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Modelling of surgical process durations in cataract surgery

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Summary

A cataract is a clouding of the human natural lens, the leading cause of visual loss worldwide. Over time, the cataract can grow larger which makes all-day activities such as driving and reading difficult. A surgery can be performed to replace the human lens with a artificial plastic lens. This surgery is one of the most frequently performed surgeries worldwide and the chance of complications or failure is very small. Leiden University Medical Centre (LUMC) registers all surgical times, defined as the time from first incision to the last closure of the eye. The distribution function of surgical times turned out to be left-skewed and the question is what causes this skewness.

The surgical process of a cataract surgery was discussed with an staff surgeon, resulting in a flowchart containing all the surgical phases. For most phases, there is more than one way to proceed, depending on the surgeon's preferences and patient characteristics. All possible actions a surgeon might perform in order to complete the surgical phases are called surgical actions. Four staff surgeons and two resident surgeons were observed. A camera in the microscope of the surgeon registered all surgical actions. A total number of 44 surgeries were registered. The video registrations were analyzed to obtain the sequences of successive actions and the corresponding durations.

The surgical process is modeled as a semi-Markov process, with the state space representing all surgical actions. The sojourn time distribution per state and the transition probabilities between states were determined from the video registrations. The sojourn times were assumed to be Normal distributed. In general, this distribution can be used to describe, at least approximately, any variable that tends to cluster around the mean. The maximum likelihood estimators for the mean and standard deviation were used to fit the observed data to the normal distribution function. A directed graph was constructed to visualize the surgical process from beginning (first incision) to end (closure of the eye).

To determine the first-passage-time distributions between start and final state we used Monte-Carlo simulation. The simulation results were compared with the Normal and Lognormal distribution functions using QQ-plots. This showed that neither of the two is a very good approximation itself, but it did show skewness of the simulated surgical time distribution.

The skewed surgical time distribution function is caused by differences in surgical speed between staff en resident surgeons in combination with the multiple possibilities to complete the surgical phases leading to parallel surgical paths. Well defined patient characteristics such as a wide iris when entering the OR mainly determines which of these paths is taken in order to complete the surgery. The skewed distribution function of surgical time is a result of the individual distribution functions of these patient categories.

The model was used to show differences in surgical time between staff surgeons and resident surgeons by estimating the model parameters with the data belonging to the groups of interest. For staff surgeons the median is found at approximately 15 minutes. For resident surgeons this value is found at approximately 26 minutes. Besides this, the surgical time distribution for staff surgeons is wider than the one for resident surgeons. This is caused by the fact that resident surgeons only perform the 'easier' surgeries. Finally, we found concrete groups of patients for which the surgical time distribution function show major differences. Categorizing patients this way results in a better approximation of the upper bound on surgical time.

The upper bounds can be used to make a more efficient OR schedule, resulting in improved operating room utilization. At this moment, for each cataract surgery a fixed amount of time is scheduled. Cataract surgery is a frequent performed surgery and there are not many variations in the surgical path. If we apply the methods of this study to more complex (longer) surgeries, the upper bounds on surgical time per category could be even more valuable with respect to operating room utilization. Besides managerial implications, the graphical Markov chain and the curves of this chapter give insight in the process. They could for example be used for educational or optimization purposes.

Preface

This report is the result of four months of work at the LUMC in Leiden and the Twente University in Enschede. With finishing this project I hope to obtain my Bachelors degree Advanced Technology, which enables me to start with my Master study applied mathematics. I really enjoyed the combination of theoretical and practical research in a relatively new environment. The enthusiasm and interest of all people I have met in Leiden made it a very pleasant time.

I would like to thank Fred Boer for enabling me to carry out this project and his useful and clear comments. I would like to thank Irene Notting for helping me with the medical parts of my project and the flexibility regarding our meetings. I also like to thank the clinical staff for their cooperation during the observations. I would like to thank Herman Hemmes, for supervising my project for Advanced Technology.

My meetings with Richard Boucherie every two weeks were of great value for the project and I would like to thank him for his honest and constructive comments. Thank you for the opportunity of doing my bachelor assignment at your chair Stochastic Operations Research and your interest in the progression of my project. Finally, I would like to thank Maartje Zonderland. The first weeks of my project you helped me to start in the right direction and introduced me to many people in the hospital. Your useful comments and suggestions during the rest of the project did help me a lot. Thank you for all the time you have spent helping me finish my project.

Siebe Brinkhof

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Chapter 1

Introduction

1.1 Motivation

Operating room (OR) management is a container term that spans all the activities undertaken to optimize the performance and outcomes of activities within the operating room. A significant body of literature exists about OR management varying from anecdotal and opiniating articles to original papers. The majority of the original scientific studies deal with OR efficiency, the concept that operations should be performed as efficient as possible with minimal 'non-surgical' times and a realization of operating times as previously planned. The time used by the surgeon for the operation (surgical time) is rarely the subject of study as it is usually assumed that this is a useful period in the operating room. It is well-known however that considerable differences exist between surgeons and their operating speed, the surgical pace[1].

Not only do surgeons differ, also the surgical times for the same operation by the same surgeon differ significantly.[2] Surgical time is the time between the first incision and the closure of the surgical wound. At the Leiden University Medical Centre (LUMC), surgical times are registered for all interventions in the operating room. For almost all interventions a wide distribution of surgical times is found[1]. It is also striking that this is an asymmetrical distribution, left-skewed, which can be frequently well described by a lognormal function[3,4]. This is illustrated by figure 1.1

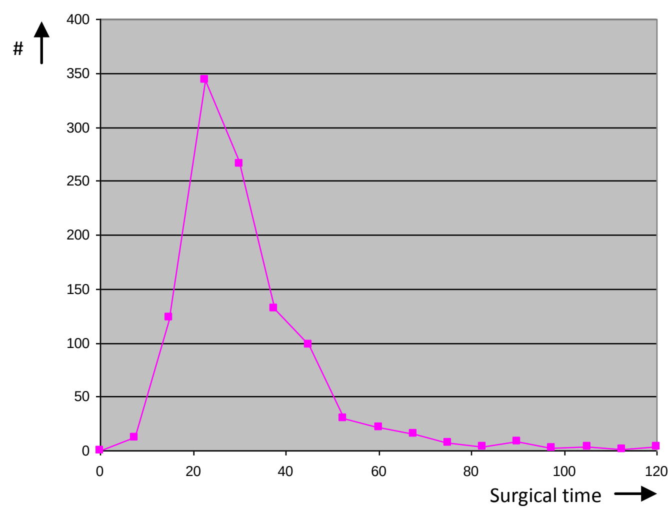

Figure 1.1 – Histogram of total surgical time based on 1080 cataract surgeries, performed in the LUMC

The question is what the source is of the skewed distribution. Possibly the skewness arises from the dichotomy of processes. Hereby the optimal process forms the shortest pathway and deviations lead to a longer pathway. It is not relevant whether the deviation of the protocol is intentional (due to anatomical variation or for reasons of postoperative functional outcome[5]) or unintentional (protocol violation or error[6]). An alternative theory is that the realized surgical times are the consequence of a composition of distribution functions of the separate activities following each other.

An operation can be described as a series of separate activities in sequence, resulting in the desired operation result. In practice, surgical actions are not always done in the same order, i.e. according to a fixed protocol. One reason for this are the (anatomical) variations per surgery, which make it necessary to adapt the order of the individual activities. Another reason is the surgeons having their own preferences.

1.2 Objective

The preceding section describes the need for a model that gives insight into the causes of process variation during surgery. This should be a quantitative model which can be adapted and applied to given preoperative initial conditions such as the operating surgeon or patient characteristics.

The objective can be translated into two main research parts:

- Development of a conceptual model, describing the surgical process in terms of the separate actions of the surgical procedure, the possible bypasses and alternative paths.
- Analysis of the surgical process using the collected data from observations and numerical techniques.

A surgeon is continuously balancing between efficiency of his actions and the patient comfort such as the time needed to rehabilitate and the final result. Therefore, judging statements about efficiency requires a high level of medical knowledge and additional after-surgical information. The results of this study are mainly observational, giving a description of the surgical process which can be used as quantitative support in the discussion about surgical efficiency.

1.3 Literature overview

A workflow is a sequence of operations declared as work of a person, a simple or complex mechanism or a group of persons.[7] Two types of workflow analysis can be distinguished, the traditional approach is designing a new (conceptual) workflow and then implement it in reality. In the past few years, a new approach is coming up based on so called data-mining and is actually the traditional method in reversed order: collecting data of the existing workflow leads to understanding of the underlying process. Obtaining such a model of an existing workflow is of great value for redesigning it.

Modeling of variability in surgical workflow was first described by Rossiter and Reynolds in 1963.[8] Since then, several models have been proposed for modeling surgical procedure times, such as lognormal and normal models.[3,9,10] Strum and Sampson showed with the analyzes of 46.322 surgical durations that variability among surgeons may be a result of their working at constant but differing rates.[1] The causes of these differences, whether in work methods, experience, an individual surgeon's natural speed or something else, would be interesting to find out. Additionally, there is considerable unexplained variability left in the operation time model, even when taking into account the prediction variables. The sources of this unexplained variability still remain an issue for future research.[11]

Wiegman[12] states that this variation is the result of surgical workflow disruptions, defined as deviations from the natural progression of an operation. Surgical workflow disruptions do affect mental readiness and the ability to maintain focus on a particular operation. This is regarded as the most important factor that affects patient outcomes, even more than technical skill or physical readiness. The rate of errors made by the surgical team increases with the rate of surgical flow disruptions.

Zheng[13] states that the natural progression of a surgery is difficult to define and is affected strongly by the type of procedure, surgeon preferences and patient conditions. Surgical workflow is therefore defined as the continuation of a designed surgical process within a specific observational period, an end-point measure regardless of the variability in the procedure. This means that within this period of time, if no surgical tasks using instruments were observed, a pause of surgical workflow was recorded. The length of the pause was recorded until tasks were resumed. The article shows that categorizing these so called disruptive events and examining their negative impact on the OR time will help to develop methods to eliminate inefficiency. OR time used for tasks such as conversation which are not directly related to surgery goals is seen as inefficient and the frequency and duration of these inefficient tasks are presented. A video-aided observational study can be used for developing objective assessment of team quality in the OR.

Rosen and Brown[14] use a discrete Markov model (DMM) to reveal the internal structure of the surgical task in order to objectively assess the performance of surgeons. The state space of the DMM represent the possible different combinations of tools used by each hand of the surgeon. The resulting skill level of a novice surgeon is a number which represents his task performance, normalized to the performance of an expert surgeon. The scoring is based on four equally weighted criteria: overall performance, economy of movement, tissue handling and the number of errors such as dropped needles.

A hidden Markov chain (HMM) is used to model the use of instruments during surgery by Blum and Padoy.[15] They state that the use of instruments represents the surgical workflow very well in the case of minimally invasive surgery (MIS), the type of surgery where only small incisions are made in the human body. Using video analysis they construct a method to automatically derive HMM's from binary data on instrument usage.

Chapter 2

Conceptual model

2.1 Cataract surgery in general

Cataract is a clouding of the human's natural lens, which lies behind the iris and the pupil. The lens works much like a camera lens, focusing light onto the retina at the back of the eye. The lens also adjusts the eye's focus, letting us see things clearly both nearby and far away. The lens is mostly made of water and protein. The protein is arranged in a precise way that keeps the lens clear and lets light pass through it. But when we get older, some of the protein may clump together and start to cloud a small area of the lens. This is a cataract, and over time, it may grow larger and cloud more of the lens, making it harder to see.

Cataracts are the leading cause of visual loss and the leading cause of blindness worldwide. By age 65, about half of the human population suffers from this condition, and at the age of 75, almost everyone does. In the Netherlands, over 150.000 cataract surgeries are performed per year. During surgery, the surgeon removes the clouded lens and in most cases replace it with a clear, plastic intraocular lens (IOL).[16]

2.2 The surgical protocol

The surgery can be split up in two parts: first the anterior chamber and the front side of the capsular bag have to be opened. After this, the human lens is replaced, and finally the wound is closed. In the next sections these two parts are described in more detail. The medical terms used in the descriptions can be found in figure 2.1.

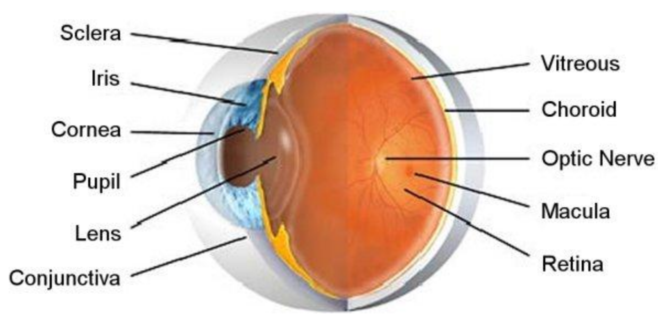

Figure 2.1 – Anatomy of the front side of the human eye[17]

2.3 Opening the eye

In order to reach the lens with the necessary instruments, the cornea and the front part of the capsular bag has to be opened. Opening the cornea can be done with three different methods: corneal incision, scleral incision and a combination of these two called corneal-scleral incision. A corneal incision is a short tunnel through the cornea, a scleral incision is a longer tunnel starting at the conjunctiva (the white part of the eye). When the patient comes out of the OR, the wound of a corneal incision is self-healing so no suturing is necessary, in contrary to scleral incisions. Consequently, the 100% sight of the patient is established faster when a corneal incision is used.

If the patient has a narrow iris when entering the OR, the iris has to be retracted. This can be done with or without cutting. Before surgery, the patient gets medical treatment in order to widen the pupil (called iris retraction). In the case of a sticky iris, no cutting is necessary. Otherwise, cutting of the iris has to be performed. In this report, when we speak of a narrow iris, we refer to a narrow pupil.

The anterior chamber is separated from the lens by the front side of the capsular bag. This layer, of approximately 14 micrometers thick, is very fragile. A circular opening is used to access the human lens. When performing this so called capsulorrhexis, it is very important that the rest of the capsular bag is undamaged. Therefore it is important to be extremely careful when performing this action. If the capsular bag tears, the lens can fall into the inner part of the eye. This is a major complication that delays the process considerably. Before the lens can be removed from the capsular bag it has to be flushed with water in order to weaken it apart from the capsular bag. This action is called hydrodissection.

2.3 Replacement of the lens

When there is full access to the lens, it is ready to be removed. Most of the time the lens is sculpted with a so called phaco-tip, using high frequency cutting. Then the lens is cracked into parts and removed from the eye. The surgeon can choose whether he sculpts the lens into four or two parts, depending on the lens hardness. After the sculpting is completed, the sculpted parts are being cracked in order to have loose parts which can be removed. Removal of the parts is also performed with help of the phaco-tip, sucking out the different parts of the lens. Here, it is even more important to leave the capsular bag undamaged because it is very sensitive in this stadium of the process being unsupported because of lens being removed. In some cases, the lens is removed without the sculpting and cracking it into different parts. The high frequency cutting uses a relatively high amount of energy and this damages the eye. It is therefore important to use as less phaco sculpting as possible.

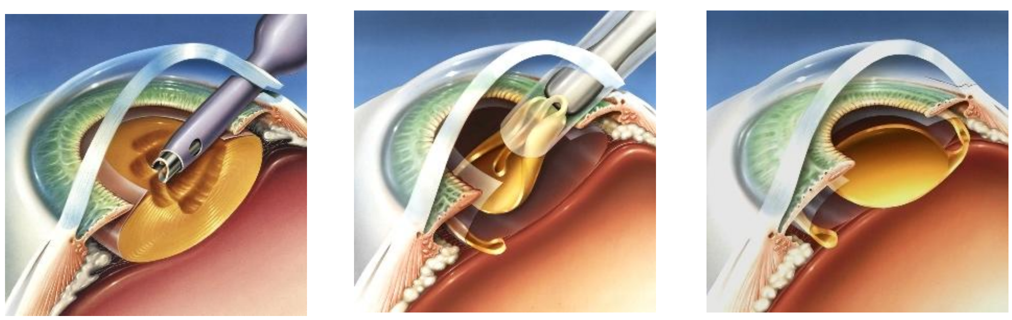

Figure 2.2 – Sculpting (left), injection of foldable lens (middle) and result of the cataract surgery (right)[18]

After removing the lens, the remaining cortex which is still inside the capsular bag need to be removed. This is the edge of the lens and is the thinnest part of the lens. An irrigation-aspiration hand piece is used. When finished, Healon is being injected into the capsular bag in order to put tension on it while injecting the artificial lens. The artificial lens is folded into a injection instrument by the assistant surgeon sitting. When the lens is injected into the capsular bag, it unfolds and is being positioned. Once the lens is in the right place, the surgery is nearly completed.

The main port is now being stitched if necessary and after closing the other ports by water injection the surgery is completed. This injection of water in the walls of the incision tunnel closes the tunnel due to the pressure admitted by the water in the walls. This closure is usually enough to keep the eye on pressure until the wound is healed. The surgeon might choose to use anti-inflammatory agents if the patient is sensitive to inflammation.

For many different reasons, the surgeon might choose to implant an alternative lens which can be non-foldable. In this case the incision has to be enlarged in case of a corneal incision, since this incision is too small to inject such a lens. If this decision is made during the process, this enlargement of the corneal incision takes a lot of additional time. Consequently, if the surgeon assumes that an alternative lens is necessary before start of the surgery, he uses a scleral opening.[19]

2.4 Flowchart of cataract surgery

The surgical phases required to complete a cataract surgery were discussed with an staff surgeon. This resulted in a flowchart containing all necessary phases during cataract surgery, which can be found in figure 2.3. However, each phase can be completed in different ways, for example there is more than one way to open the eye or implement the lens. The operating surgeon makes this decision based on patient characteristics and/or personal preferences.

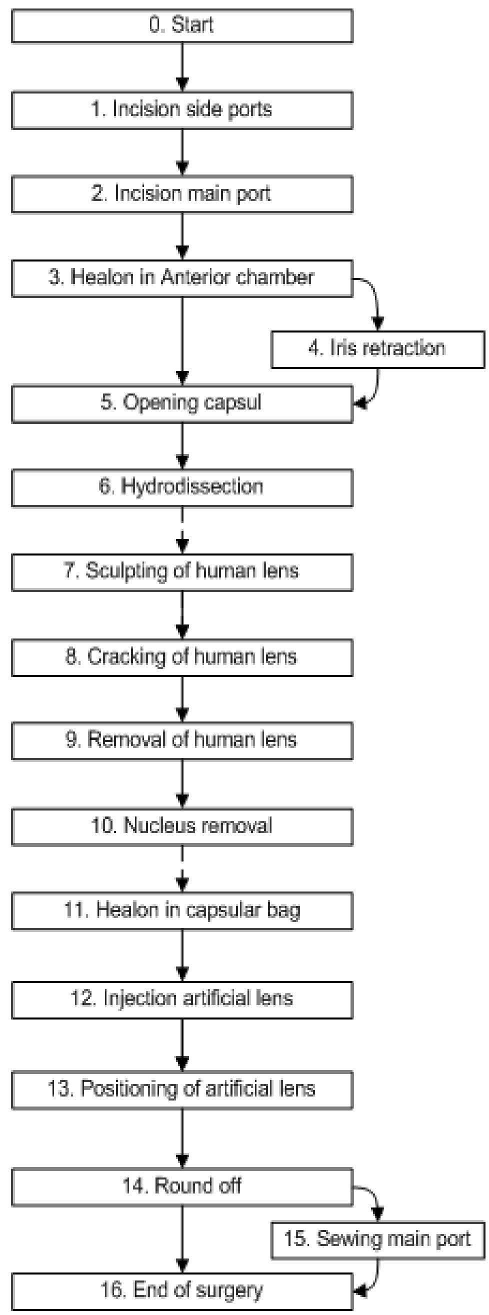

Figure 2.3 – Flowchart of cataract surgery

Chapter 3

Theoretical model

3.1 The semi-Markov model

A (discrete time) Markov chain, studied at the discrete time points $0, 1, 2, \ldots$, is characterized by a set of states and the transition probabilities between the states, defining the probability of finding the Markov chain at the next time point in state j, given the state at the current time point. A semi-Markov chain is an extension of a discrete time Markov process, it changes states in a similar way but stays at each state for a certain amount of time according to a sojourn time distribution function. The model can be described by the following parameters:[20,23]

S State space of the semi-Markov model containing all possible states of the process. $S = \{0,1,..,m\}$, where m is a countable number of states.

p_{ij} Transition probability of the embedded Markov chain moving from state i to state $(i, j \in S;\ i \neq j)$. For every state p_{ij} is defined, although the probability can equal zero. The conditions for this parameter are the same as those involved with a regular Markov chain:

$p_{ij} \geq 0$ $\quad\forall\, i, j,$ and

$\sum_j p_{ij} = 1.$

τ_{ij} Positive random variable representing the time spent in state i (sojourn time) before making a transition to state j. If this sojourn time is independent of the next state the notation τ_i *is* used. We have that

$\tau_{ij} \geq 0$ $\quad\forall\, i, j.$

$h_{ij}(\cdot)$ The probability distribution function (pdf) of τ_{ij}. If τ_i is used $h_i(\cdot)$ can be written. $H_{ij}(\cdot)$ is the cumulative distribution function (cdf). For a regular Markov process $h_{ij}(\cdot)$ is exponential and does not depend on j, so

$h_{ij}(\cdot) = h_i(\cdot)$ $\quad\forall\, j.$

One of the most important characteristics of (semi) Markov models is the memory less property. This means that given the present state, future states are independent of the past states. Formally,

$$P(X_{n+1} = x | X_n = x_n, \ldots\ldots, X_1 = x_1) = P(X_{n+1} = x | X_n = x_n),$$

where x_n are the possible states of the process, forming the set of states contained in the state space.

3.2 The state space

The possible values of X_i form a countable set *S* which is called the state space of the Markov chain. In the case of the cataract surgery, it can be defined as the set of all possible surgical actions performed in order to finish a cataract surgery. A graphical diagram of the Markov chain, used to model a cataract surgery is given in figure 3.1 on the next page. A description of the surgical actions corresponding to each state in the figure can be found in Appendix A. If for some state i the parameters p_{ij}, τ_i and h_i are independent of what happened in preceding states, this action can be modeled by a single state. Else, for every

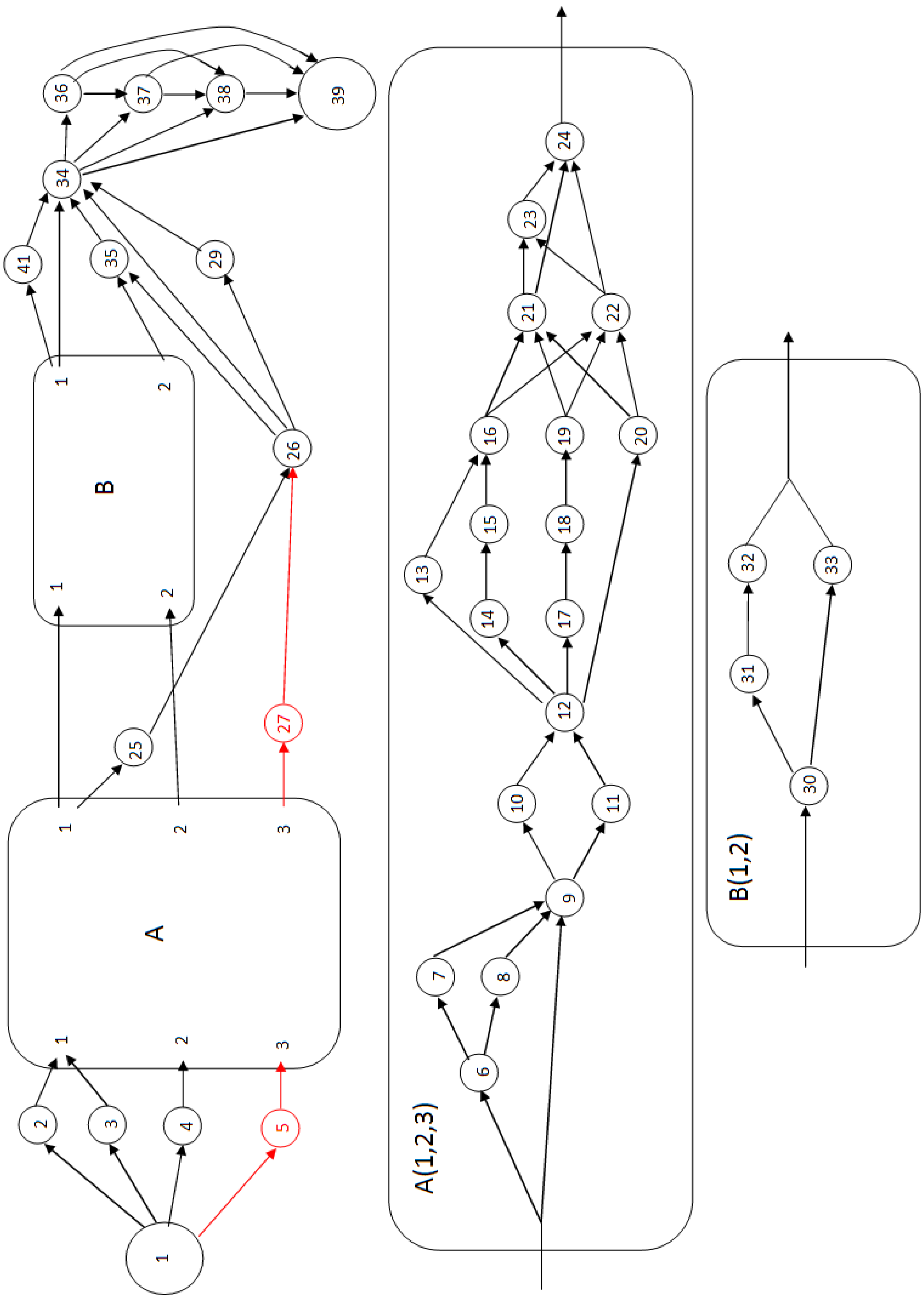

Figure 3.1 – Graphical representation of the state space. Red lines indicate states and transitions that exist but were not observed

dependent parameter a different state and a different path between these interdependent states has to be constructed. In this case, additional (duplicate) states are necessary as described in the next section. For example, if the time needed for removal of the lens is different for the two incision techniques (scleral or corneal) and is therefore dependent on the type of incision made earlier in the process, there are two different states representing lens removal: one for the scleral case and one for the corneal case, each with different h_i. These two different states are an example of duplicate states, discussed in the next section.

3.3 Duplicate states

Figure 3.2 (left) shows a directed graph of a small semi-Markov chain with two possible paths to get from state 1 to state 6. If we go to state 6 via state 2, the transition probabilities in state 4 are different from the case where we go to state 6 via state 3. Consequently, both states 4 cannot be the same state in both situations since the transition probabilities are not the same. We have to replace one of the states with a duplicate state representing the same surgical action in different circumstances, having both the same sojourn time distribution but different transition probabilities. The amended Markov chain with duplicate state is shown in figure 3.2 (right).

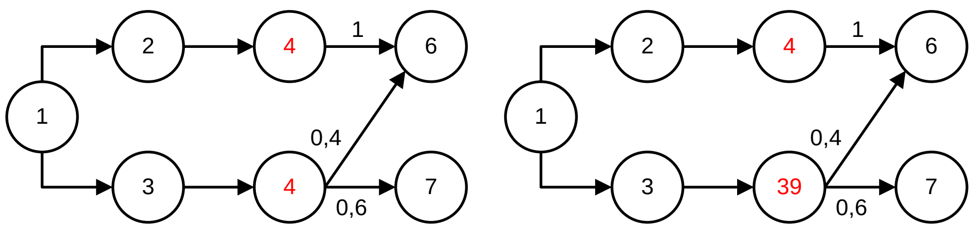

Figure 3.2 – Example of two semi-Markov chains, illustrating the concept of duplicate states

The state space of the surgical process given in figure 3.1, shows two blocks (A and B). These blocks both have more than one input and output. Block A has input 1 to 3 and B has input 1 and 2. When the process enters a block via some input, it will leave the block via the output with the same number. From the figure it is apparent that the transition probabilities of the last state of each block depend on what happened previously in the process. For example, output A1 has two possible transitions to input B1 or state 25, A2 has only one possible transition to input B2 and B3 has one possible transition to state 27. Within the blocks A and B, the surgical actions performed by the surgeon are the same but cannot be represented by a single state because of different transition probabilities per input, just like in the example given in figure 3.2. Consequently, each state in the blocks A and B has a duplicate state with the same sojourn time distribution as the original state but different transition probabilities.

3.4 First-passage-time distributions

A very powerful tool for the analysis of a semi-Markov chain is the derivation of first-passage-time distributions. A first-passage-time from state i to a non-empty set of states $\vec{j}$ is defined as:[21]

$$T_{i\vec{j}}(t) = \inf_{u}\{u > 0: X(u) \in \vec{j}\,|X(0) = i\}$$

This random variable has an associated probability density function such that:

$$P\big(a < T_{i\vec{j}} < b\big) = \int_a^b f_{i\vec{j}}(t)\ dt \qquad (0 \le a < b)$$

The aim is to determine $f_{i\vec{j}}(t)$ for given i and j in order to define the probability distribution function of the total surgical process duration. For the cataract surgery of this study, i equals 0 (start of surgery) and j equals 36 (end of surgery).

Furthermore, certain parts of the surgery can be analyzed by setting i and j at states of interest. First-passage-times can be found analytically involving Laplace transforms of the normal distribution which is complex in case of large chains. Therefore, a numerical method called Monte Carlo simulation is used.

To make filtering of certain surgery types possible, a database can be constructed with the observed data. This way the differences between surgical times, for example in the case of a hard or a soft lens can be examined. If there is a way to estimate lens hardness based on external patient characteristics such as age, this could be used to provide better surgical time approximation prior to the start of surgery.

3.5 Skewness of first-passage-time distributions in semi-Markov chains

For all states (except the first and last state) in the semi-Markov chain, two possible transition cases can be defined. When the Markov process is in some state i and has only one possible transition, the successive state j of the process is known with certainty. The concerning states i and j are in series, as depicted in figure 3.2 (left). Otherwise, in the case of more than one possible transition, the states are in parallel as depicted in figure 3.2 (right).

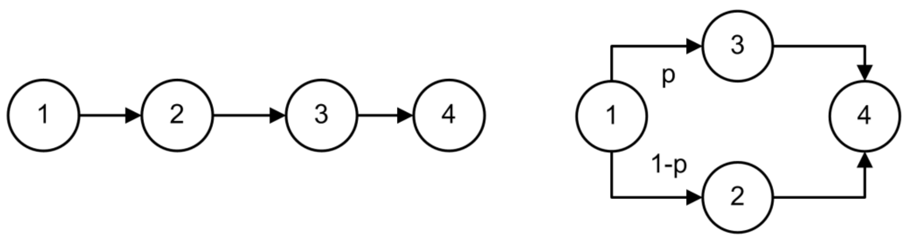

Figure 3.2 – Series (left) and parallel (right) states

Parallel states in a semi-Markov model can lead to a bimodal or even multimodal passage time distribution. A bimodal distributed random variable X is defined as Y with probability α or Z with probability $(1 - \alpha)$, where Y and Z are unimodal random variables such as the normal distribution, the mixture coefficient α is a constant between zero and one. A multimodal distribution is a mixture of more than two unimodal distributions. A mixture of two or more unimodal distributions with differing means is not necessarily bi- or multimodal. In the case of common standard deviations, a multimodal distribution is only found if the means are at least 2 standard deviations apart.[19]

In the case of cataract surgery, the individual sojourn time distributions of parallel states can be seen as unimodal distribution functions with the transition probabilities as the mixture coefficients. The parallel surgical paths together can lead to a skewed bi- or multimodal distribution. Because of the normal and therefore symmetrically distributed sojourn times, the total surgical time distribution cannot have a skewed distribution in absence of parallel intermediary states. This is a consequence of the additive property of a normal distribution, which states that the sum of two normally distributed random variables is a normal distributed random variable itself.

Chapter 4

Observational techniques and parameter estimation

4.1 Observational techniques

To analyze several cataract surgeries, video analysis is used. In the analysis, the time-action technique as described in the article by Minekus and Rozing[6] is employed. Two cameras are placed in the OR, one in the microscope of the surgeon and the second in a corner of the operating room, giving a good overview of the operating team and their interactions. During the recorded surgeries, notes were made by an observer to register events not in the sight of the cameras, such as people entering the operating room. Once all instruments are taken out of the eye, a new action starts. This choice is arbitrary to some extent because it is possible that after this moment the surgeon is still busy with the preceding action. For example, the surgeon might discuss his actions with other members of the surgical team about whether or not the action was successful. Nevertheless, this choice makes the registration of transition between states on the video registration easy and clear. We did not question the effect of this choice and future research might give better insight on this topic. Afterwards the video registrations were analyzed, and for each surgery the sequence of actions was registered in terms of the corresponding states in the semi-Markov chain. Such a sequence is called a surgical path sequence and the associated durations of each action were registered as a sequence: the surgical time sequence. Formally:

$$Surgical\ path\ sequence\ of\ surgery\ k\text{: } Y_k = \{Y_{k1}, \dots, Y_{kj}, \dots, Y_{km_k}\}$$

$$Surgical\ time\ sequence\ of\ surgery\ k\text{: } T_k = \{T_{k1}, \dots, T_{kj}, \dots, T_{km_k}\}$$

If, for example the surgical path and time sequences found for some surgery are:

$$surgical\ path\ sequence\text{: } \{1,5,8,12,16,32\}$$

$$surgical\ time\ sequence\text{: } \{2,14,8,21,30,17\}$$

then the duration of the action corresponding to state 5 was 14 seconds. The total surgery duration in the preceding example is 102 seconds, i.e. the sum of all elements in the surgical time sequence. All surgical path sequences $(Y_1, \dots, Y_n)$ and corresponding surgical time sequences $(T_1, \dots, T_n)$ form the set of data used to estimate the parameters of the semi-Markov chain. These estimators are described in the next section.

4.2 Estimating transition probabilities

In order to determine the transition probabilities for each state, the number of transitions from state i to state j are counted and divided by the total number of transitions from state i. Thus, p_{ij} is the fraction of transitions from state i to state j with respect to the total number of transition from state j:

$$p_{ij} = \frac{\#\ transitions\ from\ i\ to\ j}{\#\ transitions\ from\ i}$$

With an increasing number of observations the value of p_{ij} will be closer to the unknown real value.

4.3 Estimating Sojourn time distributions

The most complicated part of the parameter estimation is to determine the probability density function of the time spend in each state. Whenever in the process some state is visited, the length (in seconds) of the visit is measured. In the case of cataract surgery, the sojourn times are assumed to be normally distributed. We do not have enough data to test which distribution is a good fit to the observed sojourn times. The normal distribution can be used to describe, at least approximately, any variable that tends to cluster around the mean. This seems to be the case for cataract surgery. The estimators for the mean and standard deviation for some state i are the sample mean $\bar{T}_i$ and sample standard deviation S_i respectively, given by:

$$\bar{T}_i = \frac{1}{|N_i|} \sum_{(k,j) \in N_i} T_{kj}, \qquad S_i = \sqrt{\frac{1}{|N_i| - 1} \sum_{(k,j) \in N_i} \left(T_{kj} - \bar{T}_i\right)^2} \qquad (*)$$

The set N_i with cardinality $|N_i|$, contains all pairs of indices (k, j) for which element j of the surgical time sequence of surgery k corresponds to state i and corresponding duplicate state numbers, given by $i \bmod 35$:

$$N_i = \{(k, j) \mid Y_{kj} = i \bmod 35, k = 1,2, \ldots., n, j = 1,2, \ldots, m_k\},$$

Where n is the total number of surgeries, $(Y_{k1}, \ldots, Y_{kj}, \ldots, Y_{km})$ the surgical path sequence of surgery k containing m_k elements, and associated surgical time sequence $(T_{k1}, \ldots, T_{kj}, \ldots, T_{km})$. In this study, one duplication per state is sufficient. However, if for example scleral incisions would have been observed, more than one duplication would have been necessary.

4.4 Scaling of parameters

The personal preferences of surgeons performing a relative high number of surgeries per year have a higher impact on the total surgical time PDF than surgeons performing less surgeries. Therefore, the parameters of the semi-Markov chain need to be scaled using the fraction of surgeries performed by every surgeon. Scaling factors used in this study can be found in table 4.1.

Surgeon	Number of surgeries in 2008	Number of observations	Scaling factor
I	211	10	21
II	54	10	5
III	79	10	8
IV	119	6	20
Resident surgeons	93	8	12
Total	**556**	**44**	

Table 4.1 – Scaling factors

The scaling factors define how many times the observed surgeries of each surgeon are taken into account. For example, the surgical path sequences and surgical time sequences of surgeon I are included 21 times included in the data set. The number of surgeries n in the scaled case is $(10 \cdot 21) + (10 \cdot 5) + (10 \cdot 8) + (6 \cdot 20) + (8 \cdot 12) = 556$. This number equals the number of surgeries in 2008, performed by all observed surgeons. In this study, the number of surgeries performed per surgeon is small and the parameters are therefore sensitive to the differences in difficulty per surgery. If, for example, a surgeon with high scaling factor (say, 21) performed a very difficult surgery, the surgical path sequence and surgical time sequence of this surgery are found 21 times in the data set that was used to estimate the parameters.

(*) The number of times state i is observed in n surgeries is a stochastic variable, consequently there is a covariance between N_i and T_i . In this study, this covariance has been ignored but in future studies this might be a topic of interest.

Chapter 5

Implementation of the semi-Markov process in a programming environment

5.1 Monte-Carlo simulation

The semi-Markov chain of the surgery is analyzed using Monte-Carlo simulation, a problem solving technique used to approximate the probability distribution of certain outcomes of a physical or mathematical system by running multiple simulation runs, using random variables. This is a frequently used technique to analyze semi-Markov chains.

In our case, the probability transition vector P_{ij}, containing all transition probabilities in state i, was transformed into a cumulative probability vector P_{ij}^c. The j-th element of this vector p_{ij}^c is the sum of all elements with index less than or equal to j. When the process is in some state i, the next state j is determined using a uniform (0,1) random variable U:

$$X_{n+1} = min\ (\ j:\ p_{ij}^c \geq U \mid X_n = i)$$

It follows that the value of the stochastic variable X_{i+1} is equal to that j for which the element p_{ij}^c has the smallest value but is larger or equal to the stochastic variable U. In each visited state, a random variable is generated from the corresponding sojourn time distribution and the value is added to the total surgical time in the specific simulation run. Once the end-state is reached, the total process time is saved and the next simulation run is started until a fixed number of simulation runs is performed. The probability density function of the process time is approximated using a histogram with very small histogram interval width x_0. The height of the histogram 'bins' represent the number of times the total process time lay within the interval borders. Scaling this histogram results in the desired graph, where the area under the graph equals one as intended for a probability density function. A histogram converges to a PDF when the interval width x_0 approaches zero.[22]

5.2 Matlab structure

To carry out the numerical experiments, the Matlab programming environment is chosen. Figure 5.1 gives an overview of the structure of the simulation in Matlab. First of all, the process and simulation parameters are loaded from the input file. Simulation parameters are for example the number of surgeries simulated, or the start and end-state of interest. Process data are the surgical path and time sequences. Parameter values associated with the sojourn distributions and transitions probabilities are then estimated as described in chapter 4. The time loops in the process are indicated in different colors. Two time loops can be identified: The number of simulated surgeries and the state transitions within a single surgery.

After the initialization the first 'run loop' starts, this loop represents the total number of surgery simulations and possesses a small time loop representing the process of one surgery. Once a certain surgery enters the end state, the small time loop is completed and the total process time is saved. After resetting the process data a new surgery is simulated until the total number of simulation runs is reached. With the saved data the previously discussed histogram is generated.

If confidence intervals are of interest, these can be generated by looping the 'run loop', resulting in more than one data point for each histogram interval. These data points can be used to calculate the confidence intervals. The M-file can be found in appendix B.

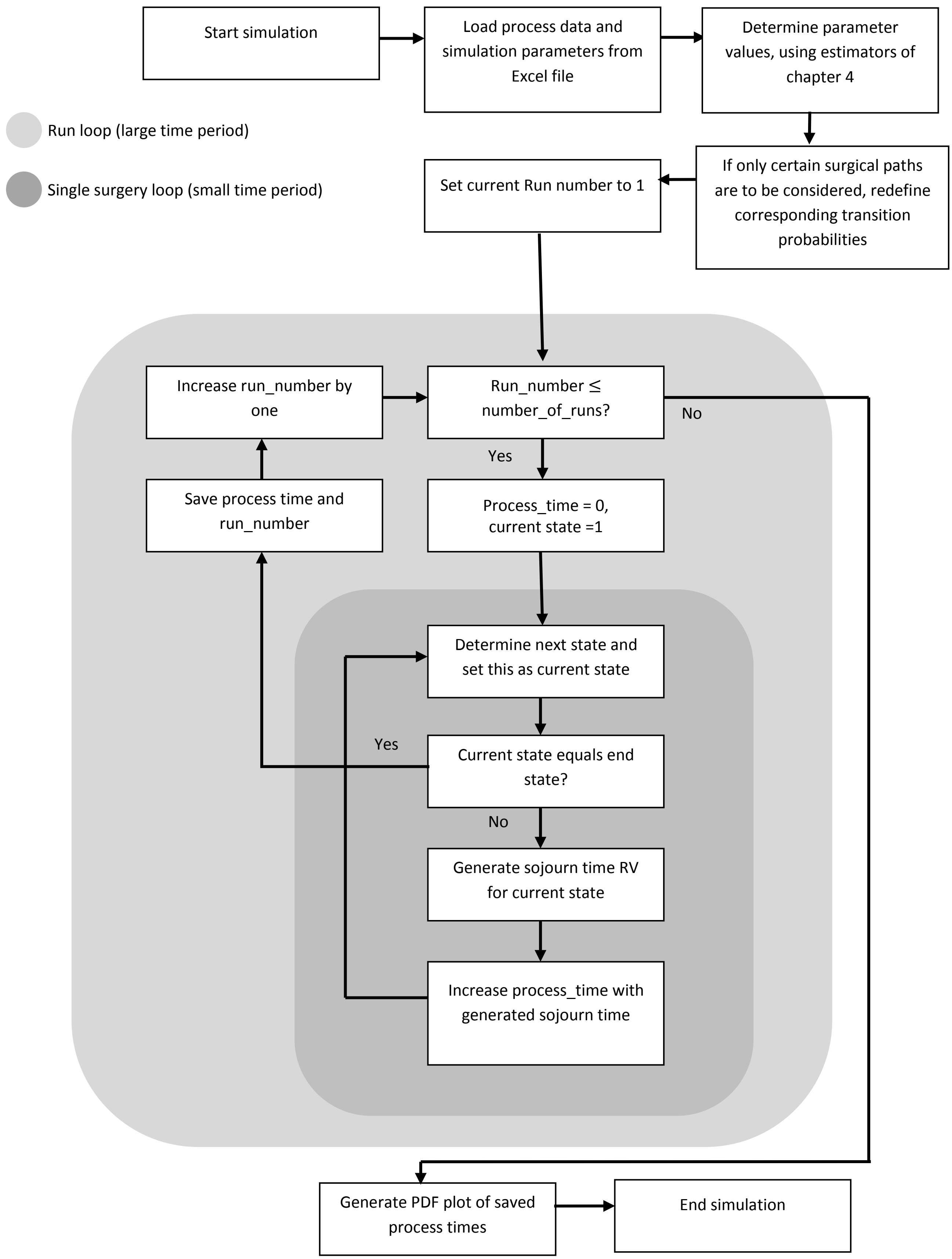

Figure 5.1 – Matlab structure of the surgical time PDF generation

Chapter 6

Results

The graphs in this chapter are based on 125.000 simulated surgeries. First, the effect of scaling parameters is presented, since for this study a small number of datasets was available, scaling might have a large effect on the parameters. The distribution of the surgical time PDF is investigated and differences in surgical time for distinct types of surgeries with respect to patient characteristics and type of surgeon performing the surgery are pointed out. Based on these results, four patient categories are proposed. For each category, upper bounds on surgical time can be provided.

6.1 The effect of scaling parameters

A difficult surgery performed by a surgeon with a high scaling factor will have a large impact on the value of the transition- and sojourn time parameters. Because of the small number of observations per surgeon, it is likely that unbalanced difficulty ranges per surgeon occur. The scaled parameters are sensitive to the type of surgeries the surgeon performed during the observations. A larger number of surgeries would have given a more accurate estimation of the parameters. The question is what the precise effect is of scaling is in this study. Probability density functions of total surgical time based on the scaled and unscaled parameters are shown by the blue and the red line in figure 6.1 on the next page. The two lines can be seen as upper and lower bounds for the real values which lie somewhere between the two curves. In the figure, the scaled curve is shifted to the right indicating differences between the observed surgeons with respect to surgical time. As stated before, the reason for this can either be a difference in difficulty range per surgeon or a difference in individual preferences leading to longer surgery durations. Because of the small difference between both curves, the effect of scaling appears to be relatively small. However, only scaled parameters will be used from now on because this would also be the case if a larger dataset with balanced surgical difficulties per surgeon would be available.

6.2 QQ-plots of the total surgical time distribution

The curves in figure 6.1 are obviously skewed but not as much as expected based on figure 1.1. The question rises whether the data follows a normal or a lognormal distribution. To answer this question, a visual goodness of fit test is used in the form of a qq-plot. If the data set agrees on the quantiles of the hypothetical distribution, the plot gives a straight line. In case of substantial deviations from linearity, the null hypothesis of sameness is rejected.[23] The normal and lognormal qq-plots are shown in figure 6.2.

Based on these figures the simulated PDF is not similar to a normal or lognormal distribution, but lies somewhere in between. The differences are mainly found for the high quantiles (over 2000 sec.) which relate to the right tail of the distribution curve. The normal and lognormal distribution functions have a respectively shorter and longer tail than the simulated PDF of surgical time. During the observations no major complications occurred in surgical procedures, but suppose these would be included, in combination with a better scaling of parameters as described in the previous section, the simulated PDF of surgical time would approach the PDF of the lognormal distribution. This is in line with the observation of Strum, stating that the lognormal model is superior to the normal model of surgical time for a large and diverse set of surgeries.[3]

6.3 The difference between staff and resident surgeons

The data for the curves in figure 6.1 is based on both resident surgeons and staff surgeons. It is obvious that there are differences in surgical time between these two groups. The medians of the two curves in figure 6.3 do illustrate this fact. For staff surgeons the median is found at approximately 15 minutes. For resident surgeons this value is found at

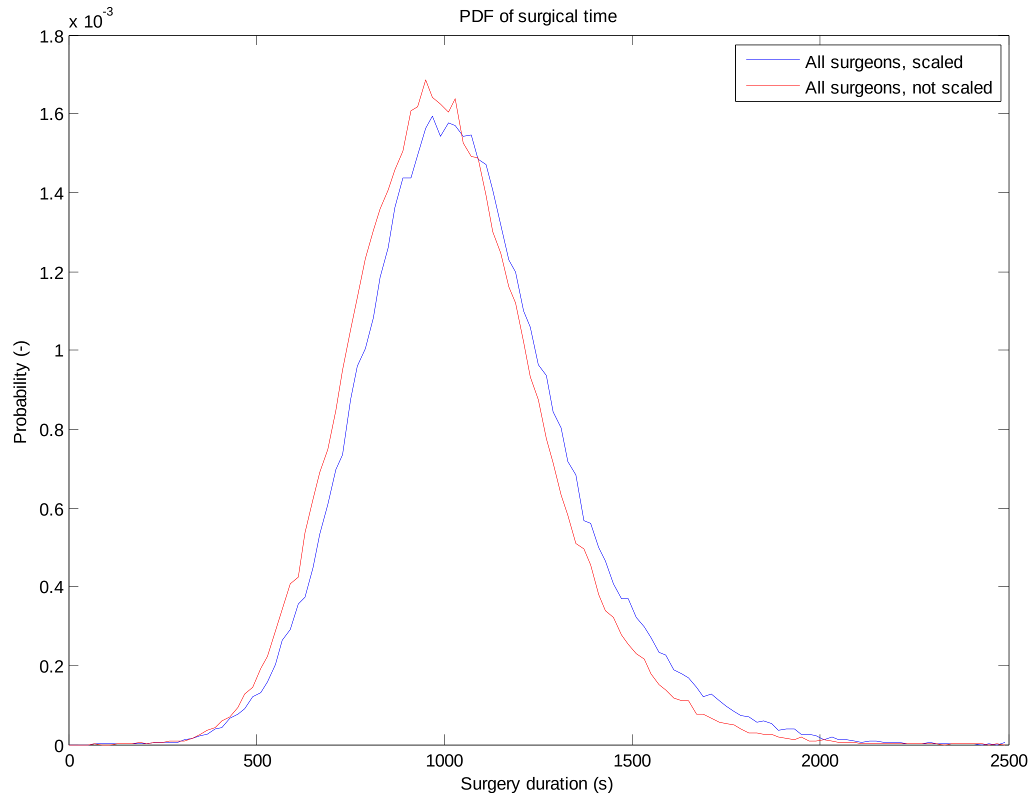

Figure 6.1 – PDF of surgical time in the case of scaled (blue) and unscaled (red) parameters

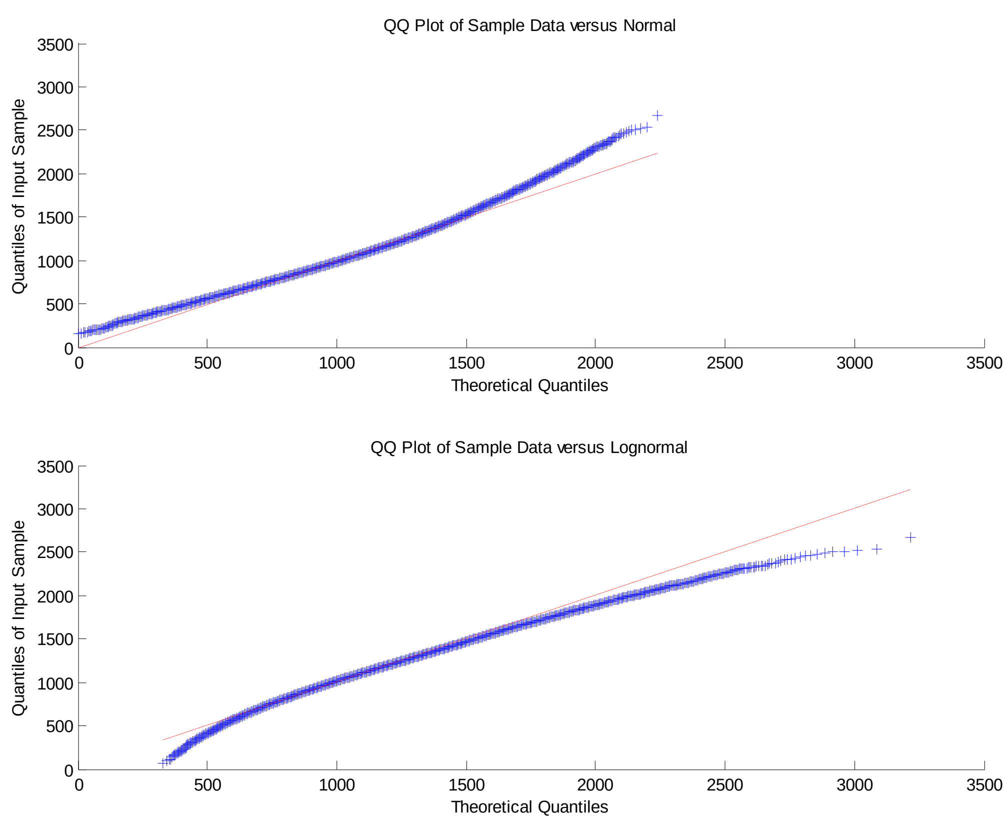

Figure 6.2 – QQ-plots of the surgical time PDF of figure 6.1 versus normal (upper) and lognormal (lower) quantiles

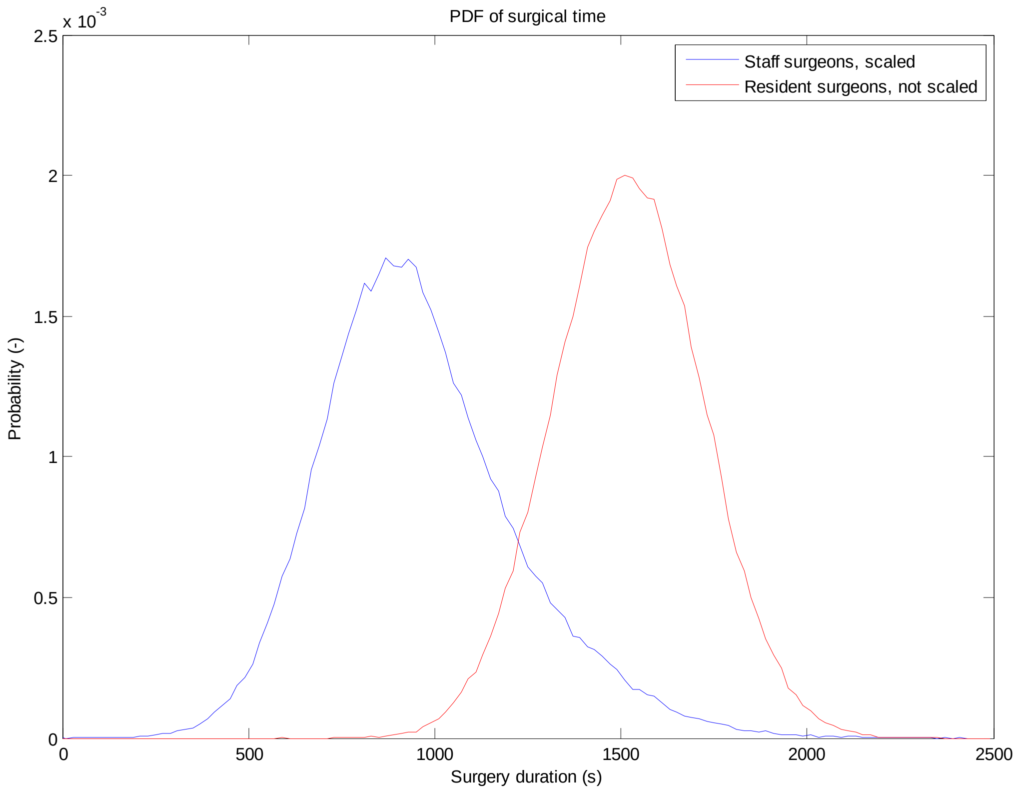

Figure 6.3 – PDF of surgical time in the case of staff surgeons (blue) and resident surgeons (red)

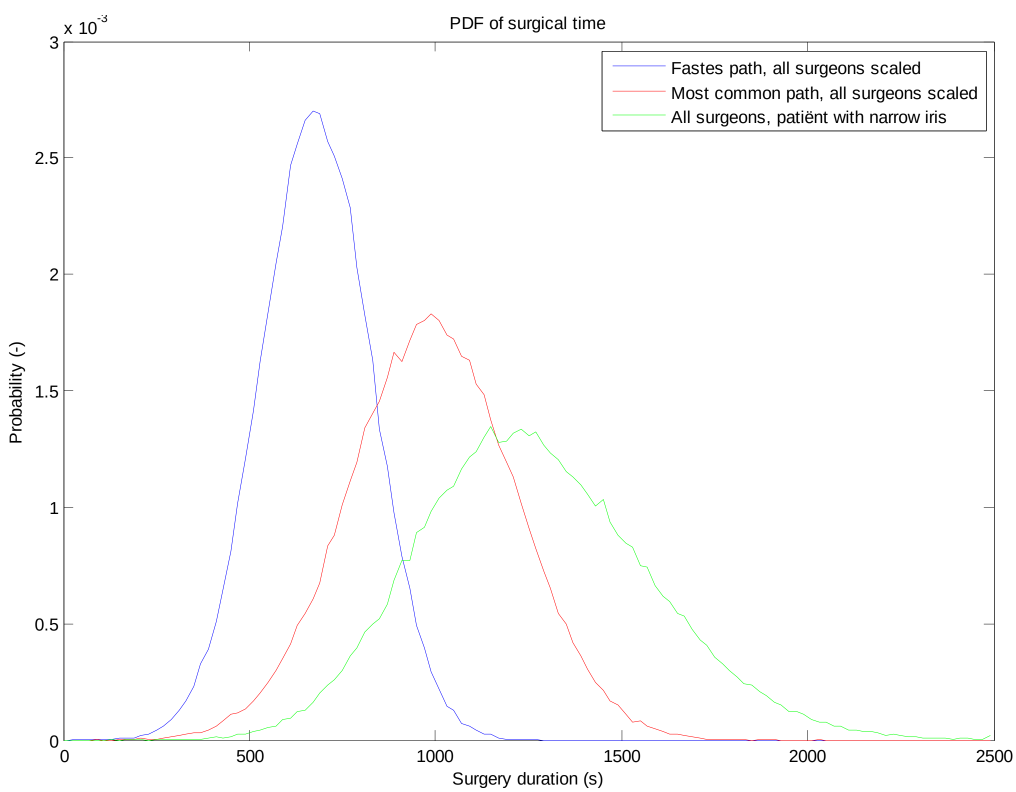

Figure 6.4 – PDF of surgical time of the fastest path (blue), the most common path (red) and in the case of a narrow iris (green)

approximately 26 minutes. We also see that the blue curve (of the staff surgeons) is wider than the red one (of the resident surgeons). A reason for this could be that resident surgeons only perform the less difficult surgeries, and therefore have a smaller variance of surgical time. If a complication occurred during the observations, the staff surgeon usually took over. These observations with a surgeon switch were excluded from the data. Besides that mean surgical time would increase if resident surgeons perform more difficult surgeries, also their observed variance would increase.

6.4 Analysis of specific surgical paths

One might also be interested in some specific path. For example, the PDF of surgeries where the iris has to be retracted or those concerning patients with a very soft lens which can be removed without sculpting can be analyzed. The specific paths in the semi-Markov chain are constructed by setting the transition probabilities of the path of interest to one and all the others to zero. In figure 6.4, the PDF´s of some surgical paths are illustrated. The fastest path appears in situations where a surgeon does not have to retract the iris and the lens is very soft so it can be removed without sculpting or cracking.

The ´most common path´ appears when the iris is wide but the lens is of normal hardness and the surgeon has to sculpt and crack the lens in four parts before it can be removed. If the patient does have a narrow iris when entering the operating room, the probability distribution function of the surgical time is the green curve in figure 6.4. For comparison, the curve in black indicates the PDF of all types of patients and is the same one as in figure 6.1. In case of the narrow iris only the transition probabilities concerning iris retraction are altered and one might argue that iris retraction also influences other parts of the surgery, in this study it is assumed not to. The surgical sequences for the fastest and most common path are found to be:

Fastest path: $1-3-9-11-12-20-21-24-30-33-34-39$
Most common path: $1-3-9-11-12-14-15-16-21-24-30-31-32-34-39$

In the case of a narrow iris, state 6 is always visited, while the rest of the transition probabilities remain unchanged. The curves appear to have a normal distribution which is a direct consequence of the chosen paths. As described in section 3.5, connecting states with normal distributed sojourn times in series gives rise to a normal distributed first-passage-time, instead of a skewed distribution that occurs in the case of parallel (multimodal distributed) states.

6.5 Patient categorization and upper bounds on surgical time

Based on the results from the previous sections the surgeries can be categorized. Presurgical patient characteristics such as lens hardness determine which surgical path is most likely and an upper bound of the surgical time can be constructed accordingly. For example, a patient that meets the criteria of a very soft lens and a wide iris has a chance of approximately 95 percent that his or her surgery will take less than 16 minutes, provided that the surgery will be performed by an staff surgeon. On the other hand, a narrow iris in combination with a hard lens raises this boundary to a maximum of 30 minutes in 95 percent of the surgeries. Categorizing surgeries upon the following characteristics provides upper bounds on surgical time:

A Surgery performed by staff surgeon or resident surgeon.

B Patient has narrow or wide iris when entering OR

C Lens hardness

D Type of artificial lens to be inserted

All categories are related to some part of the semi-Markov chain, only category A has effect on all parameters and the PDF of the surgical time for this category is shown in figure 6.1. The second category effects the parameters involved with iris retraction, in the Markov chain represented by states 6, 7 and 8. Category C has effect on the parameters involved with sculpting, cracking and removal of the human lens, represented by states 13 to 20. In certain situations the surgeon chooses to insert a non-foldable alternative lens, consequently the corneal incision has to be enlarged during surgery. This surgical path is represented by states 25 to 29. If there is some way of estimating the probability of this complication, a surgeon might choose before start of the surgery to use the alternative lens and corneal-scleral or scleral incision might be preferred leading to less additional time.

The first two categories can easily be determined pre-operatively, while the last two are more difficult to estimate before the start of a surgery. Good methods to estimate these factors would make the upper boundaries to surgical times more accurate and might be a topic for future research.

The upper bounds on surgical time can be used to make a more efficient OR schedule, resulting in improved operating room utilization. At this moment, for each cataract surgery a fixed amount of time is scheduled. The estimated amount of time needed is actually higher than necessary, since it appears that currently surgical times are not properly recorded. A positive side-effect of this study is that presurgical medication can be adjusted more accurately, and better information can be provided to patients about the time they will spend in the operating room. Cataract surgery is a frequent performed surgery and there are not many variations in the surgical path, as shown in chapter 3. If we apply the methods of this study to more complex (longer) surgeries, the upper bounds on surgical time per category could be even more valuable with respect to operating room utilization. Besides these managerial implications, the graphical Markov chain and the curves of this chapter give insight in the process. They could for example be used for educational or optimization purposes.

Chapter 7

Conclusions

The skewed surgical time distribution function is caused by differences in surgical speed between staff en resident surgeons in combination with the multiple possibilities to complete the surgical phases, leading to parallel surgical paths. Well defined patient characteristics such as a wide iris when entering the OR mainly determines which of these paths is taken in order to complete the surgery. We studied some particular cases which can be found in table 7.1

The surgical time distribution for staff surgeons is wider than the one for resident surgeons. This is caused by the fact that resident surgeons only perform the 'easier' surgeries. Differences between individual staff surgeons were not studied. We did not have enough data per surgeon to make a fair comparison with respect to their surgical speed. It is possible that differences in surgical speed lead to a skewed distribution although, based on the observations, we think this will not be the case.

The main cause of skewness is the difference in surgical difficulty, caused by patient characteristics. We found concrete groups of patients for which the surgical time distribution function show major differences. Categorizing patients in these groups gives an indication of surgical difficulty, resulting in a better approximation of the upper bounds on surgical time:

A Surgery performed by staff surgeon or resident surgeon.

B Patient has narrow or wide iris when entering OR

C Lens hardness

D Type of artificial lens to be inserted

The upper bounds can be used to make a more efficient OR schedule, resulting in improved operating room utilization. At this moment, for each cataract surgery a fixed amount of time is scheduled. Cataract surgery is a frequent performed surgery and there are not many variations in the surgical path. If we apply the methods of this study to more complex (longer) surgeries, the upper bounds on surgical time per category could be even more valuable with respect to operating room utilization. Besides managerial implications, the graphical Markov chain and the curves of this chapter give insight in the process. They could for example be used for educational or optimization purposes.

Case description	**Mean surgical time**	**Upper bound on surgical time**
Fastest path, all surgeons	10 minutes	20 minutes
Most common path, all surgeons	17 minutes	27 minutes
Most common path in combination with a narrow iris, all surgeons	22 minutes	38 minutes
Staff surgeons, all types of surgeries	15 minutes	31 minutes
Resident surgeons, all types of surgeries	26 minutes	35 minutes

Table 7.1 – Cases with corresponding mean surgical time and upper bounds.

Chapter 8

Discussion and follow-up

This project can be seen as a exploring study on Markov-modeling in (cataract) surgeries. We recommend to extend the dataset of the model to approximately 400 surgeries. Besides the statistical significance of this extension, the larger data set can be used to examine differences in surgical speed between individual surgeons. In this chapter we discuss some other topics for future research.

The memory less property as discussed in chapter 3 is not validated in this study. In case of dependency between states, duplicate states were constructed in order to remove the memory. In future work, it has to be validated that with this adjustment, the chain is indeed memory less. This could be done using visual methods such as a scatter plot or quantitative methods such as calculating the correlation coefficient for each combination of states per surgery. In the first method, for a given set of two states, each point has two coordinates corresponding to the sojourn time in these states. For example, the x-coordinate corresponds to the sojourn time in state i and the y-coordinate to the sojourn time in state j. Each point corresponds to the observed sojourn times of these states in a surgery. Such a plot will show a random pattern in case of independency between the states of interest i and j.

Another assumption is the sojourn times being normal distributed. In future work, this assumption has to be validated. A QQ-plot can be used to test the normality of the observed sojourn time data. Alternative distributions such as the Lognormal distribution can also be tested. A disadvantage of the normality assumption is the possibility of finding negative sojourn times if the variance is found to be large with respect to the mean. This is illustrated by the normal QQ-plot of figure 6.2 where the (blue) data points are intersecting the y-axis at a value greater than zero. We considered this as a consequence of our normality assumption and did not correct for this. If more data would be available, we assume that the variance will become smaller and no negative sojourn times will be found.

After testing the current model with more data some refinements can be added. For example, extension of the state space with more details on the surgical actions might lead to a more sophisticated model. For example, some of the surgical actions in our state space represent a very large part of total surgical time. Subdividing these states with possibly new parallel paths might give more detailed information about the process.

Another topic for future research is the analytical solution of the first-passage-time distribution. This involves adding up Laplace transforms of the sojourn time distributions which is a complicated task when the Markov model gets larger. Once this solution is found explicitly, characteristics of the distribution such as upper bounds can be calculated explicitly

Finally, estimating lens hardness before a patient enters the OR is a topic for future research. With this information, patients can be categorized properly as described in chapter 6.

Chapter 9

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Appendix A

Definition of states

The graphical state space of the surgical process can be found on the next page. The description of the states can be found below. Some states do not exist (28 and 40), these were deleted during the study. In the state-space, black arrows indicate states that were visited during the observations, red ones were not.

State	Description
1.	Start surgery
2.	Corneal incision of main port with one side ports
3.	Corneal incision of main port with two side ports
4.	Corneal-scleral incision of main port with two one ports
5.	Scleral incision (not observed)
6.	Injection of Healon in anterior chamber before iris retraction
7.	Iris retraction with cutting
8.	Iris retraction without cutting
9.	Opening of capsul without extra Healon
10.	Opening of capsul with extra Healon
11.	Hydrodissection
12.	Sculpting of lens in four parts
13.	Alternating sculpting and cracking
14.	Cracking of lens in four parts
15.	Removal of four parts
16.	Sculpting of lens in two parts
17.	Cracking of lens in two parts
18.	Removal of two parts
19.	Removal of two parts
20.	Removal of lens without sculpting and cracking
21.	Removal of nucleus
22.	Removal of nucleus in two parts
23.	Polishing of capsul
24.	Injection of Healon in capsular bag
25.	Enlarging main port and injection of non-folded lens after enlarging main port
26.	Positioning of alternative non-folded lens
27.	Enlarging main port and injection of non-folded lens for scleral main port
28.	Does not exist
29.	Large suture of main port
30.	Injection of folded lens
31.	Positioning of lens with sweep
32.	Positioning and flushing after positioning with sweep
33.	Positioning and flushing of the lens without first positioning with sweep
34.	Completion of surgery
35.	suturing main port in case of corneal-scleral main port
36.	Intended delay (educational)
37.	Intended delay
38.	Cutting of sclera
39.	End of surgery
40.	Does not exist
41.	Suturing main port in case of corneal incision