	73,21%	72,58%	75,09%	1,87%	ok
6	43,02%	42,82%	43,34%	42,41%	43,69%	42,23%	42,75%	41,62%	42,27%	42,53%	42,17%	43,63%	1,08%	ok
7	52,32%	52,07%	52,71%	51,57%	53,13%	51,36%	51,99%	50,62%	51,41%	51,72%	51,28%	53,05%	1,32%	ok
8	34,11%	33,95%	34,36%	33,62%	34,64%	33,48%	33,89%	33,00%	33,52%	33,72%	33,44%	34,59%	0,86%	ok
9	43,72%	43,51%	44,04%	43,09%	44,39%	42,91%	43,44%	42,29%	42,96%	43,22%	42,85%	44,33%	1,10%	ok
10	48,23%	48,01%	48,59%	47,54%	48,98%	47,35%	47,93%	46,66%	47,39%	47,69%	47,28%	48,91%	1,22%	ok
11	42,06%	41,86%	42,37%	41,45%	42,71%	41,28%	41,79%	40,69%	41,33%	41,58%	41,23%	42,65%	1,06%	ok
12	72,41%	72,07%	72,95%	71,38%	73,54%	71,08%	71,96%	70,06%	71,15%	71,59%	70,98%	73,43%	1,83%	ok
gemiddel	52,33%													
max	58,77%													
min	33,00%													

Figure B.4: An example of Markov limiting probabilities, Markov property and homogeneity for the transfer of inpatients. The Chapman-Kolmogorov equations are computed for $2, 34, 8, 16$ and 32-transition probabilities for the first month. The example is for a patient transfer from the state 'other' to the state 'discharge' for inpatients who underwent an operation.

Appendix C

Service times

This appendix contains the results of the average service times for the different specialisms. The average service times are given for clinical admissions in nursing wards (one day and more than one day) per DBC and for the operations, also per DBC. Figures C.1-C.3 provide means, standard deviations and frequencies per DBC for the operations. Figures C.4-C.8 contain means, standard deviations and frequencies per DBC for the admissions to nursing wards. The data is from 2011.

DBC	Dutch name	Number	Average time	Standard deviation
000	Traject	4	0:18:00	0:00:05
003	Kortd conserv(mede)oeh, littek	2	0:52:30	0:00:18
006	Anal buikklachten zd	2	0:26:00	0:00:01
01	Acneiforme dermatosen	2	0:48:00	0:00:24
011	Verw nt FG,tr/trc<1%kl necr.tom	2	0:42:00	0:00:07
012	Verw nt FG,tr/trt-3%/-<1%grnecr	16	0:49:41	0:00:25
013	Verw nt FG,tr/tr>3%/1-3%necr.t	15	0:50:12	0:00:14
014	Verwond FG>3%/gr gelaatstrauma	10	1:23:24	0:01:46
015	Verw,vrij/ax-lap/gelaatstrauma	1	2:46:00	0:00:00
02	trauma capitis / aangezicht	1	0:13:00	0:00:00
023	H def wo FG>3%/sl def ax lap	1	1:12:00	0:00:00
027	Herst def Tissue Expander(s)	1	0:51:00	0:00:00
03	overige	1	0:06:00	0:00:00
037	Nacorr ax/vrije lap na bovenst	6	1:33:40	0:00:48
041	Mechanisch/discogeen cervicaal	1	0:05:00	0:00:00
042	Neurogeen cervicaal	2	0:35:00	0:00:08
043	Sympatalgiform cervicaal	4	0:18:15	0:00:01
044	(chron)Degen. cervicaal	4	0:19:00	0:00:02
063	Sympatalgiform thoracaal	1	0:26:00	0:00:00
064	Combi mechan/neurogeen thorac	1	0:20:00	0:00:00
071	Mech./discogene lage rugklacht	26	0:16:30	0:00:12
072	Neurogene lage rugklacht	21	0:10:34	0:00:01
073	Sympatalgiforme lage rugklacht	14	0:09:13	0:00:00
074	(chron) Degen. lage rugklacht	71	0:11:03	0:00:05
080	Sacraal pijnsyndroom	11	0:09:49	0:00:01
090	Coccygodynie	1	0:14:00	0:00:00
10	(bij)Niertumor	56	4:05:51	0:05:20
100	Pijn bij maligniteit	2	0:40:00	0:00:01
101	Halscyste lat / med	7	1:07:17	0:00:28
103	Jicht (artritis urica)	1	0:16:00	0:00:00
11	Niersteen	95	1:52:04	0:05:24
110	Ischaem pijn a/d extremiteiten	1	0:17:00	0:00:00
111	Acute buik (peritonitis)	70	1:41:07	0:01:11
112	Juveniele Idiopath Artritis	1	0:20:00	0:00:00
1120	Benigne skelet	17	0:46:21	0:00:12
113	Appendicitis	340	1:07:36	0:00:23
1130	Benigne weke delen	15	0:33:24	0:00:03
1140	Maligne skelet	3	2:33:20	0:03:11
115	Abces perianaal	117	0:29:46	0:00:05
116	Fissuur en fistel ano-rectaal	218	0:36:15	0:00:08
117	hemorroiden	126	0:37:20	0:00:07
12	Cerum,rad.holte,ot ext,corp al	61	1:05:48	0:02:05
120	Hernia diaphragmatica	21	2:12:00	0:06:30
121	Hernia femoralis/inguinalis	611	1:11:49	0:00:19
123	Hernia umbilicalis / epigastr	135	1:09:10	0:00:29
124	Hernia cicatricalis	123	1:47:54	0:03:48
126	Pylorospasme	2	1:14:30	0:00:04
127	sinus pilonidalis	128	0:41:07	0:00:11
129	Overige (buik)kl algemeen	29	1:23:35	0:01:47
13	OMA, OME, tubadysfunctie	406	0:09:54	0:00:02
130	Perifere zenuwpijn (incl PHN)	15	0:07:20	0:00:01
1301	Arthr/spondylos thora/lumb wk	5	1:47:00	0:04:25
1302	Spondl/osteomyel thora/lumb wk	2	0:10:00	0:00:04
1303	Tumoren NSCLC	1	1:02:00	0:00:00
1304	Tumoren SCLC	1	0:52:00	0:00:00
131	bleph.plast,onder/bov enk/dubz	15	0:57:48	0:00:14
132	Carpaal tunnel syndroom	14	0:28:30	0:00:02
133	Epicondylitis med / lateralis	6	0:56:40	0:00:31
134	Tendovaginitis stenosans,M.Que	14	0:36:17	0:00:16
1350	Kanaal stenose	84	1:27:14	0:00:14
136	Ooglidreconstructie	2	0:53:00	0:00:00
1365	Failed back surgery syndroom	3	2:56:00	0:00:24
1370	Spondylolysis/Isthesis	32	3:14:04	0:01:04
1392	Scoliose	9	3:58:00	0:01:21
1396	Posttrau afw thora/lumbale wk	1	0:56:00	0:00:00
1397	Aangeb afw thoracale/lumb wk	1	0:57:00	0:00:00
14	Chronische otitis media	208	1:32:11	0:02:19
140	Fantoom pijn	2	0:29:00	0:00:00
1401	Arthrosis schouderg/bovenarm	136	1:10:12	0:01:14
1402	Arthr/osteomye schouderg/b.arm	4	1:00:15	0:00:27
1403	Loslat/inf/mal proth sch/b.arm	9	1:31:07	0:00:18
1404	Avasculaire necrose sch/b.arm	2	0:51:30	0:00:05
141	Bursitis prepatellaris	7	0:40:26	0:00:06
1450	Tendinitis supraspin/biceps	434	0:51:30	0:00:25
1460	Rupt rotator cuff /bicepspees	137	1:13:00	0:00:28
1470	Frozen shoulder	82	0:17:04	0:00:10
1480	AC en SC afwijking	71	0:47:46	0:00:08
1495	Instabiliteit:Schouderg/b.arm	73	1:23:00	0:00:22
1496	Posttrauma afw sch/b.arm	2	1:27:00	0:01:24
1497	Aangeboren afw sch/b.arm	4	0:32:45	0:00:09
1499	Nno schoudergordel/bovenarm	2	0:51:30	0:00:01
15	Overige nierpathologie	33	1:15:15	0:01:11
150	Complex regionaal pijnsyndr	7	0:38:09	0:00:15
1501	Arthrosis elleboog/onderarm	5	0:59:12	0:00:34
1503	Losl/inf/mal proth elleb/o.arm	1	0:25:00	0:00:00
1504	Corp lib/ostchondr elleb/o.arm	9	1:00:13	0:00:16
152	Corr benige+kraakbenige skelet	1	3:49:00	0:00:00
154	Rhinophyma shaving of laser	1	1:07:00	0:00:00
1550	Bursitis olecrani	7	0:35:17	0:00:01
1560	Epicondylitis lateral/medialis	42	0:35:39	0:00:06
159	Kl bew.app nno(surmen,PHS etc)	15	0:37:24	0:00:05
1596	Posttraum afw elleb/o.arm	8	1:00:07	0:00:50
16	Perceptieves slechthorendheid	1	1:01:00	0:00:00
160	Lokale inf huid en subcutis	94	0:50:26	0:12:09
1601	Arthrosis hand/pols	20	0:58:48	0:00:25
1602	Arthrit/ostmyelitis hand/pols	2	0:29:00	0:00:00
161	Panaritium	16	0:37:19	0:00:03
162	Corr oorskelet enk-/dubbelz	12	1:26:25	0:00:04
1620	Ganglion pols	8	0:30:15	0:00:03
163	Abces weke delen	117	0:35:03	0:00:27
1630	Carpaal tunnel syndroom	21	0:31:49	0:00:08
1650	Tendovaginitis	68	0:27:27	0:00:03
1695	Instabiliteit hand/pols	10	0:50:12	0:00:26
1696	Posttrauma afw hand/pols	8	1:05:53	0:00:24
1697	Aangeboren afw hand/pols	2	0:31:30	0:00:00
170	Ganglion,gr lipoom,ung incarn	253	0:48:33	0:02:55
1701	Arthrosis bekken/heup/b.been	611	1:25:00	0:00:24
1702	Pneumothorax	5	1:04:48	0:00:23
1703	Los/inf/mal pr bek/heup/b.been	141	1:45:46	0:02:18
1704	Avasc necrose bek/heup/b.been	4	2:14:00	0:01:20
171	Naevus,klein lipoom,atheroom	23	0:48:55	0:00:30
1710	Chronische bursitis	66	0:59:55	0:00:19
173	Palatorafia ant/post/ totalis	1	1:57:00	0:00:00
174	Retentio testis/torsio testis	7	1:36:34	0:00:36
175	Vasectomie	1	0:27:00	0:00:00
1750	Congenitale dysplasie/luxatie	6	1:45:30	0:01:39
176	Phimosis, preputium afw.	1	0:36:00	0:00:00
1760	Strid/Ingte afw bek/heup/b.been	7	1:10:43	0:00:25
179	overige algemene diagnoses	10	0:42:30	0:00:27
1796	Posttraum afw bek/heup/b.been	6	1:29:00	0:00:29
1797	Aangeb afw bek/heup/b.been	5	0:39:48	0:00:09
18	hydronefrose overig	23	1:05:13	0:01:17
180	Herpes zoster acuta	1	1:11:00	0:00:00
1801	Arthrosis knie	861	1:13:36	0:00:52
1802	Arthritis knie	46	0:54:39	0:13:39
1803	Losl/inf/malpos proth knie	76	1:25:52	0:01:15
1804	Corpus liberum knie	38	0:37:08	0:00:04
1805	Meniscuslaesie	1621	0:36:43	0:00:08
1810	Collateraal bandlesie	5	1:28:12	0:01:18
1820	Voorste kruisbandlesie	188	1:23:41	0:00:13
1830	Achterste kruisbandlesie	3	0:25:00	0:00:05
1840	Gecombin meniscus/bandlesie	13	0:48:55	0:00:52
1850	Patellofemoraal pijnsyndroom	65	0:30:51	0:00:06
1860	Recidiverende patella luxatie	8	0:55:45	0:00:08
1870	Tendinitis patellae	24	0:45:30	0:06:22
1880	Osteochondritis dissecans	18	0:40:47	0:00:06
1890	Osgood Schlatter	6	0:33:20	0:00:01
1896	Post-traumatische afw: Knie	59	0:31:53	0:00:14
1897	Aangeboren afwijking: Knie	6	0:56:50	0:00:37
1899	N.n.o. knie	9	0:27:00	0:00:05
1910	Compartimentsyndroom	2	0:34:30	0:00:09
1920	Osteomyelitis onderbeen	1	0:26:00	0:00:00
199	Diagnose n.n.o.	4	0:56:45	0:00:31
1996	Posttraumatisch afw onderbeen	3	1:26:40	0:03:02
1997	Aangeboren afw onderbeen	1	0:39:00	0:00:00
20	Uretertumor	9	3:03:07	0:09:51
200	Arthralgie / arthritis	2	0:05:30	0:00:00
2001	Arthrosis enkel en voet	45	1:09:04	0:01:10
2002	Art/ostmyelitis enkel/voet	7	1:21:51	0:02:54
2004	Corpus liberum enkel	9	0:45:47	0:00:05
2006	Achillespees verkorting	12	0:45:40	0:00:35
2010	Exostose voet	50	0:41:56	0:00:04
2015	Impingement enkel	40	0:47:39	0:00:06
2020	OD talus	5	0:53:24	0:00:05
2025	Enthesiopathie	8	0:50:22	0:00:10
203	Wervelkolom	3	0:38:00	0:00:06
2030	Platvt/spreidvt/metatarsalgie	25	0:50:14	0:00:16
2035	Holvoet	1	1:18:00	0:00:00
204	Concomitant scheelzien	65	1:11:35	0:00:22
2040	Klompvoet	9	1:24:13	0:00:47
2045	Mortonse neuralgie	10	0:28:18	0:00:02
205	Clavicula	88	1:20:52	0:00:41
2050	Hallux valgus	121	0:54:01	0:00:13
2055	Hallux rigidus	19	0:53:57	0:00:20
2060	Standafwijking overige tenen	84	0:33:57	0:00:07
207	Humerus proximaal en schacht	68	1:56:49	0:01:30
2070	Rheumatische voet	5	1:06:24	0:01:22
208	Dist humerus / (epi)condyl(en)	59	1:29:11	0:02:06

Figure C.1: Average service times for operations, standard deviations and frequencies, table 1.

DBC	Dutch name	Number	Average time	Standard deviation
209	Olecranon	20	1:12:36	0:00:30
2095	Instabiliteit enkel	13	0:47:51	0:00:04
2096	Posttraum afw enkel en voet	20	0:44:21	0:00:22
2097	Aangeboren afw enkel en voet	34	1:07:21	0:00:43
21	uretersteen	99	1:17:07	0:00:36
210	radiuskop	21	1:06:34	0:00:30
211	Mammareduct,ptos.corr enk/dubz	153	1:38:36	0:02:44
212	Pols	123	1:01:10	0:00:39
2120	Entrapment perifere zenuw	6	0:45:50	0:00:14
213	Gynaecomastie enk/dubbelzijdig	14	1:36:51	0:00:32
2130	Bursitiden, overig	7	0:46:43	0:00:02
214	Metacarpalia	59	1:09:33	0:00:34
2140	Contracturen	2	0:23:00	0:00:00
215	Falangen van de hand	42	0:59:30	0:00:26
2150	Endoprothese controle	1	1:01:00	0:00:00
216	Capsul(ect)omie evt protheses	17	1:27:46	0:01:17
218	Femur, proximaal (+ collum)	305	1:28:33	0:02:37
219	Femur overig	22	1:44:14	0:02:26
220	Patella	9	1:40:07	0:00:38
221	Inbr/vervang prothese,enk/dubz	65	1:40:42	0:01:48
222	Inbr tissue expand,enkz+insufl	81	1:30:18	0:01:11
223	Inbr tissue expand,dubz+insufl	5	2:06:12	0:02:15
224	Enkel	148	1:16:18	0:00:47
23	Urticaria	10	1:09:12	0:02:49
231	Abdom.plastiek,incl nav/fc abd	4	2:05:30	0:03:19
233	Mini-abd.plastiek+/-liposuctie	1	1:08:00	0:00:00
236	Calcaneus	2	3:06:00	0:00:12
237	tarsus	2	1:39:00	0:01:00
238	Metatarsalia	25	1:18:29	0:00:20
239	Falangen van de voet	5	0:47:48	0:00:03
24	Ureterobstructie overig	44	1:36:16	0:15:03
250	Hals	1	0:38:00	0:00:00
252	Knie (incl meniscusletsel)	44	0:52:59	0:00:06
253	Enkel / voet	11	0:50:00	0:00:13
254	artrose nno(schoud,knie,enkel)	2	1:01:30	0:00:03
255	Schouder (humerus)	9	0:43:00	0:01:13
256	Elleboog	10	0:55:06	0:00:45
257	Vinger, incl MCP	3	0:38:00	0:00:01
258	Chalazion/hordeolum	13	0:25:23	0:00:05
259	Overige pathologie oogleden	1	0:19:00	0:00:00
261	Mallet pees, biceps	4	0:41:30	0:00:15
262	achillespees	44	0:53:31	0:00:08
263	Kniebband(en)	1	0:51:00	0:00:00
269	overige rupturen	21	1:19:11	0:00:31
27	Diagnose nno	4	0:26:15	0:00:05
279	Letsel organen buik en bekken	1	1:43:00	0:00:00
28	Overige ureterpathologie	8	1:35:45	0:07:10
280	Open wond eenvoudig,bijv snijw	5	0:31:36	0:00:02
281	Open wond multipel/uitgebreid	39	0:43:35	0:00:18
282	Open wond gecompliceerd	59	0:58:32	0:00:56
284	Brandwond ernstig	1	0:39:00	0:00:00
29	Congenitale ureterpathologie	2	0:28:30	0:00:04
290	corpus al, natuurlijke opening	4	0:31:30	0:00:19
291	Corpus alienum perforerend	12	0:36:25	0:00:20
292	Verwijderen osteosynthese mat	336	0:51:38	0:00:21
293	Osteitis / osteomyelitis	66	0:58:27	0:01:29
295	multitrauma nno	41	1:56:56	0:02:18
297	Posttraum afw onder extrem	51	1:28:01	0:04:52
298	posttraum afw boven extrem	63	1:16:52	0:01:58
299	overige endocr en metab aand	1	1:40:00	0:00:00
30	blaastumor	346	1:01:29	0:02:38
3004	Wervelkolom	4	1:15:30	0:00:07
3005	Wervelkolom met ruggemerglets	4	2:46:30	0:00:56
3006	Clavicula	14	1:36:13	0:00:36
3007	Scapula	6	1:49:40	0:00:16
3008	Humerus proximaal en schacht	33	1:50:00	0:01:40
3009	Humerus dist/(epi)condyl(len)	8	1:01:08	0:00:44
301	Neoplasma bijschildklier	16	2:02:34	0:02:28
3011	Radiuskopje	3	0:59:00	0:00:22
3012	Onderarm	10	0:50:42	0:00:32
3013	Pols	25	1:01:12	0:00:52
3014	Carpus	2	0:55:00	0:00:01
3015	Metacarpalia	5	1:15:36	0:02:01
3016	Falangen van de hand	4	0:34:30	0:00:04
3019	Femur proximaal (+collum)	135	1:15:44	0:00:49
302	Chronisch hartfalen	41	2:54:20	0:03:19
3020	Femur overig	17	1:51:39	0:01:45
3021	Patella	4	1:12:30	0:00:05
3022	Fibula	2	1:04:30	0:00:10
3023	Tibiaplateau	3	1:47:40	0:00:24
3024	Tibia(met/znd fibula)nnc-enkel	12	1:16:55	0:00:51
3025	Enkel	28	1:03:06	0:00:46
3026	Calcaneus	1	2:49:00	0:00:00
3028	Tarsus	1	0:27:00	0:00:00
3029	Metatarsalia	2	0:48:30	0:00:13
303	Extirpatie ganglion, cyste	51	1:04:48	0:03:12
304	Benigne neoplasma parotis	9	3:19:20	0:07:33
305	Ben neopl overige speekselkl	2	1:18:00	0:00:01
306	Maligne neopl speekselklieren	5	0:54:36	0:03:06
307	Oesofagus/cardia maligniteit	1	0:10:00	0:00:00
31	Allergie / hyperreactiviteit	87	0:39:38	0:00:23
310	Mediast.scop/-tomie/thor.scop	71	1:23:14	0:00:38
3103	Onderste extremiteit	1	1:15:00	0:00:00
311	Pneuthorax,niet trau(trau274)	7	1:52:09	0:01:17
312	Thoraxempyeem	6	1:08:50	0:00:44
313	neoplasma bronchus, long	35	2:59:00	0:03:34
314	Verwond,tr/tr>1%/ herst struct	8	1:30:38	0:00:41
315	maligne neoplasma oesophagus	25	5:14:46	0:17:16
316	Verw,vingerrepl/revasc arm/bn	3	2:05:00	0:01:18
317	Benign neopl mamma/mastopathie	89	0:50:29	0:00:55
318	Maligne neoplasma mamma	380	1:48:58	0:01:35
32	Septumafwijkingen	236	0:47:03	0:00:24
320	Abces intra-abdominaal	9	0:36:20	0:00:44
3201	AC + SC	2	1:15:00	0:00:02
3202	Schouder	4	1:17:00	0:02:49
3205	Vinger, incl. M.C.P.	2	0:35:00	0:00:07
3207	Heup, prothese	11	0:27:16	0:00:13
321	Ulcus duodeni/ventriculi +perf	5	1:54:48	0:01:12
322	fractuur,lux,plaat/schroef fix	11	1:11:11	0:01:17
323	Cholecystitis / cholelithiasis	525	1:25:01	0:00:32
324	Chron nierinsuff (gn dialyse)	7	1:04:17	0:00:57
325	Chron nierinsuff predial fase	3	2:22:20	0:07:00
326	Crohn (enteritis regionalis)	17	0:04:52	0:04:12
327	Diverticulosis / -itis	40	2:55:45	0:05:06
328	Ileus:paralyt,obstr znd hernia	49	2:00:06	0:04:57
329	Overige niet maligne GI aand	88	1:25:14	0:04:22
33	A-(hypo-)contractiele blaas	20	1:11:00	0:00:35
330	maligne neoplasma maag	22	2:49:41	0:09:16
3301	Enkelvoudig	1	1:56:00	0:00:00
3304	Coeliakie	5	0:30:00	0:00:01
3308	Gastro-enteritis (ac,bact/vir)	1	0:41:00	0:00:00
331	Maligne neoplasma galblaas	28	0:43:36	0:00:20
3314	Inflamm darm:z (col ulc/Crohn)	2	1:03:30	0:00:00
332	Tenolyse	22	0:46:03	0:00:34
3320	Obstipatie (habitueel)	1	0:28:00	0:00:00
3326	Ulcera (maag, duodenum)	2	0:31:00	0:00:01
3328	Voedingsproblemen/ -fouten	1	0:42:00	0:00:00
333	Maligne neoplasma colon	140	2:55:30	0:05:09
334	Maligne neopl recto-sigmoid	90	2:59:22	0:03:58
335	Maligne neoplasma rectum	106	3:43:22	0:09:53
336	Pees herstel met transplantaat	6	1:35:00	0:01:24
337	Pees transpositie / reinsertie	9	1:12:13	0:00:17
338	Rectum prolaps	11	2:11:38	0:06:06
339	Incontinentie voor faeces	11	2:18:27	0:03:15
34	Stress-incontinentie/prolaps	72	0:40:33	0:00:07
340	Obstipatie	1	1:35:00	0:00:00
3401	Bicepspees	1	2:53:00	0:00:00
3402	Malletvinger	1	0:27:00	0:00:00
3403	Achillespees	12	0:52:25	0:00:07
3404	Kniebanden	1	0:40:00	0:00:00
3409	Overige rupturen	3	1:07:00	0:00:09
341	Morbide obesitas BMI <45	36	1:50:02	0:00:36
342	Morbide obesitas BMI >45	21	1:30:29	0:01:06
344	Herst lets buigpees peeskoker	10	1:11:36	0:00:12
345	Herstel letsel buigpees	5	1:50:00	0:00:14
346	Herst peeslets,pols/oa:arm,1-3	1	0:53:00	0:00:00
348	Herst buigp.lets+zen/vaatlets	4	2:08:00	0:01:28
349	Overige maligne neoplasm abd	18	2:24:50	0:03:18
35	Urge-incontinentie/OAB	47	0:33:38	0:00:12
350	Maligne melanoom van huid	84	1:07:45	0:01:34
351	lymphadenopathie eci, nno	54	0:49:23	0:00:20
352	Maligne neoplasma weke delen	71	0:59:14	0:00:22
3520	Retardatie (combinatie)	1	0:41:00	0:00:00
353	Beh neuroom, zenuw tumor	20	0:51:33	0:00:27
354	microchir herstel 1-2digit zen	6	1:24:30	0:00:21
355	Microchir herst hoofdzen/-2dlg	1	0:47:00	0:00:00
356	Zenuwherst incl nemen transpl	3	3:13:40	0:04:17
359	Overige oncologische diagnosen	15	0:43:16	0:00:08
36	Sinusitis	266	0:46:09	0:00:09
361	Artrodese IG / MCP / CMC	5	1:16:00	0:00:35
362	Artroplast IG/MCP+strekp.tpos	1	0:27:00	0:00:00
363	Multip artroplast+strekp-repos	2	1:31:00	0:00:20
364	CMC1 resectie artroplastiek	19	1:23:16	0:00:46
365	Artrolyse	5	0:49:12	0:00:15
37	neurogene blaas	9	1:29:40	0:03:36
3701	Open wond eenv bijv snijwonden	1	1:00:00	0:00:00
371	Excochl,seq.tom,exost,carp bos	8	0:45:30	0:00:08
372	Verwijd K-draden,ost.synth mat	9	0:40:20	0:00:06
373	Botstandcorr,ost.tom,pseudartr	2	2:02:00	0:00:22
375	Amputatie vinger part/geheel	10	0:56:36	0:00:42
38	Dysfunctional voiding	4	0:48:15	0:00:04

Figure C.2: Average service times for operations, standard deviations and frequencies, table 2.

DBC	Dutch name	Number	Average time	Standard deviation
381	Sel fasciectomie,tr/tr 1straal	45	0:56:45	0:00:25
382	Sel fasc.tom,tr/tr mult straal	43	1:06:00	0:00:18
383	Synovectom buig/strekp/1straal	1	1:03:00	0:00:00
384	Synovectom buig/strek/mult str	1	1:12:00	0:00:00
385	Intrinsic release/transpositie	2	1:38:00	0:00:01
391	Separatie syndactylie 1 straal	1	0:46:00	0:00:00
393	Correctie complexe syndactylie	2	1:15:00	0:00:02
40	Prostaatcarcinoom	83	3:03:59	0:14:25
402	Carotispathologie	46	2:02:33	0:00:21
403	Oorz ac bloedverlgn varices)	2	1:14:00	0:01:48
404	Impuls- en geleidingsst	2	1:54:30	0:00:32
405	Aneurysma aorta illiacaal	76	2:54:30	0:03:38
406	Aneurysma aorta abd, ruptuur	19	2:56:57	0:02:39
407	Maagcarcinoom,excl cardiacarc	15	0:34:48	0:00:27
409	Vaat afw abdominaal / bekken	7	1:36:17	0:03:17
41	BPH/BH obstructie	299	1:13:24	0:00:33
410	Vaatletsel bovenste extremit	3	1:00:20	0:00:03
4103	Te verw osteosynthesemat	24	0:50:05	0:00:19
4104	Te verw osteosynth wervelkolom	8	0:56:00	0:00:26
4105	Te verw ov osteosynth(excwk)	160	0:41:45	0:00:15
416	Aneurysma onderste extremiteit	19	3:00:57	0:01:55
417	Arteriële embolie+trombose,336	10	1:38:30	0:01:27
418	P.A.O.D. 2, claudicatio interm	78	2:37:33	0:02:40
419	P.A.O.D. 3, rustpijn	86	2:24:40	0:03:44
42	Prostaatontsteking/abces	5	1:01:36	0:00:06
420	P.A.O.D. 4, gangreen	103	1:24:20	0:02:32
421	Vaatletsel lies / bovenbeen	4	0:49:45	0:00:06
422	Vaatletsel knie / onderbeen	1	0:32:00	0:00:00
423	Varices onderste extremiteiten	39	1:00:23	0:00:09
427	Ulcus cruris	4	0:59:00	0:00:16
431	Bacteriaemie/sepsis	2	1:01:00	0:00:03
432	Diabetische voet(diabetes mo)	13	1:12:05	0:02:44
433	Flebitis en tromboflebitis	1	0:43:00	0:00:00
435	Shuntchir+revisie tbv nierlijd	114	1:06:45	0:00:32
441	Resectie carp/prox carpectomie	2	2:00:00	0:00:00
442	Intercarpale artrodese	1	3:00:00	0:00:00
449	Overige vaat-diagnosen	1	0:33:00	0:00:00
45	Lymfnodi prostaatcarcinoom	5	1:37:12	0:00:40
454	Corneaerosie / corp.alienum	4	0:18:00	0:00:02
456	Perforatie, alleen cornea	2	1:31:00	0:00:17
457	Corneadystrofie / keratoconus	1	0:10:00	0:00:00
459	overige pathologie cornea	1	0:08:00	0:00:00
48	Prostaatcarcinoom (orchidect)	11	0:54:05	0:00:04
50	peniscarcinoom	2	1:10:30	0:00:10
501	Defect tekort nt FG,tr/tr<1%	5	0:49:12	0:00:12
502	Uveitis anterior	1	0:11:00	0:00:00
503	Def/t nt FG,tr/tr1-3/sl def<1%	27	1:09:47	0:01:31
504	Littc nt FG,tr/tr1-3/sl def<1%	3	1:36:00	0:00:23
505	Def t nt FG,tr/tr>3%/sl def1-3	24	1:49:10	0:12:45
507	Abces drain, kleine necrotec	17	0:49:07	0:00:11
508	E 1-3 ben tum/naevi nt FG litt	12	0:38:20	0:00:03
509	Mal. tumor niet in FG	8	0:54:23	0:00:41
51	Afwijkingen mondholte	14	0:17:30	0:00:08
510	Excl-3 ben tum/naev wo FG/etc	35	0:56:17	0:06:08
511	maligne tumor in FG tr/tr<1%	34	1:02:37	0:00:43
512	Exc ben tumor/PW tr/tr1-3% etc	18	0:53:27	0:00:22
513	exc mal tum/ PW tr/tr>3% nt FG	8	1:12:38	0:00:30
514	exc ben tum/ PW tr/tr>3% nt FG	5	1:22:24	0:00:26
52	Ziekten adenoid & tonsillen	625	0:25:05	0:00:12
53	Dysfonie	114	0:36:09	0:00:10
54	Impotentie/sexuele dysfunctie	1	0:34:00	0:00:00
55	Globus / slikklachten	7	0:28:34	0:00:04
554	Cataract	2585	0:14:03	0:00:40
559	Overige pathologie lens	1	0:37:00	0:00:00
56	Corp al hypofarynx/oesofagus	19	1:39:54	0:01:06
57	Diagnostiek slaapstn.	71	0:15:06	0:00:05
58	Overige penispathologie	7	0:36:51	0:00:05
59	OSAS	7	0:38:26	0:00:12
60	Testistumor	14	1:04:04	0:00:15
601	ICC	3	2:34:20	0:01:09
603	Endophthalmitis	1	0:24:00	0:00:00
606	Adenomateuze pollepen	1	0:52:00	0:00:00
608	Familiaire pollepsyndromen	1	0:37:00	0:00:00
609	diverticulitis	1	0:35:00	0:00:00
61	Torsio testis	22	0:47:16	0:00:07
610	Colorectale maligniteit	1	0:29:00	0:00:00
613	chronische obstipatie	1	0:52:00	0:00:00
62	Ontsteking testis/epididymis	14	0:44:26	0:00:03
63	Mal orofarynx tum stad III&IV	82	1:07:01	0:00:15
64	Mal hypofarynxtumor stad I&II	2	0:45:30	0:00:10
65	Hydro/spermatocele	76	0:46:58	0:00:06
66	Vasectomieverzoek	15	0:44:32	0:00:12
67	Liesbreuk/hydroce communicans	10	1:02:36	0:00:08
68	Overige (intra)scrotumpathol	10	0:49:30	0:00:10
705	Maculopathie	1	0:07:00	0:00:00
71	Urethrastrictuur	53	0:34:58	0:00:13
72	Maligne tumor speekselklieren	3	2:08:40	0:08:22
73	Benigne tumor speekselklieren	16	2:00:41	0:02:26
732	Choledocholithiasis	1	1:04:00	0:00:00
74	Urethrasteen/corp.alienum	1	0:33:00	0:00:00
75	Urethra(meatus) stenose/carunc	10	0:38:06	0:00:06
751	Geen DRP	1	0:26:00	0:00:00
752	NHL laaggradig	2	5:39:00	1:13:48
76	Overige urethrapathologie	4	0:52:45	0:00:11
77	urethradivertikel	1	1:38:00	0:00:00
79	Congenitale urethrapathologie	1	0:30:00	0:00:00
800	Niet classificerb diversen	1	0:23:00	0:00:00
806	Perfor(> of anders co.perfor)	1	1:55:00	0:00:00
81	Congenitale afwijkingen	3	1:12:40	0:00:04
82	Zwelling in hals diagnostiek	17	1:02:28	0:00:33
83	Diepe hals abces	8	1:08:30	0:03:32
839	Overige maligh tr uro/genit	1	0:01:00	0:00:00
904	Maligniteit slokdarm/cardia	4	0:49:15	0:00:00
907	Secundair glaucoom	2	0:17:30	0:00:00
92	Acute luchtwegobstructie	3	0:13:00	0:00:02
927	Maligniteit colorectaal	3	0:39:20	0:00:09
94	Phimosis/phrenulum	145	0:43:05	0:00:06
959	Overige oogafwijkingen	1	1:29:00	0:00:00
96	Spiltoptant na sterilisatie	8	1:33:07	0:00:04
98	Divers urologische diagnose(n)	14	0:44:56	0:00:12
99	ICC	15	0:18:24	0:00:12
-99	onbekende diagnose	1253	0:34:03	0:02:10
998	ICC	3	0:14:00	0:00:04
999	Overig	1	0:00:00	0:00:00
F11	Orient fert.ondz/bas beh vrouw	47	0:54:33	0:00:09
F21	Gespecialiseerde technieken	10	0:40:48	0:00:06
G11	Cyclusstn	592	0:59:20	0:01:45
G12	Fluor vaginalis	2	0:36:00	0:00:04
G13	PID	3	1:52:00	0:01:56
G14	Buikpijn zonder gyn oorz	4	0:40:30	0:00:01
G15	Uterus myomatosus	91	2:10:56	0:03:28
G16	benigne adnexafwijking	184	1:28:33	0:00:39
G17	Endometriose	60	1:26:49	0:01:13
G18	Anticonceptie	40	0:43:22	0:00:09
G19	Cervixafw incl afw cervixcytol	70	0:42:57	0:00:41
G23	Vulvaire en vaginale afw	111	0:35:58	0:00:08
G25	Incontinentie / prolaps	391	1:31:36	0:02:00
G27	Screening familiaire tumoren	13	1:36:28	0:02:52
M11	Maligniteit vulva	8	1:07:38	0:01:31
M12	maligniteit vagina	3	1:55:20	0:10:01
M13	Maligniteit cervix	5	3:20:12	0:22:15
M14	Maligniteit endometrium	51	2:27:59	0:04:26
M15	maligniteit myometrium	3	1:23:40	0:01:31
M16	Maligniteit ovarium / tuba	41	2:44:03	0:07:58
M99	Maligniteit overige	14	1:51:00	0:06:00
V21	Pathologie bij 1e wk grav	298	0:36:50	0:03:11
V41	Begeleiding grav in 2e lijn	9	0:29:33	0:00:04
V51	Begel partus met naz/nacontr	811	0:53:15	0:00:15
V60	Compl na partus uit 1e lijn	46	0:38:56	0:00:14
V61	Complicaties partus 2e lijn	3	0:41:20	0:00:15

Figure C.3: Average service times for operations, standard deviations and frequencies, table 3.

DBC	Dutch name	Number	Average sercie time	Standard deviation
000	Trajecten	297	296:48:14	9095:02:32
001	ALGEMEEN	1	2:18:00	0:00:00
002	ALGEMEEN	41	72:00:25	1280:27:52
003	ALGEMEEN	167	149:57:06	1681:05:45
004	ALGEMEEN	76	149:42:48	3678:54:52
005	ALGEMEEN	173	53:04:38	749:30:35
006	ALGEMEEN	1003	44:21:06	447:13:22
007	ALGEMEEN	44	128:16:25	980:37:51
008	ALGEMEEN	32	250:03:58	3912:56:01
01	Diagnose Algemeen	23	4:52:31	0:05:58
010	ALGEMEEN	9	77:54:07	220:25:10
0101	Neuro-infecties	6	529:49:10	6059:20:46
0102	Neuro-infecties	11	266:53:05	1951:46:12
011	Algemeen	7	258:51:00	3730:37:18
0111	Neuro-infecties	5	371:50:12	5447:50:45
012	Algemeen	22	30:16:35	186:37:39
0121	Neuro-infecties	1	7:18:00	0:00:00
013	Algemeen	13	72:55:55	844:53:36
0131	Neuro-infecties	2	102:12:00	10:34:41
014	Algemeen	16	67:56:26	153:02:42
015	ALGEMEEN	121	157:45:09	1600:15:37
016	ALGEMEEN	228	92:34:25	989:53:06
017	ALGEMEEN	9	23:06:47	32:31:45
018	ALGEMEEN	24	55:10:53	1352:12:50
0191	Neuro-infecties	48	24:09:33	196:10:58
0199	Neuro-infecties	5	3:54:12	0:02:17
02	Restgroep	3	53:16:20	146:36:19
020	ALGEMEEN	3	100:39:40	269:27:49
0201	Neuro-oncologie	78	277:09:39	5841:38:40
021	ALGEMEEN	60	101:34:02	2465:55:38
0211	Neuro-oncologie	4	261:12:00	1573:51:39
022	ALGEMEEN	1	2:54:00	0:00:00
0221	Neuro-oncologie	2	213:13:00	577:23:02
023	ALGEMEEN	43	11:28:40	106:56:45
0231	Neuro-oncologie	10	387:40:24	10825:57:29
024	ALGEMEEN	4	52:25:45	304:14:51
025	ALGEMEEN	23	6:05:21	3:23:03
0251	Neuro-oncologie	2	9:49:30	0:00:00
026	ALGEMEEN	83	11:38:55	5:19:23
027	Algemeen	1	7:57:00	0:00:00
0299	Neuro-oncologie	7	166:44:09	231:30:33
03	Restgroep	3	13:57:40	2:37:12
0311	Deficiënties,metabool,voeding	1	208:48:00	0:00:00
0312	Deficiënties,metabool,voeding	10	135:36:12	1175:29:58
0313	Deficiënties,metabool,voeding	1	612:27:00	0:00:00
037	Algemeen	7	46:44:00	121:23:33
0399	Deficiënties,metabool,voeding	1	151:02:00	0:00:00
04	Diagnose Algemeen	13	227:35:55	418:11:09
0401	Psychische stoornissen	100	6:34:53	0:22:23
0402	Psychische stoornissen	67	22:25:42	450:28:45
041	Cerv syndr/brachialgie/hfdpijn	71	140:23:45	1276:21:53
042	ALGEMEEN	257	50:28:32	2393:10:09
043	ALGEMEEN	31	115:37:54	2512:00:53
044	Cerv syndr/brachialgie/hfdpijn	35	5:59:21	7:10:09
0499	Psychische stoornissen	16	86:58:11	376:55:57
05	Diagnose Algemeen	6	241:22:20	625:18:41
0501	Systeemaandoeningen CZS	19	341:52:44	1805:08:05
0502	Systeemaandoeningen CZS	10	28:52:36	87:25:46
0503	Systeemaandoeningen CZS	3	66:21:00	302:59:08
0511	Systeemaandoeningen CZS	245	2:42:42	0:08:06
0531	Systeemaandoeningen CZS	532	13:02:13	123:08:39
0541	Systeemaandoeningen CZS	1	54:21:00	0:00:00
0542	Systeemaandoeningen CZS	8	377:19:38	3616:07:52
0543	Systeemaandoeningen CZS	4	81:36:00	749:55:07
0551	Systeemaandoeningen CZS	1	265:20:00	0:00:00
0591	Systeemaandoeningen CZS	4	77:23:00	134:32:02
0599	Systeemaandoeningen CZS	1	87:10:00	0:00:00
06	onbekende hoofd groep	7	719:59:34	15403:59:05
0601	Paroxysmale afwijkingen	121	53:42:20	445:17:17
0602	Paroxysmale afwijkingen	17	92:53:46	1199:50:57
061	Thoracaal pijnsyndroom	16	19:57:26	160:29:05
0611	Paroxysmale afwijkingen	141	21:32:55	2:21:30
0612	Paroxysmale afwijkingen	193	19:35:52	1:25:28
062	Thoracaal pijnsyndroom	16	5:07:41	1:02:45
0621	Paroxysmale afwijkingen	18	6:53:37	2:07:16
063	Thoracaal pijnsyndroom	1	1:53:00	0:00:00
064	Thoracaal pijnsyndroom	6	3:22:30	0:14:17
0699	Paroxysmale afwijkingen	90	30:06:54	170:06:54
07	onbekende hoofd groep	1	1342:54:00	0:00:00
0701	Migraine + Hoofdpijn	21	45:40:03	198:11:27
071	Lumbago /(pseudo)radicul syndr	317	3:23:37	0:47:21
0711	Migraine + Hoofdpijn	4	49:07:00	200:20:51
072	Lumbago /(pseudo)radicul syndr	226	3:49:41	5:18:06
073	Lumbago /(pseudo)radicul syndr	73	3:53:21	0:08:11
074	Lumbago /(pseudo)radicul syndr	829	3:21:14	1:04:30
0799	Migraine + Hoofdpijn	100	42:09:04	270:49:14
08	Diagnose Algemeen	2	178:02:30	57:59:47
080	Sacraal pijnsyndroom	116	3:19:41	0:22:01
0801	Perifere zenuwen	1	4:21:00	0:00:00
0802	Perifere zenuwen	1	2:02:00	0:00:00
0804	Perifere zenuwen	1	69:00:00	0:00:00
0805	Perifere zenuwen	3	3:27:20	0:00:17
0809	Perifere zenuwen	2	4:00:00	0:06:16
0811	Perifere zenuwen	37	152:28:02	2915:16:19
0812	Perifere zenuwen	8	110:14:08	887:33:59
0821	Perifere zenuwen	6	5:43:50	0:19:25
0823	Perifere zenuwen	5	38:47:12	85:34:36
0829	Perifere zenuwen	3	3:45:00	0:01:10
09	Diagnose Algemeen	25	96:59:19	1412:32:52
090	Coccygodynie	20	2:40:39	0:05:08
0901	Neuromusculaire aandoeningen	11	7:34:33	0:07:26
0911	Neuromusculaire aandoeningen	19	16:50:19	27:48:08
0999	Neuromusculaire aandoeningen	1	10:02:00	0:00:00
10	NIER	80	100:27:48	911:47:06
100	Pijn bij maligniteit	13	76:19:55	620:21:48
1001	Zintuigsystemen	5	49:32:36	363:50:33
101	De uitkomst v/h consult/onderz	644	131:33:32	2676:43:39
1010	Algemeen en/of systemisch	1	31:17:00	0:00:00
1011	Zintuigsystemen	31	64:54:14	182:09:12
102	CARDIOVASCULAIR	8	75:04:23	408:32:12
103	Artritiden	10	158:10:18	1399:03:55
104	Artritiden	1	88:35:00	0:00:00
105	Artritiden	1	138:25:00	0:00:00
106	CARDIOVASCULAIR	4	48:01:45	45:43:01
107	Artritiden	29	190:18:14	1246:43:42
109	Artritiden	18	188:22:13	1610:53:51
1099	Zintuigsystemen	2	118:18:30	532:44:53
11	NIER	304	20:50:27	62:20:58
110	Ischaem pijn a/d extremiteiten	3	10:36:40	2:13:32
1101	CerebroVasculaireAandoeningen	20	170:37:27	1708:57:40
1102	Evaluat kl znd duid diagn/ther	138	134:29:25	1743:03:23
1103	Evaluat kl znd duid diagn/ther	115	95:06:39	2191:49:05
1104	Evaluat kl znd duid diagn/ther	49	5:16:22	1:37:49
1105	Evaluat kl znd duid diagn/ther	51	33:49:19	211:31:02
1106	Evaluat kl znd duid diagn/ther	2	2:46:30	0:03:04
111	Alg chir en chir bij kinderen	75	164:49:01	869:40:46
1110	Bot en weke delen tumoren	2	629:07:30	15919:56:17
1111	CerebroVasculaireAandoeningen	451	196:43:28	1500:52:58
1112	CerebroVasculaireAandoeningen	213	38:17:56	229:52:55
112	Artritiden	1	7:09:00	0:00:00
1120	Bot en weke delen tumoren	21	11:51:03	3:31:24
1121	CerebroVasculaireAandoeningen	12	608:00:45	7150:56:21
113	Alg chir en chir bij kinderen	384	54:24:22	114:51:40
1130	Bot en weke delen tumoren	16	23:53:11	190:23:01
1140	Bot en weke delen tumoren	4	345:39:45	3798:13:38
115	Alg chir en chir bij kinderen	127	19:46:34	25:38:54
116	Alg chir en chir bij kinderen	241	21:20:23	275:01:32
117	Alg chir en chir bij kinderen	151	19:00:59	56:48:35
119	CARDIOVASCULAIR	1	458:12:00	0:00:00
1199	CerebroVasculaireAandoeningen	16	189:48:45	3263:16:14
12	Otologie	149	77:08:23	1557:24:08
120	Alg chir en chir bij kinderen	22	99:21:38	266:08:58
1201	Astma / COPD	170	43:00:51	188:21:43
1202	Astma / COPD	29	4:00:48	0:28:09
1203	Bewegingsstelsel	60	86:53:12	594:26:14
1204	Bewegingsstelsel	20	66:36:18	516:52:48
121	Alg chir en chir bij kinderen	640	16:43:05	112:31:23
1211	Bewegingsstelsel	5	31:32:12	39:59:23
122	CARDIOVASCULAIR	6	171:03:10	2534:21:03
1221	Bewegingsstelsel	1	335:25:00	0:00:00
123	Alg chir en chir bij kinderen	144	31:46:16	91:02:32
1231	Bewegingsstelsel	6	40:47:10	182:30:11
124	Alg chir en chir bij kinderen	162	99:50:45	2747:53:17
1241	Astma / COPD	469	147:06:27	1276:59:22
125	Gelaat	6	2:00:00	0:00:00
126	CARDIOVASCULAIR	2	195:33:00	881:29:15
127	Alg chir en chir bij kinderen	135	14:47:37	5:04:38
129	Alg chir en chir bij kinderen	797	32:33:08	163:54:40
1299	Bewegingsstelsel	13	98:27:37	931:21:39
13	Diagnose Algemeen	820	6:07:09	87:31:06
130	Perifere zenuwpijn (incl PHN)	190	5:45:30	13:17:45
1301	Longtumoren	25	75:01:22	1263:37:46
1302	Thoracale/lumbale wervelkolom	18	183:47:20	6114:57:52
1303	Longtumoren	491	44:36:20	372:06:22
1304	Longtumoren	95	76:04:11	659:57:24
1305	Longtumoren	21	57:13:09	146:19:00
1306	Longtumoren	1	213:46:00	0:00:00
1307	Longtumoren	14	56:24:43	728:58:28
1308	Longtumoren	42	31:40:17	184:33:11
131	Gelaat	68	5:14:44	3:51:46
132	Alg chir en chir bij kinderen	44	7:10:33	13:14:11

Figure C.4: Average service times for admissions in the department nursing wards, standard deviations and frequencies, table 1.

DBC	Dutch name	Number	Average sercie time	Standard deviation
133	Alg chir en chir bij kinderen	8	8:13:15	2:22:32
1330	Thoracale/lumbale wervelkolom	1	454:09:00	0:00:00
134	Alg chir en chir bij kinderen	20	10:26:27	8:56:11
1340	Thoracale/lumbale wervelkolom	3	4:21:40	0:00:20
1350	Thoracale/lumbale wervelkolom	104	108:10:08	208:20:41
136	Gelaat	3	19:20:40	20:33:03
1360	Thoracale/lumbale wervelkolom	5	84:22:24	165:03:29
1365	Thoracale/lumbale wervelkolom	4	103:50:30	45:39:44
1370	Thoracale/lumbale wervelkolom	34	123:14:32	112:43:47
139	CARDIOVASCULAIR	4	3:18:00	0:02:17
1392	Thoracale/lumbale wervelkolom	10	114:51:24	98:43:59
1395	Thoracale/lumbale wervelkolom	29	62:34:48	752:35:51
1396	Thoracale/lumbale wervelkolom	2	14:28:00	4:51:36
1397	Thoracale/lumbale wervelkolom	1	25:30:00	0:00:00
14	Diagnose Algemeen	714	13:26:43	71:23:03
140	Alg chir en chir bij kinderen	6	27:22:00	77:18:28
1401	Bronchopneumonie ea infecties	776	123:36:39	773:22:34
1402	Letsel + intoxicatie	107	62:57:28	749:13:56
1403	Schoudergordel/bovenarm	9	76:09:40	51:47:49
1404	Bronchopneumonie ea infecties	28	105:29:09	557:36:25
1405	Bronchopneumonie ea infecties	79	106:21:07	422:05:55
1409	Letsel + intoxicatie	6	17:34:10	21:09:21
141	Alg chir en chir bij kinderen	9	26:00:27	38:03:56
1411	Letsel + intoxicatie	5	220:02:00	858:51:52
1414	Diagnose Neonatologie	1	71:04:00	0:00:00
1421	Letsel + intoxicatie	1	3:05:00	0:00:00
1422	Letsel + intoxicatie	6	153:40:40	2582:20:04
1431	Letsel + intoxicatie	11	19:19:16	26:09:27
1450	Schoudergordel/bovenarm	480	24:23:52	13:47:16
1460	Schoudergordel/bovenarm	151	28:32:25	77:53:03
1470	Schoudergordel/bovenarm	85	11:38:49	11:21:05
1480	Schoudergordel/bovenarm	78	22:32:12	3:25:32
1495	Schoudergordel/bovenarm	88	21:24:34	16:37:22
1496	Schoudergordel/bovenarm	2	18:20:30	6:52:16
1497	Schoudergordel/bovenarm	4	8:20:45	2:59:24
1499	Schoudergordel/bovenarm	4	28:54:00	56:47:18
15	NIER	50	37:34:31	149:25:55
150	Complex regionaal pijnsyndr	77	42:12:19	320:12:32
1501	Elleboog/onderarm	5	34:48:00	72:42:39
1503	Elleboog/onderarm	1	221:15:00	0:00:00
1504	Elleboog/onderarm	9	8:43:53	1:12:03
151	Gelaat	1	6:38:00	0:00:00
1511	(Non)Tuberculose	6	5:08:00	0:18:09
152	Gelaat	2	28:02:00	0:00:33
1521	(Non)Tuberculose	3	149:37:20	914:29:52
154	Gelaat	1	7:00:00	0:00:00
1550	Elleboog/onderarm	7	27:38:17	133:20:23
1560	Elleboog/onderarm	44	7:05:31	2:02:38
159	Alg chir en chir bij kinderen	42	24:33:29	108:00:51
1596	Elleboog/onderarm	8	46:46:23	292:50:12
16	onbekende hoofd groep	2	25:25:00	23:10:26
160	Alg chir en chir bij kinderen	244	87:57:44	872:08:41
1601	Interstitiële longafwijkingen	77	80:38:26	1470:42:58
1602	Interstitiële longafwijkingen	6	16:20:00	33:34:19
1603	Interstitiële longafwijkingen	39	43:51:32	499:55:06
161	Alg chir en chir bij kinderen	29	69:53:23	149:53:55
162	Gelaat	13	7:03:32	0:06:07
1620	Hand/pols	8	4:17:23	0:01:15
163	Alg chir en chir bij kinderen	140	43:37:01	209:22:32
1630	Hand/pols	22	7:45:00	2:55:06
1650	Hand/pols	70	4:38:00	0:47:22
1695	Hand/pols	10	11:12:42	3:38:57
1696	Hand/pols	8	17:09:37	21:59:05
1697	Hand/pols	2	5:42:00	0:00:04
1699	Hand/pols	1	3:09:00	0:00:00
17	Diagnose Algemeen	327	6:44:51	0:15:58
170	Alg chir en chir bij kinderen	298	8:38:25	4:07:56
1701	Bekken/heup/bovenbeen	791	129:35:03	706:11:41
1702	Pleurale aandoeningen	73	151:07:48	1479:18:21
1703	Bekken/heup/bovenbeen	132	272:38:45	4852:12:25
1704	Bekken/heup/bovenbeen	5	715:56:36	41707:26:17
171	Alg chir en chir bij kinderen	24	10:32:00	8:56:09
1710	Bekken/heup/bovenbeen	72	25:03:26	9:36:37
1720	Bekken/heup/bovenbeen	1	3:14:00	0:00:00
173	Gelaat	1	57:00:00	0:00:00
1730	Bekken/heup/bovenbeen	2	7:24:00	0:03:01
174	Alg chir en chir bij kinderen	9	50:34:07	43:06:38
175	Alg chir en chir bij kinderen	2	10:58:30	0:15:56
1750	Bekken/heup/bovenbeen	5	59:52:36	73:31:45
176	Alg chir en chir bij kinderen	1	5:35:00	0:00:00
1760	Bekken/heup/bovenbeen	8	32:58:08	9:40:37
179	Alg chir en chir bij kinderen	32	17:08:34	25:12:40
1796	Bekken/heup/bovenbeen	10	78:39:12	454:03:00
1797	Bekken/heup/bovenbeen	5	9:38:36	3:33:33
1799	Bekken/heup/bovenbeen	1	3:27:00	0:00:00
18	NIER	44	34:01:26	141:15:26
180	Herpes zoster acuta	14	3:49:51	0:13:49
1801	Knie	917	81:28:17	314:11:06
1802	Vasculaire aandoeningen	159	119:33:38	481:26:39
1803	Knie	78	184:09:12	1626:10:29
1804	Knie	39	21:00:02	313:46:05
1805	Knie	1632	6:30:32	19:31:19
1810	Knie	7	23:38:51	23:12:03
1820	Knie	193	25:09:25	2:26:08
1830	Knie	3	4:58:40	0:10:55
1840	Knie	13	11:33:23	16:24:24
1850	Knie	65	15:41:55	29:13:54
1860	Knie	10	26:37:00	21:59:41
1870	Knie	24	8:24:30	5:31:27
1880	Knie	19	8:10:09	2:41:45
1890	Knie	6	9:39:10	5:31:08
1896	Knie	62	21:20:57	37:28:30
1897	Knie	6	30:29:20	40:30:55
1898	Knie	1	4:57:00	0:00:00
1899	Knie	11	4:32:49	0:08:47
19	Diagnose Algemeen	3	326:56:00	1676:03:27
1901	Slaap apnoe behandeling	1	231:50:00	0:00:00
1902	Slaap apnoe behandeling	11	35:28:27	138:34:03
191	Viscerale pijn	2	3:46:30	0:07:53
1910	Onderbeen	2	26:22:30	0:00:21
192	Viscerale pijn	1	2:00:00	0:00:00
1920	Onderbeen	1	21:00:00	0:00:00
199	Kort consult	1	193:52:00	0:00:00
1996	Onderbeen	3	33:30:00	34:05:25
1997	Onderbeen	1	5:52:00	0:00:00
20	Diagnose Algemeen	32	82:34:30	528:15:54
200	Arthralgie / arthritis	36	3:00:25	0:06:57
2001	Enkel en voet	46	31:43:27	245:12:55
2002	Enkel en voet	5	422:54:12	1288:16:05
2004	Enkel en voet	9	8:09:13	1:42:32
2006	Enkel en voet	12	16:10:50	4:19:20
201	POBD	1185	19:04:23	131:41:52
2010	Enkel en voet	50	11:34:13	3:08:57
2015	Enkel en voet	41	9:14:00	7:03:19
202	POBD	923	12:14:24	46:19:16
2020	Enkel en voet	5	12:34:48	3:32:19
2025	Enkel en voet	9	13:01:27	3:41:47
203	POBD	855	75:05:53	520:32:11
2030	Enkel en voet	26	17:00:37	3:54:53
2035	Enkel en voet	1	25:30:00	0:00:00
204	Syndromen	492	45:52:27	219:53:25
2040	Enkel en voet	9	25:09:27	18:03:16
2045	Enkel en voet	10	5:11:30	0:17:02
205	POBD	688	57:53:58	368:21:19
2050	Enkel en voet	127	31:42:22	314:51:55
2055	Enkel en voet	20	17:27:21	13:57:09
206	Syndromen	13	113:39:18	1257:42:18
2060	Enkel en voet	85	9:26:16	14:21:04
207	Traumatologie en SEH	138	59:56:27	350:47:27
2070	Enkel en voet	6	14:52:40	4:27:30
208	Traumatologie en SEH	83	29:52:47	173:14:39
209	Traumatologie en SEH	26	24:53:09	28:16:16
2095	Enkel en voet	16	25:01:19	56:13:21
2096	Enkel en voet	20	10:24:54	2:58:11
2097	Enkel en voet	38	20:24:03	6:59:17
2098	Enkel en voet	1	10:00:00	0:00:00
21	URETER	199	37:03:15	56:11:01
210	Traumatologie en SEH	36	7:17:43	2:33:40
2101	Aand, mogelijk resp insuff	24	116:42:13	375:01:21
2102	Aand, mogelijk resp insuff	4	367:22:30	12142:11:39
2103	Aand, mogelijk resp insuff	7	100:36:43	313:16:21
2104	Aand, mogelijk resp insuff	1	172:00:00	0:00:00
2106	Diagnose Neonatologie	2	408:13:00	4680:41:44
211	Lichaam	175	33:44:43	82:51:13
212	Traumatologie en SEH	247	21:37:19	626:02:00
2120	Overige/diversen	6	17:16:20	11:20:12
213	Lichaam	31	9:00:35	3:35:12
2130	Overige/diversen	8	10:58:45	2:32:03
214	Traumatologie en SEH	102	16:43:48	89:11:42
2140	Overige/diversen	2	120:15:00	22:31:24
215	Traumatologie en SEH	96	11:54:36	81:58:56
2150	Overige/diversen	3	49:28:00	51:41:34
216	Traumatologie en SEH	50	83:39:34	641:08:06
217	Traumatologie en SEH	90	169:27:15	1408:16:20
218	Traumatologie en SEH	337	245:24:34	2320:26:28
219	Traumatologie en SEH	28	239:19:24	2725:43:44
22	Diagnose Algemeen	14	468:52:47	3566:33:02
220	Traumatologie en SEH	14	66:02:09	126:39:45
2202	Diagnose Neonatologie	1	44:46:00	0:00:00
221	ENDOCRINOLOGIE EN STOFWIS.ZKT	147	106:37:49	869:19:26
222	Lichaam	217	110:08:02	1324:10:16
223	Lichaam	30	98:39:24	843:17:37
224	Traumatologie en SEH	218	51:12:04	376:42:55
226	Lichaam	1	2:00:00	0:00:00
23	URETER	12	43:44:40	658:47:00
231	Lichaam	6	79:29:50	174:27:47
232	Bloed en bloedvormende organen	3	35:36:00	70:49:03

Figure C.5: Average service times for admissions in the department nursing wards, standard deviations and frequencies, table 2.

DBC	Dutch name	Number	Average sercie time	Standard deviation
233	ENDOCRINOLOGIE EN STOFWIS.ZKT	5	110:25:48	643:45:10
234	ENDOCRINOLOGIE EN STOFWIS.ZKT	3	2:00:00	0:00:00
236	Traumatologie en SEH	9	64:51:13	278:33:18
237	Traumatologie en SEH	6	150:54:20	1735:07:19
238	Traumatologie en SEH	46	17:47:12	26:01:07
239	ENDOCRINOLOGIE EN STOFWIS.ZKT	29	98:58:41	7923:05:17
24	URETER	73	45:54:51	554:59:04
240	Traumatologie en SEH	7	188:59:51	2037:43:52
241	Psychische stoornissen	41	60:30:37	3933:53:10
242	Psychische stoornissen	128	15:39:48	137:18:39
243	ENDOCRINOLOGIE EN STOFWIS.ZKT	17	326:56:11	4039:46:44
244	Psychische stoornissen	3	4:45:00	0:10:44
245	Psychische stoornissen	1	3:53:00	0:00:00
246	ENDOCRINOLOGIE EN STOFWIS.ZKT	1	3:22:00	0:00:00
247	ENDOCRINOLOGIE EN STOFWIS.ZKT	2	3:05:30	0:02:59
248	ENDOCRINOLOGIE EN STOFWIS.ZKT	1	43:45:00	0:00:00
249	Traumatologie en SEH	4	26:59:00	66:17:29
25	Diagnose Algemeen	2	82:06:30	264:50:11
250	Traumatologie en SEH	10	5:02:36	0:40:16
251	Zenuwstelsel en zintuigen	15	27:51:20	147:31:44
252	Traumatologie en SEH	59	16:01:52	90:56:18
253	Traumatologie en SEH	24	4:45:30	0:10:24
254	Traumatologie en SEH	4	62:52:00	395:38:09
255	Traumatologie en SEH	45	9:04:48	27:13:52
256	Traumatologie en SEH	12	26:52:40	88:54:15
257	Traumatologie en SEH	13	6:17:18	1:43:52
258	Oogleden	18	4:33:20	0:07:24
259	Oogleden	1	4:15:00	0:00:00
26	Hartvaatstelsel	1	235:40:00	0:00:00
261	Traumatologie en SEH	14	28:40:13	224:58:20
262	Traumatologie en SEH	60	49:05:32	479:33:56
263	ENDOCRINOLOGIE EN STOFWIS.ZKT	14	26:22:30	257:33:38
264	ENDOCRINOLOGIE EN STOFWIS.ZKT	1	209:11:00	0:00:00
269	Traumatologie en SEH	46	24:33:26	73:20:06
27	Diagnose Algemeen	21	5:25:23	0:04:25
270	Traumatologie en SEH	211	18:37:02	148:44:55
271	Traumatologie en SEH	160	31:07:03	225:13:22
272	Traumatologie en SEH	30	20:21:56	31:33:28
273	Traumatologie en SEH	9	256:58:00	2401:20:19
274	Traumatologie en SEH	5	152:56:12	355:39:13
275	Traumatologie en SEH	2	19:21:00	0:11:33
279	Traumatologie en SEH	11	215:10:00	5054:50:56
28	URETER	6	26:41:50	48:24:00
280	Traumatologie en SEH	112	5:20:55	4:21:11
281	Traumatologie en SEH	149	45:37:49	740:38:58
282	Traumatologie en SEH	106	55:43:52	645:19:20
283	ENDOCRINOLOGIE EN STOFWIS.ZKT	10	2:42:18	0:00:49
284	Traumatologie en SEH	18	40:10:13	387:40:20
29	URETER	2	20:22:00	3:02:03
290	Traumatologie en SEH	3	14:19:20	1:32:13
291	Traumatologie en SEH	31	7:06:45	4:30:45
292	Traumatologie en SEH	337	12:58:39	89:18:12
293	Traumatologie en SEH	76	233:19:16	2291:38:13
294	Traumatologie en SEH	447	30:59:04	383:08:46
295	Traumatologie en SEH	106	180:59:12	3058:28:15
296	Traumatologie en SEH	2	168:56:00	1144:28:51
297	Traumatologie en SEH	59	96:04:08	1437:49:34
298	Traumatologie en SEH	66	22:51:50	52:35:08
299	Traumatologie en SEH	26	100:31:30	1824:24:36
3	BLAAS	426	51:57:43	370:56:37
3003	Fracturen	1	4:29:00	0:00:00
3004	Fracturen	38	64:09:27	730:05:15
3005	Fracturen	2	155:58:00	936:27:31
3006	Fracturen	19	17:21:09	7:20:39
3007	Fracturen	6	22:08:10	1:37:57
3008	Fracturen	38	89:40:17	471:31:54
3009	Fracturen	8	14:38:38	3:12:44
301	Kortademigheid	475	144:17:06	864:06:56
3011	Fracturen	3	7:42:20	0:44:44
3012	Fracturen	12	10:37:35	2:35:55
3013	Fracturen	46	23:54:35	339:38:49
3014	Fracturen	3	6:38:20	0:22:23
3015	Fracturen	6	27:42:00	53:59:34
3016	Fracturen	9	5:46:13	0:16:59
3017	Fracturen	17	155:57:07	1057:34:31
3018	Fracturen	6	152:03:00	419:54:05
3019	Fracturen	132	222:03:49	1795:36:55
302	Kortademigheid	264	94:26:46	824:02:19
3020	Fracturen	25	195:56:19	2025:04:44
3021	Fracturen	5	237:10:12	1243:19:10
3022	Fracturen	2	38:27:00	6:27:30
3023	Fracturen	9	112:43:53	353:30:15
3024	Fracturen	18	44:39:27	165:48:58
3025	Fracturen	37	49:23:57	216:45:33
3026	Fracturen	1	309:44:00	0:00:00
3028	Fracturen	1	3:00:00	0:00:00
3029	Fracturen	5	4:38:12	0:07:38
303	Hand, voet, extremiteiten	69	10:45:07	8:01:34
3030	Fracturen	3	2:58:00	0:00:31
304	Oesofagus	19	26:26:13	72:28:30
305	Oesofagus	19	6:40:35	4:59:29
306	systeemaandoeningen	7	14:52:00	12:10:27
307	Oesofagus	33	44:39:44	286:40:43
308	Oesofagus	12	34:02:05	347:48:44
309	systeemaandoeningen	5	39:45:00	244:22:38
31	Rhinologie	91	15:49:22	32:21:27
310	Oncol,long,gastrointestin chir	62	39:13:25	70:25:43
3102	Distorsies	3	61:05:20	88:56:28
3103	Distorsies	9	12:12:07	7:40:13
3104	Diagnose Alg kindergeneeskunde	133	44:00:09	460:59:16
3105	Diagnose Alg kindergeneeskunde	28	24:55:11	15:04:43
3106	Diagnose Alg kindergeneeskunde	5	33:31:00	39:07:21
3107	Diagnose Alg kindergeneeskunde	5	80:18:36	30:31:34
311	NEFROLOGIE	94	47:13:17	515:15:21
312	Hand, voet, extremiteiten	4	58:41:45	324:06:35
313	Oncol,long,gastrointestin chir	33	178:24:05	854:50:02
314	Hand, voet, extremiteiten	8	62:48:00	204:20:32
315	Oncol,long,gastrointestin chir	33	246:52:49	2655:34:51
316	Oncol,long,gastrointestin chir	1	5:37:00	0:00:00
317	Oncol,long,gastrointestin chir	94	12:06:52	13:54:03
318	Oncol,long,gastrointestin chir	425	43:34:22	80:59:01
319	systeemaandoeningen	1	176:30:00	0:00:00
3199	Diagnose Alg kindergeneeskunde	12	73:12:55	353:38:41
32	Rhinologie	294	40:27:04	156:40:28
320	Oncol,long,gastrointestin chir	28	126:08:04	1478:39:54
3201	Luxaties	2	25:15:00	0:00:37
3202	Luxaties	152	39:56:38	108:37:40
3203	Diagnose Alg kindergeneeskunde	19	5:19:35	3:34:38
3204	Luxaties	1	24:54:00	0:00:00
3205	Diagnose Alg kindergeneeskunde	14	2:56:47	0:36:00
3206	Diagnose Alg kindergeneeskunde	4	23:10:15	12:22:36
3207	Luxaties	46	31:44:40	50:49:07
3208	Diagnose Alg kindergeneeskunde	136	66:43:20	197:58:09
3209	Luxaties	2	3:15:00	0:04:01
321	Bewegingsstelsel & bindweefsel	28	47:10:47	289:25:54
3210	Diagnose Alg kindergeneeskunde	137	88:36:56	265:34:28
3211	Luxaties	1	2:41:00	0:00:00
322	Oncol,long,gastrointestin chir	26	254:13:32	12933:39:13
323	Oncol,long,gastrointestin chir	723	69:24:06	509:42:29
324	NEFROLOGIE	229	46:47:24	461:53:15
325	NEFROLOGIE	48	176:42:40	6601:36:32
326	Oncol,long,gastrointestin chir	93	113:08:14	1077:06:42
327	Oncol,long,gastrointestin chir	185	112:57:09	774:10:03
328	Oncol,long,gastrointestin chir	114	148:48:44	779:09:31
329	Oncol,long,gastrointestin chir	143	75:42:32	937:05:59
3299	Diagnose Alg kindergeneeskunde	15	35:11:44	60:15:24
33	BLAAS	60	45:44:44	679:55:18
330	Oncol,long,gastrointestin chir	23	238:25:31	1484:18:45
3301	Contusies	40	68:17:18	679:58:41
3302	Contusies	19	59:49:22	229:40:30
3303	Diagnose Alg kindergeneeskunde	73	40:42:52	211:43:09
3304	Diagnose Alg kindergeneeskunde	20	24:34:12	86:40:33
3305	Diagnose Alg kindergeneeskunde	4	48:31:00	59:58:09
3306	Diagnose Alg kindergeneeskunde	1	48:55:00	0:00:00
3308	Diagnose Alg kindergeneeskunde	254	50:35:23	159:40:28
331	Oncol,long,gastrointestin chir	124	41:19:17	2271:06:27
3310	Diagnose Alg kindergeneeskunde	41	73:30:41	287:27:26
3311	Diagnose Alg kindergeneeskunde	5	110:55:12	423:04:57
3313	Diagnose Alg kindergeneeskunde	15	45:42:28	67:34:09
3314	Diagnose Alg kindergeneeskunde	27	90:31:04	562:26:55
3315	Diagnose Alg kindergeneeskunde	1	28:47:00	0:00:00
3316	Diagnose Alg kindergeneeskunde	4	17:00:30	0:56:41
3318	Diagnose Alg kindergeneeskunde	5	68:48:12	223:47:41
332	NEFROLOGIE	35	42:24:15	310:56:18
3320	Diagnose Alg kindergeneeskunde	142	40:06:59	352:43:06
3321	Diagnose Alg kindergeneeskunde	3	52:04:20	42:12:17
3323	Diagnose Alg kindergeneeskunde	5	26:23:36	24:02:18
3324	Diagnose Alg kindergeneeskunde	7	60:53:51	325:39:17
3326	Diagnose Alg kindergeneeskunde	6	48:01:00	94:53:48
3327	Diagnose Alg kindergeneeskunde	31	17:19:27	98:39:01
3328	Diagnose Alg kindergeneeskunde	83	118:47:25	663:19:54
333	Oncol,long,gastrointestin chir	186	148:36:37	1775:17:22
334	Oncol,long,gastrointestin chir	92	220:11:48	2421:33:21
335	Oncol,long,gastrointestin chir	155	152:34:09	2707:14:35
336	Hand, voet, extremiteiten	6	97:30:30	223:50:39
337	Oncol,long,gastrointestin chir	41	171:03:51	1625:25:05
338	Oncol,long,gastrointestin chir	19	85:16:03	316:30:38
339	Oncol,long,gastrointestin chir	10	157:00:24	1006:22:08
3399	Diagnose Alg kindergeneeskunde	10	64:21:48	421:22:49
34	BLAAS	75	19:03:17	17:59:01
340	Oncol,long,gastrointestin chir	60	43:33:39	154:54:54
3401	Kapsel-band/pees/spier-ruptuur	1	25:40:00	0:00:00
3402	Kapsel-band/pees/spier-ruptuur	2	7:14:00	0:00:11
3403	Kapsel-band/pees/spier-ruptuur	19	110:24:25	3175:56:02
3404	Diagnose Alg kindergeneeskunde	3	3:52:00	0:13:27
3405	Diagnose Alg kindergeneeskunde	3	3:12:40	0:23:23
3406	Diagnose Alg kindergeneeskunde	3	96:20:40	150:14:55

Figure C.6: Average service times for admissions in the department nursing wards, standard deviations and frequencies, table 3.

DBC	Dutch name	Number	Average sercie time	Standard deviation
408	Diagnose Alg kindergeneeskunde	5	35:18:24	173:07:12
409	Kapsel-band/pees/spier-ruptuur	5	59:12:48	78:16:35
341	Hand, voet, extremiteiten	42	35:31:37	58:36:32
410	Diagnose Alg kindergeneeskunde	2	22:23:00	0:19:22
342	Oncol,long,gastrointestin.chir	24	19:54:30	16:27:24
344	NEFROLOGIE	14	53:22:00	185:33:24
345	Hand, voet, extremiteiten	5	10:05:48	1:27:58
346	NEFROLOGIE	5	26:43:00	47:31:46
347	NEFROLOGIE	1	67:10:00	0:00:00
348	Oncol,long,gastrointestin.chir	7	148:03:09	2406:49:02
349	Oncol,long,gastrointestin.chir	18	257:05:33	4366:54:34
3499	Diagnose Alg kindergeneeskunde	16	1:25:38	0:01:49
35	BLAAS	102	43:27:56	242:30:08
350	Oncol,long,gastrointestin.chir	92	27:10:33	121:33:31
502	Diagnose Alg kindergeneeskunde	64	24:24:52	44:28:33
503	Diagnose Alg kindergeneeskunde	64	23:24:18	46:05:10
505	Diagnose Alg kindergeneeskunde	13	9:24:28	7:32:02
3506	Diagnose Alg kindergeneeskunde	7	199:29:00	1513:32:11
3507	Diagnose Alg kindergeneeskunde	2	3:54:30	0:04:58
3508	Diagnose Alg kindergeneeskunde	8	9:48:22	8:05:38
351	Hand, voet, extremiteiten	524	3:38:25	6:09:10
3510	Diagnose Alg kindergeneeskunde	1	3:28:00	0:00:00
3511	Diagnose Alg kindergeneeskunde	9	152:27:20	682:08:09
3513	Diagnose Alg kindergeneeskunde	6	16:45:10	26:41:30
3514	Diagnose Alg kindergeneeskunde	1	4:13:00	0:00:00
3515	Diagnose Alg kindergeneeskunde	2	7:49:30	0:00:16
3516	Diagnose Alg kindergeneeskunde	4	18:39:45	11:31:42
3517	Diagnose Alg kindergeneeskunde	1	5:22:00	0:00:00
3518	Diagnose Alg kindergeneeskunde	4	3:16:00	0:01:46
352	Oncol,long,gastrointestin.chir	84	23:03:06	140:06:41
3520	Diagnose Alg kindergeneeskunde	19	28:31:44	82:04:54
3522	Diagnose Alg kindergeneeskunde	2	4:05:30	0:00:03
3523	Diagnose Alg kindergeneeskunde	20	39:44:33	106:07:24
3524	Diagnose Alg kindergeneeskunde	91	16:36:18	3:45:09
353	Hand, voet, extremiteiten	20	20:47:30	57:57:57
354	Hand, voet, extremiteiten	9	22:20:00	25:38:04
355	Hand, voet, extremiteiten	1	13:21:00	0:00:00
356	Hand, voet, extremiteiten	3	25:11:20	18:50:00
359	Oncol,long,gastrointestin.chir	17	32:59:39	113:00:25
3599	Diagnose Alg kindergeneeskunde	12	49:24:35	265:57:13
36	Rhinologie	275	12:05:19	10:01:09
361	Hand, voet, extremiteiten	6	14:29:40	4:43:18
362	Hand, voet, extremiteiten	1	4:58:00	0:00:00
363	Hand, voet, extremiteiten	2	8:15:30	0:03:10
364	Hand, voet, extremiteiten	20	22:06:36	3:55:09
365	Hand, voet, extremiteiten	3	38:17:20	84:36:55
37	BLAAS	21	80:49:34	621:47:05
3701	Wonden	3	2:47:40	0:00:17
3702	Wonden	2	2:27:30	0:00:14
371	Hand, voet, extremiteiten	9	6:23:33	0:09:45
372	Hand, voet, extremiteiten	9	13:37:13	7:53:08
373	Hand, voet, extremiteiten	2	85:15:00	153:46:24
375	Hand, voet, extremiteiten	8	7:32:22	0:09:41
38	BLAAS	14	18:40:17	67:49:53
381	Hand, voet, extremiteiten	46	6:26:17	0:07:44
382	Hand, voet, extremiteiten	41	7:32:00	0:26:22
383	Hand, voet, extremiteiten	1	7:00:00	0:00:00
384	Hand, voet, extremiteiten	1	6:46:00	0:00:00
385	Hand, voet, extremiteiten	2	8:16:00	0:00:12
39	BLAAS	2	40:38:30	11:50:31
391	Hand, voet, extremiteiten	1	7:03:00	0:00:00
393	Hand, voet, extremiteiten	1	5:37:00	0:00:00
399	systeemaandoeningen	9	60:47:33	205:50:48
40	PROSTAAT	215	54:13:23	371:56:25
4001	Diagnose Alg kindergeneeskunde	4	60:59:15	160:40:37
4002	Diagnose Alg kindergeneeskunde	2	3:07:00	0:04:20
4003	Diagnose Alg kindergeneeskunde	6	2:15:10	0:05:10
4004	Diagnose Alg kindergeneeskunde	7	99:40:51	306:35:57
4005	Diagnose Alg kindergeneeskunde	1	47:30:00	0:00:00
4006	Diagnose Alg kindergeneeskunde	2	2:32:30	0:00:13
401	Ritme	1478	31:58:14	343:34:48
402	Ritme	190	45:10:40	236:08:47
403	Ritme	140	102:03:32	1898:57:18
404	Ritme	474	60:13:39	531:04:02
405	Vaatchirurgie	127	86:23:42	469:41:02
406	Vaatchirurgie	38	160:49:17	2348:59:52
407	Maag en dunne darm	33	72:26:05	1297:14:33
409	Ritme	83	75:15:49	1430:03:09
4099	Diagnose Alg kindergeneeskunde	2	4:08:30	0:00:14
41	PROSTAAT	434	45:12:13	97:54:14
410	Maag en dunne darm	82	5:45:07	7:40:23
4101	Overige diagn traumatologie	47	25:38:32	123:34:07
4102	Overige diagn traumatologie	33	67:39:05	59:56:43
4103	Overige diagn traumatologie	24	12:45:55	9:08:09
4104	Overige diagn traumatologie	8	34:39:30	111:50:41
4105	Overige diagn traumatologie	167	28:11:15	475:03:02
4106	Diagnose Alg kindergeneeskunde	3	5:13:20	0:07:17
4107	Diagnose Alg kindergeneeskunde	2	8:31:00	1:43:28
4108	Diagnose Alg kindergeneeskunde	1	15:45:00	0:00:00
411	INFECTIEZIEKTEN	61	158:08:31	966:24:25
4110	Diagnose Alg kindergeneeskunde	28	79:50:13	176:55:57
4112	Diagnose Alg kindergeneeskunde	39	42:21:22	194:49:16
4113	Diagnose Alg kindergeneeskunde	45	56:44:21	287:03:31
4114	Diagnose Alg kindergeneeskunde	36	5:31:15	6:28:33
412	Vaatchirurgie	14	165:43:39	3509:51:18
413	INFECTIEZIEKTEN	8	290:48:30	1655:00:08
416	Vaatchirurgie	21	174:26:00	6196:36:24
417	Vaatchirurgie	16	222:18:45	5111:42:56
418	Vaatchirurgie	262	60:34:02	251:26:58
419	Vaatchirurgie	157	145:38:06	2911:07:46
4199	Diagnose Alg kindergeneeskunde	5	10:36:00	3:22:47
42	PROSTAAT	24	69:01:25	128:17:56
420	Vaatchirurgie	142	328:13:35	6512:16:23
421	INFECTIEZIEKTEN	84	176:50:40	1439:22:26
422	Vaatchirurgie	1	17:07:00	0:00:00
423	Vaatchirurgie	346	2:24:57	0:34:35
425	Vaatchirurgie	3	21:45:40	32:49:57
426	Vaatchirurgie	5	186:50:00	787:46:06
427	Vaatchirurgie	6	509:14:00	3993:29:33
431	INFECTIEZIEKTEN	118	190:52:08	1848:32:03
432	Vaatchirurgie	57	335:08:35	4362:13:03
433	Vaatchirurgie	5	92:03:12	227:05:48
434	Vaatchirurgie	2	360:56:30	21:12:12
435	Vaatchirurgie	101	52:03:29	966:29:04
439	Vaatchirurgie	1	2:19:00	0:00:00
44	PROSTAAT	1	2:35:00	0:00:00
441	Pols / onderarm	3	280:07:00	5413:07:42
442	Vaatchirurgie	7	69:38:51	917:55:19
449	Vaatchirurgie	7	128:50:26	1588:07:45
45	PROSTAAT	5	35:15:00	2:53:15
451	INFECTIEZIEKTEN	1	115:19:00	0:00:00
452	INFECTIEZIEKTEN	1	1070:27:00	0:00:00
453	INFECTIEZIEKTEN	3	323:21:20	3593:26:28
454	Cornea	4	6:33:15	0:08:50
456	Cornea	2	20:25:30	0:10:05
457	Cornea	1	4:05:00	0:00:00
459	Cornea	1	2:24:00	0:00:00
463	INFECTIEZIEKTEN	5	104:00:36	289:41:34
469	INFECTIEZIEKTEN	9	144:53:53	536:24:28
48	PROSTAAT	10	117:04:18	2517:33:48
491	INFECTIEZIEKTEN	49	219:57:07	4540:00:45
493	INFECTIEZIEKTEN	2	2:00:00	0:00:00
499	INFECTIEZIEKTEN	25	183:42:53	1293:22:10
50	PENIS	7	41:09:34	136:59:36
5001	Diagnose Alg kindergeneeskunde	14	2:50:34	0:06:45
5002	Diagnose Alg kindergeneeskunde	7	48:11:09	346:09:57
5003	Diagnose Alg kindergeneeskunde	1	2:17:00	0:00:00
5004	Diagnose Alg kindergeneeskunde	3	131:42:00	168:10:26
5005	Diagnose Alg kindergeneeskunde	5	17:56:12	38:37:58
501	Structurele hartafwijking	175	30:28:14	435:36:06
502	Structurele hartafwijking	23	85:15:47	565:31:23
503	Algemeen	29	22:48:02	111:59:38
504	Algemeen	3	7:08:40	0:04:20
505	Algemeen	27	43:36:07	159:49:42
506	SYSTEEMZIEKTEN	12	67:20:10	538:34:11
507	Algemeen	13	39:40:09	194:56:48
508	Algemeen	12	8:57:00	2:35:18
509	Algemeen	22	48:38:55	312:08:30
5099	Diagnose Alg kindergeneeskunde	2	83:52:30	269:37:09
51	Mondholte, pharynx, larynx	27	5:19:02	0:48:28
510	Algemeen	37	5:47:16	0:12:48
5101	Diagnose Alg kindergeneeskunde	3	5:33:00	0:04:46
5105	Diagnose Alg kindergeneeskunde	1	42:27:00	0:00:00
5107	Diagnose Alg kindergeneeskunde	17	204:16:42	175:01:05
511	Algemeen	77	9:04:02	26:25:18
5110	Diagnose Alg kindergeneeskunde	3	2:46:20	0:00:54
512	Algemeen	18	9:08:07	1:26:42
513	Algemeen	15	37:57:28	292:00:05
514	Algemeen	5	54:57:24	219:30:13
5199	Diagnose Alg kindergeneeskunde	8	127:03:15	748:36:26
52	Mondholte, pharynx, larynx	1177	11:39:03	5:05:05
523	SYSTEEMZIEKTEN	1	2:28:00	0:00:00
526	SYSTEEMZIEKTEN	5	68:49:00	261:47:42
527	SYSTEEMZIEKTEN	1	4:29:00	0:00:00
53	Mondholte, pharynx, larynx	114	7:51:32	1:05:46
54	PENIS	1	22:00:00	0:00:00
55	Mondholte, pharynx, larynx	52	12:05:53	26:42:49
554	Lens	3840	3:43:41	8:41:21
557	Lens	1	4:00:00	0:00:00
559	Lens	1	3:22:00	0:00:00
56	Mondholte, pharynx, larynx	25	14:23:43	4:35:56
57	Mondholte, pharynx, larynx	154	4:16:27	0:06:08
58	PENIS	14	6:48:00	0:21:35
59	Mondholte, pharynx, larynx	8	12:35:45	3:15:30
599	SYSTEEMZIEKTEN	6	40:04:10	76:06:21
60	TESTIS & SCROTUM	16	15:52:11	3:20:12
6001	Diagnose Alg kindergeneeskunde	3	7:05:40	0:41:33

Figure C.7: Average service times for admissions in the department nursing wards, standard deviations and frequencies, table 4.

DBC	Dutch name	Number	Average sercie time	Standard deviation
6002	Diagnose Alg kindergeneeskunde	14	25:12:39	122:16:49
6003	Diagnose Alg kindergeneeskunde	4	32:12:45	45:53:40
6004	Diagnose Alg kindergeneeskunde	1	44:58:00	0:00:00
6005	Diagnose Alg kindergeneeskunde	2	12:37:30	0:04:17
601	Colon	378	26:06:50	431:02:27
602	Colon	234	20:40:42	238:15:48
603	Corpus Vitreum	1	2:44:00	0:00:00
605	Colon	31	26:50:14	181:39:37
606	Colon	660	6:14:24	11:17:02
607	Colon	36	2:28:47	0:01:42
608	Colon	93	3:13:41	1:15:30
609	Colon	112	19:53:41	223:44:45
6099	Diagnose Alg kindergeneeskunde	23	24:13:44	69:52:34
61	TESTIS & SCROTUM	23	10:49:13	1:15:08
610	Colon	227	12:59:11	93:56:02
6101	Diagnose Alg kindergeneeskunde	1	3:25:00	0:00:00
6104	Diagnose Alg kindergeneeskunde	16	67:34:38	140:01:27
6105	Diagnose Alg kindergeneeskunde	75	29:34:54	143:47:31
611	Colon	4	49:44:00	84:31:25
612	Colon	89	13:33:07	36:26:48
613	Colon	58	15:40:42	60:52:37
614	PULMOLOGIE / ALLERGOLOGIE	3	23:52:00	24:53:26
619	PULMOLOGIE / ALLERGOLOGIE	37	22:29:06	108:32:11
6199	Diagnose Alg kindergeneeskunde	1	19:27:00	0:00:00
62	TESTIS & SCROTUM	20	60:06:06	214:53:42
6202	Diagnose Alg kindergeneeskunde	2	2:15:30	0:00:09
6203	Diagnose Alg kindergeneeskunde	1	1:29:00	0:00:00
6204	Diagnose Alg kindergeneeskunde	4	210:53:30	1829:45:18
621	PULMOLOGIE / ALLERGOLOGIE	1	2:30:00	0:00:00
629	PULMOLOGIE / ALLERGOLOGIE	2	119:08:00	550:52:55
63	Mondholte, pharynx, larynx	85	11:43:40	36:38:17
631	Anorectum	28	11:14:09	32:55:41
632	Anorectum	15	2:39:20	0:02:24
64	TESTIS & SCROTUM	15	8:02:36	0:59:13
65	TESTIS & SCROTUM	77	8:47:46	0:52:52
657	Retina	81	1:46:22	0:02:55
659	Retina	2	0:48:30	0:00:02
66	TESTIS & SCROTUM	15	7:41:20	0:57:35
67	TESTIS & SCROTUM	10	6:15:24	0:07:50
68	TESTIS & SCROTUM	13	16:18:05	17:04:32
701	HEMATOLOGIE	389	31:16:48	258:49:56
702	Ontstekingen	19	319:10:03	904:800:30
703	HEMATOLOGIE	5	43:26:48	205:32:27
704	Macula	1141	0:47:02	0:24:19
705	Macula	84	2:56:48	4:38:46
706	HEMATOLOGIE	5	133:27:24	597:42:03
707	Macula	69	2:19:45	4:21:15
708	Lever	5	13:41:48	11:44:12
709	HEMATOLOGIE	147	63:49:11	765:47:34
71	URETHRA	61	20:30:51	20:56:10
7101	Diagnose Alg kindergeneeskunde	1	1:54:00	0:00:00
7104	Diagnose Alg kindergeneeskunde	19	43:13:35	192:03:22
7108	Diagnose Alg kindergeneeskunde	4	158:56:00	3005:30:56
711	Lever	3	4:27:40	0:30:17
7110	Diagnose Alg kindergeneeskunde	55	10:18:24	51:54:10
7111	Diagnose Alg kindergeneeskunde	1	6:02:00	0:00:00
7112	Diagnose Alg kindergeneeskunde	21	3:50:20	0:10:48
7113	Diagnose Alg kindergeneeskunde	14	14:20:51	4:26:27
7114	Diagnose Alg kindergeneeskunde	18	68:53:40	196:40:33
712	Lever	10	74:23:18	348:34:19
713	Lever	5	17:58:12	30:25:49
714	Lever	1	3:44:00	0:00:00
716	Overige diagnosen	1	100:30:00	0:00:00
718	Lever	3	418:36:00	163:19:09
719	HEMATOLOGIE	9	30:56:40	138:09:53
7199	Diagnose Alg kindergeneeskunde	3	33:24:40	38:47:08
72	Speekselklieren	5	35:05:36	71:15:10
7202	Diagnose Alg kindergeneeskunde	1	3:20:00	0:00:00
7203	Diagnose Alg kindergeneeskunde	1	916:00:00	0:00:00
7204	Diagnose Alg kindergeneeskunde	8	2:23:53	0:02:10
721	HEMATOLOGIE	11	276:21:05	1255:08:36
7289	Diagnose Alg kindergeneeskunde	2	2:51:00	0:01:48
729	HEMATOLOGIE	2	26:27:00	24:04:00
7299	Diagnose Alg kindergeneeskunde	4	3:31:45	0:08:06
73	Speekselklieren	18	40:20:33	23:16:45
7302	Diagnose Alg kindergeneeskunde	1	54:36:00	0:00:00
731	HEMATOLOGIE	87	34:08:38	328:34:52
732	Galwegen	94	67:29:39	440:27:50
733	HEMATOLOGIE	7	23:13:26	69:43:52
734	HEMATOLOGIE	1	3:45:00	0:00:00
735	Galwegen	16	90:26:49	1121:30:42
736	Galwegen	31	68:27:37	408:32:23
739	HEMATOLOGIE	1	2:00:00	0:00:00
7399	Diagnose Alg kindergeneeskunde	1	2:27:00	0:00:00
74	URETHRA	1	11:26:00	0:00:00
7401	Diagnose Alg kindergeneeskunde	4	4:01:30	0:00:43
7403	Diagnose Alg kindergeneeskunde	27	66:59:56	75:46:19
7405	Diagnose Alg kindergeneeskunde	5	33:53:24	80:02:27
7406	Diagnose Alg kindergeneeskunde	1	3:30:00	0:00:00
749	HEMATOLOGIE	9	13:03:53	8:52:52
7499	Diagnose Alg kindergeneeskunde	1	4:45:00	0:00:00
75	URETHRA	12	12:37:40	3:17:07
7501	Diagnose Alg kindergeneeskunde	9	165:29:53	1893:32:01
7502	Diagnose Alg kindergeneeskunde	3	10:39:00	3:37:17
751	Pancreas	9	137:05:13	494:17:31
752	HEMATOLOGIE	46	32:20:10	194:08:00
753	HEMATOLOGIE	57	212:09:49	2450:33:27
754	HEMATOLOGIE	167	34:01:15	358:17:52
755	Pancreas	43	65:03:01	302:09:59
757	HEMATOLOGIE	45	90:16:20	918:02:27
759	HEMATOLOGIE	54	8:31:30	48:44:54
76	URETHRA	5	11:50:00	1:27:13
7601	Diagnose Alg kindergeneeskunde	3	5:03:40	0:18:38
7602	Diagnose Alg kindergeneeskunde	1	2:26:00	0:00:00
7603	Diagnose Alg kindergeneeskunde	9	11:09:33	24:43:12
7604	Diagnose Alg kindergeneeskunde	19	244:24:35	2380:23:32
7605	Diagnose Alg kindergeneeskunde	13	82:20:28	583:40:31
7606	Diagnose Alg kindergeneeskunde	55	242:01:41	1272:41:42
7607	Diagnose Alg kindergeneeskunde	4	26:29:45	6:52:34
7608	Diagnose Alg kindergeneeskunde	3	34:15:40	76:04:40
761	HEMATOLOGIE	12	21:39:35	124:57:32
7611	Diagnose Alg kindergeneeskunde	15	276:57:08	2551813:13:18
7612	Diagnose Alg kindergeneeskunde	12	153:07:05	185:47:43
762	HEMATOLOGIE	64	15:29:00	52:10:24
763	HEMATOLOGIE	51	9:02:12	3:35:07
7699	Diagnose Alg kindergeneeskunde	5	217:36:24	1320:51:46
77	URETHRA	2	29:01:00	22:58:40
7701	Diagnose Alg kindergeneeskunde	1	13:41:00	0:00:00
7702	Diagnose Alg kindergeneeskunde	4	31:31:45	54:40:35
7703	Diagnose Alg kindergeneeskunde	4	3:03:00	0:01:29
7704	Diagnose Alg kindergeneeskunde	3	2:13:20	0:08:23
7705	Diagnose Alg kindergeneeskunde	3	49:18:20	163:22:37
7708	Diagnose Alg kindergeneeskunde	2	73:38:30	10:14:16
771	HEMATOLOGIE	14	96:42:56	1651:59:33
7710	Diagnose Alg kindergeneeskunde	5	138:01:12	936:08:12
7711	Diagnose Alg kindergeneeskunde	3	171:25:00	558:57:06
772	HEMATOLOGIE	6	66:52:10	223:25:40
774	HEMATOLOGIE	13	33:29:55	149:21:07
779	HEMATOLOGIE	2	8:39:30	0:00:00
7801	Diagnose Alg kindergeneeskunde	1	99:13:00	0:00:00
7802	Diagnose Alg kindergeneeskunde	1	2:04:00	0:00:00
7803	Diagnose Alg kindergeneeskunde	3	64:53:40	70:21:51
7804	Diagnose Alg kindergeneeskunde	4	3:16:30	0:05:21
7805	Diagnose Alg kindergeneeskunde	19	55:03:19	167:20:40
7806	Diagnose Alg kindergeneeskunde	2	20:17:00	13:55:42
7807	Diagnose Alg kindergeneeskunde	1	76:16:00	0:00:00
7808	Diagnose Alg kindergeneeskunde	4	51:59:15	127:01:26
781	HEMATOLOGIE	4	170:00:00	2074:40:10
7810	Diagnose Alg kindergeneeskunde	55	46:20:56	72:16:23
7811	Diagnose Alg kindergeneeskunde	7	58:10:00	120:58:14
7899	Diagnose Alg kindergeneeskunde	15	138:06:00	1002:53:45
79	URETHRA	1	4:51:00	0:00:00
799	HEMATOLOGIE	8	10:03:30	4:14:41
800	Overige gastro-enterolog diagn	90	16:03:34	205:06:49
801	Follow up	40	57:50:26	418:41:05
802	Follow up	86	90:42:24	1379:20:10
803	Follow up	39	34:36:37	276:59:04
804	Follow up	2	169:46:30	69:33:31
806	Follow up	28	104:06:13	2102:20:42
808	Follow up	3	176:08:00	560:52:04
81	Hals	3	25:32:20	8:16:13
810	Follow up	2	120:07:00	574:56:03
811	MALIGNITEITEN	526	31:29:17	401:43:49
82	Hals	19	38:09:47	126:44:36
820	Overige gastro-enterolog diagn	11	2:22:22	0:00:49
821	Follow up	207	125:20:59	473:20:43
822	MALIGNITEITEN	1	285:31:00	0:00:00
823	MALIGNITEITEN	5	48:56:36	74:52:47
83	BLAAS	12	72:24:55	757:08:03
832	MALIGNITEITEN	92	15:55:03	56:56:29
833	MALIGNITEITEN	47	29:35:33	56:40:53
834	MALIGNITEITEN	29	37:00:29	340:58:43
839	MALIGNITEITEN	19	99:01:09	673:25:05
841	MALIGNITEITEN	7	30:07:00	125:58:23
842	MALIGNITEITEN	7	84:50:26	893:47:53
843	MALIGNITEITEN	5	26:19:24	34:01:50
8902	Diagnose Alg kindergeneeskunde	18	259:02:07	1540:34:52
8903	Diagnose Alg kindergeneeskunde	5	7:27:24	1:22:32
8904	Diagnose Alg kindergeneeskunde	24	173:09:10	1509:40:45
8905	Diagnose Alg kindergeneeskunde	7	2:16:17	0:00:32
8906	Diagnose Alg kindergeneeskunde	24	478:05:20	4911:39:50

Figure C.8: Average service times for admissions in the department nursing wards, standard deviations and frequencies, table 5.

Appendix D

Model comparison

This appendix contains results for the model comparisons. Recall, we have two different models. The first is the holistic model with the three components, ARIMA-models, Markov models and average service times. The second is the 4 year average model. Figure D.1 provides the differences between the 4 year average model and the actual data and between the outcomes of our model and the actual data of week 5 to 24 of 2011. A negative value in Figure D.1 denotes an underestimation of the weekly patient volumes at a certain specialism, a positive value denotes an overestimation. Figure D.2 provides the total costs per class of 10 patients for our model and the 4 year average model for two described scenarios in Section 5.4.2.

week	norm	Cardiology	Surgery	Gastroenterology	Gynecology	Internal Medicine	Pediatrics	Pulmonology	Neurology	Other	Urology	Midwifery
5	average	-4,75	91,00	14,00	17,75	4,25	20,00	-1,00	-1,00	319,25	9,75	-13,00
5	model	-3,67	14,74	-4,68	6,75	-22,33	-7,79	9,29	-16,56	378,32	-40,79	25,71
6	average	15,00	105,75	19,25	15,00	39,50	18,75	0,50	15,00	399,00	2,25	23,25
6	model	-49,05	15,93	-3,91	13,83	0,26	-5,74	-16,97	-3,75	-412,40	-50,52	12,16
7	average	3,50	60,50	19,00	19,75	29,50	2,25	16,75	9,75	372,50	5,00	23,75
7	model	-15,95	-14,69	-3,07	-5,28	1,74	0,04	-5,18	-5,12	825,25	-50,71	10,86
8	average	14,75	35,00	16,00	15,25	30,75	16,25	15,00	19,25	-31,25	2,75	10,75
8	model	18,47	69,87	1,92	-5,48	-1,30	-0,63	16,65	14,40	948,13	-44,32	35,20
9	average	3,75	1,25	35,50	9,75	29,00	-7,25	-2,00	-4,25	410,00	8,25	7,00
9	model	14,82	-60,52	4,12	1,59	-7,07	-9,57	-20,26	-29,06	-99,55	-58,12	-8,17
10	average	12,75	97,25	28,00	3,00	0,00	4,75	4,25	-2,50	372,00	12,75	13,25
10	model	22,34	-19,14	3,53	-4,27	-19,57	7,87	-12,11	-9,77	174,96	-37,60	13,01
11	average	17,50	65,50	37,75	5,25	34,50	-23,25	33,75	2,25	224,50	11,75	-30,25
11	model	-5,98	51,00	9,89	2,58	-0,67	-9,45	24,25	-25,57	505,34	-39,94	9,28
12	average	12,50	73,00	38,75	9,50	4,50	-9,25	12,25	16,00	15,50	-9,75	-35,25
12	model	0,62	66,16	16,11	19,08	-17,23	7,29	-13,51	14,95	475,11	-55,46	-18,70
13	average	12,50	72,00	20,50	35,50	6,00	10,50	13,00	9,75	123,50	6,75	8,00
13	model	-2,60	33,60	-4,10	3,65	-18,36	-18,18	1,89	-6,70	389,62	-51,93	11,90
14	average	27,00	72,50	38,75	22,25	10,75	-6,75	1,50	3,00	352,75	15,00	15,25
14	model	-10,43	-18,35	21,35	14,10	-10,25	-4,07	-6,60	-14,27	470,99	-40,53	-22,55
15	average	17,00	64,50	32,25	14,00	24,25	12,00	19,75	8,00	295,25	20,25	-20,00
15	model	-3,94	25,18	-4,01	8,48	1,90	-22,67	1,06	-6,23	49,21	-48,23	39,28
16	average	-2,00	32,75	39,50	21,75	0,25	-11,00	-0,75	20,50	273,50	21,00	14,50
16	model	10,13	-51,57	8,61	-18,58	-28,83	-5,10	-19,90	-10,23	-397,15	-28,30	10,17
27	average	22,50	-2,00	40,75	20,75	41,00	4,75	15,00	22,50	191,50	10,50	10,75
17	model	-12,67	45,06	20,19	-31,01	9,10	-14,99	5,79	9,76	941,88	-47,84	-19,01
18	average	23,50	32,75	37,25	-6,50	35,25	8,00	24,50	7,00	162,25	15,00	25,00
18	model	-10,02	26,35	4,97	-3,29	3,97	-4,54	9,93	-17,33	762,66	-26,83	-2,70
19	average	-9,00	80,75	1,25	2,75	-0,50	5,50	16,50	-19,00	513,75	5,75	2,25
19	model	-19,98	-89,23	-28,61	-15,24	-41,82	-1,53	-5,24	-34,33	-19,06	-71,87	8,61
20	average	22,25	124,25	28,25	33,75	35,75	-6,25	6,75	29,75	524,75	29,75	-19,50
20	model	8,24	55,39	-7,19	-17,18	1,68	16,83	-7,85	4,10	52,70	-19,51	-21,29
21	average	2,50	37,25	47,50	8,00	37,50	-1,75	10,50	14,00	283,75	8,50	-19,75
21	model	-22,43	-15,95	3,69	-3,70	-2,00	-15,46	-3,16	1,12	417,07	-64,28	8,17
22	average	12,25	53,50	15,50	-15,25	13,50	18,25	-3,00	8,50	11,25	4,75	27,25
22	model	-15,67	46,47	-6,34	6,86	-9,10	-8,34	-15,93	10,52	484,04	-32,42	-8,32
23	average	-27,25	-28,50	3,75	17,25	8,00	-1,50	11,75	-6,75	94,00	0,00	5,25
23	model	-7,57	-5,15	-22,02	-11,54	-31,48	-15,59	-0,67	-42,69	243,36	-60,82	30,71
24	average	-17,00	-29,50	10,50	8,25	29,25	-8,25	3,25	30,75	-83,75	8,50	1,75
24	model	24,54	13,00	2,81	23,38	-0,67	8,35	-6,99	16,06	538,56	-21,92	20,59

Figure D.1: Differences between 4-year average and actual data and our model and the actual data, for weeks 5-24 of 2011. Negative values are an underestimation of the true value; positive values are an overestimation.

class	model (average)	model (worst-case)	4 year (average)	4 year average (worst-case)	difference (average)	difference (worst-case)
110-120 overestimated	€ 360,000.00	€ 720,000.00	€ 0.00	€ 0.00	-€ 360,000.00	-€ 720,000.00
100-110 overestimated	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00
90-100 overestimated	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00
80-90 overestimated	€ 270,000.00	€ 540,000.00	€ 0.00	€ 0.00	-€ 270,000.00	-€ 540,000.00
70-80 overestimated	€ 960,000.00	€ 1,920,000.00	€ 0.00	€ 0.00	-€ 960,000.00	-€ 1,920,000.00
60-70 overestimated	€ 1,680,000.00	€ 3,360,000.00	€ 0.00	€ 0.00	-€ 1,680,000.00	-€ 3,360,000.00
50-60 overestimated	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00
40-50 overestimated	€ 1,050,000.00	€ 2,100,000.00	€ 0.00	€ 0.00	-€ 1,050,000.00	-€ 2,100,000.00
30-40 overestimated	€ 960,000.00	€ 1,920,000.00	€ 600,000.00	€ 1,200,000.00	-€ 360,000.00	-€ 720,000.00
20-30 overestimated	€ 360,000.00	€ 720,000.00	€ 90,000.00	€ 180,000.00	-€ 270,000.00	-€ 540,000.00
10-20 overestimated	€ 1,140,000.00	€ 2,280,000.00	€ 300,000.00	€ 600,000.00	-€ 840,000.00	-€ 1,680,000.00
0-10 overestimated	€ 1,020,000.00	€ 2,040,000.00	€ 360,000.00	€ 720,000.00	-€ 660,000.00	-€ 1,320,000.00
no over- or underestimation	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00
10-20 underestimated	€ 1,020,000.00	€ 2,040,000.00	€ 1,560,000.00	€ 3,120,000.00	€ 540,000.00	€ 1,080,000.00
20-30 underestimated	€ 1,140,000.00	€ 2,280,000.00	€ 2,940,000.00	€ 5,880,000.00	€ 1,800,000.00	€ 3,600,000.00
30-40 underestimated	€ 360,000.00	€ 720,000.00	€ 450,000.00	€ 900,000.00	€ 90,000.00	€ 180,000.00
40-50 underestimated	€ 360,000.00	€ 720,000.00	€ 1,320,000.00	€ 2,640,000.00	€ 960,000.00	€ 1,920,000.00
50-60 underestimated	€ 300,000.00	€ 600,000.00	€ 3,000,000.00	€ 6,000,000.00	€ 2,700,000.00	€ 5,400,000.00
60-70 underestimated	€ 540,000.00	€ 1,080,000.00	€ 360,000.00	€ 720,000.00	-€ 180,000.00	-€ 360,000.00
70-80 underestimated	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00
80-90 underestimated	€ 240,000.00	€ 480,000.00	€ 240,000.00	€ 480,000.00	€ 0.00	€ 0.00
90-100 underestimated	€ 540,000.00	€ 1,080,000.00	€ 1,080,000.00	€ 2,160,000.00	€ 540,000.00	€ 1,080,000.00
100-110 underestimated	€ 0.00	€ 0.00	€ 300,000.00	€ 600,000.00	€ 300,000.00	€ 600,000.00
110-120 underestimated	€ 0.00	€ 0.00	€ 330,000.00	€ 660,000.00	€ 330,000.00	€ 660,000.00
120-130 underestimated	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00
130-140 underestimated	€ 0.00	€ 0.00	€ 780,000.00	€ 1,560,000.00	€ 780,000.00	€ 1,560,000.00
140-150 underestimated	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00	€ 0.00
150-160 underestimated	€ 0.00	€ 0.00	€ 450,000.00	€ 900,000.00	€ 450,000.00	€ 900,000.00
160-170 underestimated	€ 0.00	€ 0.00	€ 480,000.00	€ 960,000.00	€ 480,000.00	€ 960,000.00
total costs	€ 12,300,000.00	€ 24,600,000.00	€ 14,640,000.00	€ 29,280,000.00	€ 2,340,000.00	€ 4,680,000.00

Figure D.2: Overview of the two scenarios for the total costs per class for the 10 specialisms in week 5 to week 24 of 2011.