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Toni Ruohonen

Improving the Operation of an Emergency Department by Using a Simulation Model

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ABSTRACT

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During the past few years the efficiency in health care has not been as good as expected, and a need to improve the operations in different units has arisen. The operation of acute care units, emergency departments especially, is generally regarded as inefficient. Waiting times are too long and patients have to spend too much time in the process before being discharged, forwarded or even seen by a doctor for the first time.

Although it is quite easy to develop new alternative proposals for these kinds of problems, the difficulty lies in finding the best solutions and validating their effects on the whole operation. Because hospital environment is very complex and contains many random features, appropriate and effective tools should be used in improving the operations there. These tools should be able to show the effects of different alternative solutions before being implemented, to avoid risking or disturbing other everyday activities.

A suitable tool for the purpose is simulation, which in decision making can give important information on the present operation and on the effects of proposed alterations. In many studies, simulation has been used to model the operation of an emergency department, using patient waiting times and throughput time as the main target variables. However, in these studies the solutions have mainly been sought only from a single point of view. Under examination have usually been either resources or processes or in some rare situations both. This kind of an approach is very narrow and provides only small and local improvements.

In our study, simulation was used to create a new universal mode of action for emergency departments. Processes, resources and technological solutions were taken under examination. The focus was on the main patient process: this made it possible to find solutions, which would reduce passive waiting time, decrease the throughput time and still keep the quality of care at a good level.

The results of the simulation run showed that implementing all the solutions proposals at the same time would decrease the patients' length of stay over 40 %. As can be seen from the results of this study, with the use of new technologies, alternative strategies, and resource reallocation it is possible to improve the operation of different heath care units and meet the challenges in the health care.

Keywords: simulation, health care, patient process, emergency department

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PREFACE

I can still remember the day when I first came to Jyväskylä without any great expectations or dreams. My employment in Pori was about to end and I had decided to continue my studies either in Pori or in Jyväskylä. I had been accepted for university studies in both of those towns, and the time had come to make a decision about which place to choose.

It was a sunny July morning in 2003 when I arrived in Jyväskylä with my parents. I had not been in Jyväskylä before and I did not know anybody there, but as soon as I saw the beautiful landscape and visited Agora, I was sure that it would be the right place for me.

I started my studies in September. I did not have any great plans to talk of at the beginning, but after a few months my objective was clear. I received an email from my present supervisor, Professor Pekka Neittaanmäki. It was addressed to all students but since I was on the mailed list, I decided to answer. Although I was just starting my Masters studies, I had already started to dream of postgraduate studies. Professor Neittaanmäki started to guide me and under his efficient and wonderful supervision I graduated within a year. It was not easy but I put all my efforts on studying and I was one step closer to my dream.

In May 2004 I started to work in Agora Center as a trainee and after a few months I got in on the Tekes NOVA-project which started in the Central Finland Health Care District. It offered me a possibility to start working with my doctoral thesis on simulation in health care and of course I seized that opportunity. Now, after 2,5 years hard work, I have finally reached the point where I am finishing my doctoral studies and defending my thesis.

However, It would have been very difficult to realize my dream alone without the invaluable support of many people along the way. First of all I want to thank Central Finland Health Care District, especially Jorma Teittinen and all the other members of the Tekes NOVA-project, who have supported me during the project.

I wish to express my sincere gratitude to my supervisor, Professor Pekka Neittaanmäki, for his excellent guidance and continued support during the studies. I owe him a lot, because without him I would not be where I am now. I am also grateful to Reeta Neittaanmäki who helped me greatly in statistical issues concerning the simulation model. For valuable assistance with the english language, I want to thank Steve Legrand. I owe my thanks to all my colleagues and other experts at the University of Jyväskylä as well.

I would like to thank the reviewers, Professor Amir Averbuch from Tel Aviv University, Israel, and Docent Erkki Laitinen from the University of Oulu, Finland for their valuable comments. I would like to express my appreciation to Professor Timo Tiihonen and Mr. Edward J. Williams for their constructive criticism and valuable comments as well.

I appreciate the help of Hannu Lähdevaara from the Jyväskylä University of Applied Sciences. He has given me invaluable support and constructive criticism concerning the development of the simulation model.

For financial support I am grateful to Tekes (the NOVA-project) and the COMAS graduate school of the University of Jyväskylä. Furthermore I want to thank also Agora Center for the continued support.

Finally, I would like to thank all my near relatives and friends, who have supported and motivated me during my studies. Special thanks especially to my wife to be Merjaana Nurminen and to my parents Antti and Pirjo Ruohonen, whose love, support and encouragement has given me strength without which I never would have got this far - thank you all from the bottom of my heart!

Jyväskylä 18.5.2007

Toni Ruohonen

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1 INTRODUCTION

Public services are an important talking point today. Everyone wants good services but what counts as good can be interpreted in many different ways. There are usually different demands for different services. In health care, the main requirements are the quality of care and efficiency. People expect to be diagnosed as soon as possible, without any unnecessary waiting, and be treated with good care through the whole process.

During the past few years the efficiency in health care has not been as good as expected, and a need to improve the operations in different units has arisen. The operation of acute care units, emergency departments especially, is generally regarded as inefficient. Waiting times are too long and patients have to spend too much time in the process until they are discharged, forwarded or even seen by a doctor for the first time. These things have created dissatisfaction among patients and personnel.

However, patients and personnel are not the only ones who are not satisfied with the situation. If the operation is inefficient, it increases costs as well, and this should be of concern to the decision-makers. These things are presenting an extreme challenge to health care managers, who have to solve these problems somehow.

Attempts to improve operations usually consist of hiring more staff or equipment. Insufficient resources are thought to be the cause of the problems, which include inefficient operations as well. Although hiring new employees and purchasing new equipment may make the operation more efficient, it increases the costs as well. This is not desirable where cost-effective solutions are being sought. Operations should be improved without increasing costs, which should be lowered instead. That is why the solutions have to be sought from somewhere else than personnel hiring.

There are, in fact, other ways to approach and solve these problems. Besides employing more personnel, the operation can be improved by examining the processes, allocating existing resources more effectively and using technological solutions. This kind of improvement can decrease the passive waiting times, which truly is the biggest problem in today's emergency departments.

Although it is quite easy to develop new alternative proposals for these kinds of problems, the difficulty lies in finding the best solutions and validating their effects on the whole operation. At this moment these decisions are based mainly on the experience of managers and staff or they are evaluated with traditional and analytical methods, which cannot take all the variables into account very efficiently. Decisions based only on experience and analytical methods can be very risky and costly as well. Because hospital environment is very complex and contains many random features, appropriate and effective tools should be used in improving the operations there. These tools should be able to show the effects of different alternative solutions before being implemented, to avoid risking or disturbing other everyday activities.

A suitable tool for the purpose is simulation, which has been used in the manufacturing industry for decades to examine processes and product flows. It has been used to make the operation of different production lines more effective by reorganizing the operations in the process. During the past few years it has enhanced its popularity in health care as well, because there is a certain analogy between manufacturing industry and health care. Both systems consist of processes, which is why simulation can be used as a decision support tool. Simulation in decision making can give important information on the present operation and on the effects of proposed alterations in health care as well.

In many studies, simulation has been used to model the operation of an emergency department using patient waiting times and throughput time as the main target variables. However, in these studies the solutions have mainly been sought only from a single point of view. Under examination have usually been either resources or processes or in some rare situations both. This kind of an approach is very narrow and provides only small and local improvements. If the aim is to improve the operations on a larger scale, processes, resources and technological solutions should be taken under examination. To be able to exploit these solutions more widely than just within a certain unit they should be examined at a general level. It is possible to do that by concentrating on the main process of the ED.

In our study, simulation was used to create a universal mode of action for emergency departments. Processes, resources and technological solutions were taken under examination. The focus was on the main patient process: this makes it possible to find solutions, which would reduce passive waiting time and still keep the quality of care at a good level. Alternative solution proposals were developed with the staff in order to create solutions, which would follow the hospital protocols and be appropriate for implementation. The main idea of the scenarios developed is to find answers to the problems encountered and in that way reduce patients’ passive waiting time and decrease the throughput time. When passive waiting time is reduced, it increases patients' and personnel satisfaction as well.

This study starts with an introduction to simulation. In Chapter 2 the basic operation of simulation and its use are described. The research method is then introduced making it easy to understand how the method works and how it can be used.

After the introduction, the use of simulation in health care is considered in Chapter 3. Relevant literature is reviewed and all the simulation studies known to the author and performed in health care and especially in emergency departments are presented. The literature review provides a good and clear understanding of how simulation has been used in health care earlier and of the kind of solutions that have been found by using it.

After the method has been introduced and the earlier studies presented, the actual simulation project phase is described in Chapter 4. The simulation project as well as the model development is described phase by phase. The operation of the model is described at a very detailed level in order to give a clear understanding for health care personnel about how the model was constructed. Without detailed examination it would be impossible to validate the present operation of the model or construct new solution proposals properly.

Chapter 5 concentrates on the use of the model. The developed and validated model is used to test and present solutions for problems found by taking into account processes, resources and technological solutions. First the bottlenecks are located and then the best solution proposals and their effect on the patient process are described. These are tested separately as well as together in order to find out the effects on the efficiency of an ED in every situation.

In Chapter 6 other possible application areas are discussed, among them a simulation of a clinical laboratory.

In Chapter 7, the last chapter, the results of this study are summarized and possibilities for future exploitation of the developed model are discussed.

2 SIMULATION AS A RESEARCH METHOD

Simulation has many definitions. On a basic level it is thought to mean mimicking. This is a definition which most people are familiar with and it is usually related to real life situations. Child's play is a good example of this kind of simulation. There are also many other everyday situations, where simulation can be exploited very efficiently.

However, when we are talking about simulation as a scientific research method, the definition is a little bit broader. In science and especially in computer science, simulation refers to a numerical method which can be used to perform different kinds of tests by exploiting mathematical models. It is a designing process where a real system is built into a mathematical-logical form and experimented with on a computer.

Simulation is also an experiment, which is a major difference between mathematical methods and simulation modeling. Mathematical optimization offers usually the most optimal solution, whereas simulation cannot solve the problem as such. A simulation model does not search any certain solution but calculates only effects based on assumptions. It is used in exploring the qualities of real systems under certain circumstances. Only by analyzing the operation of a modeled system, it is possible to draw conclusions related to the optimal solutions.

Activities and operations should be simulated in cases where it is impossible to solve the model mathematically in a closed form. Contingency, nonlinearity and dynamics are the factors which can cause this. Static, deterministic and linear models are usually possible to solve with mathematical models (Law & Kelton, 2000) (Pritsker, 1986).

2.1 Simulation models

Simulation models are dynamic and may include nonlinear and contingency elements. They are an important part of the operation research along with optimization models. Simulation models can be defined to be models of reality which does not include unsolved equations or inequality of decision and target variables. A generic simulation model is shown in Figure 1.

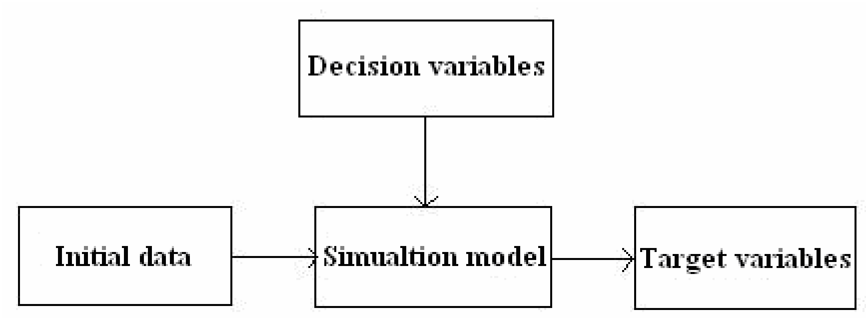


FIGURE 1 A generic simulation model

In simulation modeling, changes in a state of a system can occur at discrete instants in time or continuously over time. The discrete instants in the simulation model can be constructed stochastically or deterministically. The way how these are established depends on the system being modeled and the nature of model inputs. There are four types of models used in simulation:

- Continuous simulation model
- Stochastic simulation model
- Deterministic simulation model
- Discrete event simulation model

The principles of these models are presented in the following sections. Continuous, stochastic and deterministic simulation models are presented at a fairly coarse level. The main focus is on discrete event simulation, the type of which we are using in this study.

2.1.1 Continuous simulation model

Continuity in simulation means that the main interest is not in single events (they are not differentiated) but that the model consists of state variables and their relations instead. Continuous simulation model can be said to be a representation of a system in which state variables change continuously with respect to time (Figure 2). The results are usually illustrated with time series or over time changing graphs (Law & Kelton, 2000). Running the model with a certain set of parameters always generates a graph. A good example of this kind of simulation is, for example, a definition of a flight path of an airplane.

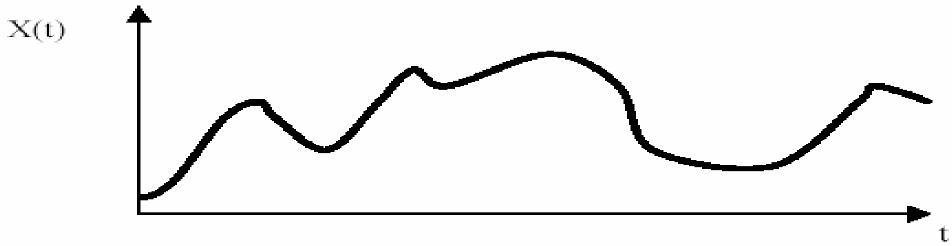


FIGURE 2 The development of a continuous state function over time

In continuous simulation the intention is not to generate artificial statistical data, the way it is done in discrete simulation, by using random number generators. The main idea in continuous simulation is to find out the dynamic behavior features under examination. Stochastic numbers are not needed, nor random ones. The model is executed by using few, closely selected sets of parameter combinations which represents situations such as a “pessimistic” option and an “optimistic” option (Law & Kelton, 2000). If the model is executed for example 100 times and certain parameters change according to desired random distributions, this would result in 100 graphs. The analysis of all those graphs would be very difficult if not even impossible.

2.1.2 Stochastic simulation model

Stochastic simulation model is a model where all the random features have been taken into account. In these models results and events are impossible to know in advance.

2.1.3 Deterministic simulation model

Deterministic model is a model which doesn’t include any random features. In these kinds of models events and results can be determined with certainty based on initial values.

2.1.4 Discrete event simulation model

Discrete event simulation is one way of developing a model to observe the dynamic behavior of a proposed system. There are several key parts in this kind of simulation system (Figure 3):

- Entities and their relations (logical statements)
- A simulation executive
- A central clock
- Random number generators

- Results collection and analysis

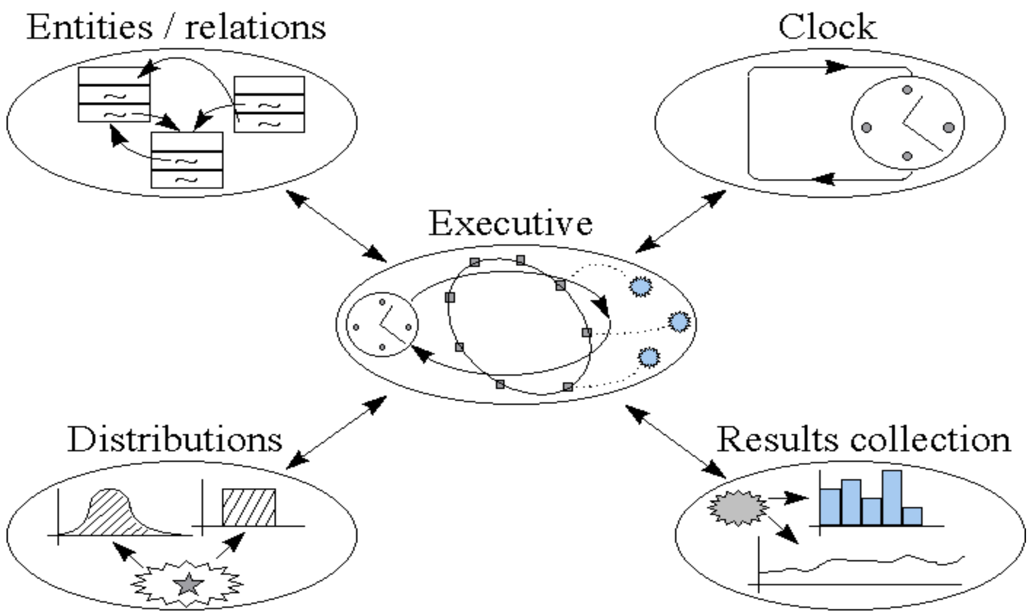


FIGURE 3 Structure of a discrete event simulation system

Entities and their relations

Entities are elements of a modeled system found in the real world. In health care, for example, these can be human beings, blood samples, documents and medical applications. Entities can be either permanent or temporary. Temporary entities are entities which pass through the model (for example patients) while permanent entities remain in the model throughout the simulation (for example staff members and medical machines). Usually the main objective of the simulation is to observe the behavior of the temporary entities and collect information on them.

Logical relationships define the overall behavior of the model. They link the different entities together (for example the staff member entity will process the patient entity). Every logical statement is also simple to formulate (Law & Kelton, 2000) (Pritsker, 1986).

Simulation executive and central clock

One of the central components of a discrete event simulation system is the simulation executive. It is responsible for controlling the logical relationships between the entities as well as the time advance. It provides the dynamic, time-based behavior of the model.

However, in order to control the time advance, it is also necessary to have a clock in the system. This is, along with the simulation executive, one of the key parts of a discrete event simulation system. The central clock is used to keep track of time, and it is controlled by the simulation executive, which will advance the clock whenever necessary.

There are two basic ways for controlling the time advance. These approaches are:

- Next event
- Time slicing

In the case of next event the model is advanced from the time of the present event to the time of the next notable event. It means that if nothing is going to happen in a certain period of time the executive will move the model forward to the next event directly. This kind of jumping behavior makes the next event mechanism effective and allows the model to be evaluated reasonably quickly. However, if there is a graphical display in the software and the next event method is used, the status and movement of entities may become misleading. This aspect should be taken into account when using the next event mechanism.

The time slicing mechanism differs somewhat from the next event mechanism. In the time slicing approach the model is forwarded in time at fixed intervals, for example, every second, every 5 seconds, every 10 seconds, etc. This means that the time executive would advance the model in time even if nothing happened between the defined time intervals (Law & Kelton, 2000).

Random number generators and results collection

All the elements mentioned above are key parts in a discrete event simulation. In addition, there are two other elements which are vital to any simulation system, including discrete event simulation: random number generators and results collection and analysis.

Random number generators provide stochastic behavior for the model, defining a variation between certain ranges for every operation in the model. This makes it possible to mimic the operation of a real system being modeled very accurately. In health care, for example, the operation times of each staff member will rarely be fixed but will vary between certain ranges depending on the staff members' skills and on the patient receiving treatment. This is why it is important that a simulation system is capable of handling these stochastic features. The variations of the operation times are defined in the model usually by using a random distribution, such as normal distribution.

In order to get some meaningful information out of the simulation system, it is important to have the results collection and display features implemented in the system. These features provide meaningful analysis of the system being modeled. They will typically display tabulated data and posses some graphing capabilities (Law & Kelton, 2000) (Pritsker, 1986).

Logic description mechanisms in a discrete event simulation

There are three different ways of representing the logic. It is possible to use these approaches for modeling the same system and each should give the same results. These mechanisms are (Figure 4):

- Event based model
- Activity based model
- Process based model

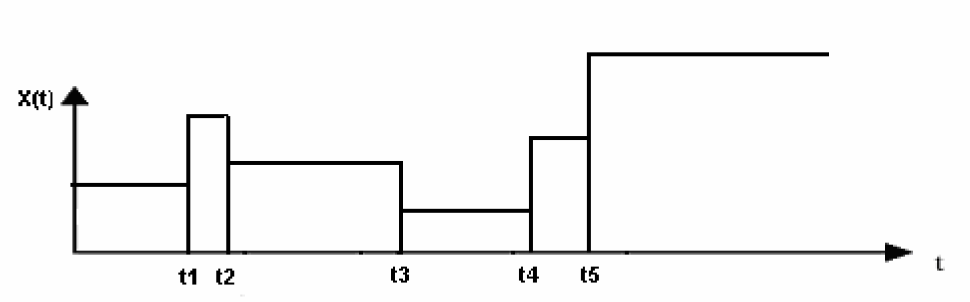


FIGURE 4 The development of a discrete event simulation model over time

In an event-based model the system is built by defining the events and the consequences caused by the event for the different entities of the model. The actual simulation of the system includes monitoring of the defined events and start-up of right activities under different events based on the created event list. The event list includes all durations of the activities of the model and hence the next event is determined by the activity the duration of which is the shortest. An activity which is related to a certain event, updates the parameters of the model as well as the event list of the model.

In an activity-based model the activities, to which the entities of the model are connected, are described. States which will cause the start-up or the termination of an activity are defined as well. During the simulation the states of the system are observed and the decision about starting or terminating a certain activity is made based on the predominant state. If a fixed state is appropriate for a certain activity, it will be executed. To be sure that every activity has been defined, it is necessary to examine the whole activity group at every interval point all over again. This kind of a model is suited for situations where the duration of an activity cannot be defined accurately in advance as the activity is selected based on the state of the system. Because every activity needs to be brought to completion when the state of the system changes, the model is quite inefficient compared to the event-based model.

Many simulation models include a series of events, which trigger certain activities in them. The events can be alike for every process but the consequences of an event for the process are individual. In this case the best discrete model is the process-based model. In a process-based model the operation of a system can be described as a group of processes related to each other. The model also provides a description of the motion of the entities in the system (Law & Kelton, 2000) (Pritsker, 1986).

3 THE USE OF SIMULATION IN HEALTH CARE

Health care processes differ quite considerably from industrial processes, which is why there are number of things which should be taken under examination when simulating such systems. First of all, the operations in health care are far more complicated than in other industries. Each patient may be different, the occurrence of a symptom is a random event, there is variation in the quantity and types of services provided, and different staff members and locations have to interact with each other in order to provide the required care. Secondly, it has to be remembered that health care systems are not simply variations of an industrial theme; the human side of the problem has to be taken into account as well. Patients are not parts, staff members are not machines, and providing care is not manufacturing health.

Besides the differences in complexity, there are other things also which differentiate the health care industry from other industries. Because there are certain protocols in the health care which have to be followed, the decision makers cannot be the technological experts who build the model. The health care personnel have to be involved as well. Without health care experts it is impossible to develop right kinds of solutions to be implemented in real systems.

Data collection is also slightly different and more challenging in the health care environment when compared to other industries. There is rarely information directly available on operation times in health care systems although treatment-time evaluation is one of the key parameters in any health care simulation model. Health care systems are usually designed to provide information on patients but not directly on the operation times, which is why in the latter case the data often have to be collected by observing the operation. There may be a lot of variation in treatment times as well, because each patient is different and the time the doctor has to spend with the patient depends on the patient's symptoms and their severity. In manufacturing industry the machines do usually have quite standardized procedures and operation times for performing a certain operation.

Although there are some differences between health care and other industries, simulation is a very appropriate method for examining the operations and it can be effectively used as decision support tool. Simulation is a tool which is able to take the complexity and the stochastic nature of health care systems into account. It also has to be remembered that in the field of health care it is not possible to test different solution proposals in real environments, as this might put the patients and the work in the hospital in jeopardy. Real patients and real personnel cannot be used for testing different activities, even though this might improve the operations, because the consequences of such an approach might be serious (Healy, et al., 1997) (Farrington, et al., 1999).

Simulation has been used more frequently in other industries, but there are also studies where simulation has been used to model the operation of different health care units using patient waiting times and throughput times as the main target variables. These simulation studies will be reviewed next. The main aim is to examine how simulation has been used in health care and what kind of solutions have been found in these studies.

The review is divided into two parts. First, we examine studies where the operation of an emergency department has been under development. These studies relate directly to our study and provide information on the research work which has been performed in this area before. Secondly, we examine simulation studies performed in other health care units. This kind of an approach can yield information that is useful for our study as well.

3.1 A review of the Emergency Department simulation studies

Emergency department operations have been studied during the past few decades in many different ways and with many different methods. Solutions for the problems have been sought with the help of statistical methods, process analysis, mathematical modeling, etc. However, emergency department operations are very complex and wrought with uncertainties, which is why simulation has gained more popularity as an effective research method during the past few years. Simulation has been employed to find answers to problems such as too long waiting times, too long LOS (Length of Stay), ineffective resource allocation and too low resource utilization. How simulation has been used in improving the operations of an ED is examined in this chapter. The examination is done from two different points of view, from the viewpoint of resources and from the viewpoint of processes.

3.1.1 Improving the operation of ED by allocating resources effectively

Resource allocation has been noticed to have an enormous effect on the operation of emergency departments during the past years. Often the resources are wrongly proportioned to patients on different shifts. Re-allocation of resources can create quite big effects on the selected target variables. The usual target variables are the waiting times and LOS. Let's first have a look on the simulation studies where the decision variables have been resources (doctors, nurses, technicians, etc.).

Saunders, et al. (1989) performed a simulation from a general resources point of view. Their intention was to examine the effects of resource allocation and laboratory operation changes on the throughput time of patients, queue sizes and resource utilization. Their results indicate that resource allocation has a considerable effect on the operation of an emergency department. Lane, et al. (2003) came to the same conclusion. They noticed that, by reallocating the resources carefully, bottlenecks located could be partially dissolved. Their study also emphasizes the importance of bed occupancy.

Several other researchers and research groups have conducted similar kinds of research. Kirkland, et al. (1995) showed that the throughput time of patients in the emergency department can be reduced by over 38 minutes by allocating the resources in the most effective way. Evans, et al. (1996), for their part, concentrated on the throughput time problem by examining work shifts. The best scenario decreased the throughput time by a little over five minutes. McGuire found the answer from resource allocation as well. By reorganizing shifts he managed to reduce the throughput time by 50 minutes.

In the studies described above, all the resources in the emergency department were under examination. However, in several studies in the literature the focus has been only on certain resources at a time. Kumar & Kapur (1989) for example focused only on nurses and their efficient allocation. The same kind of work was undertaken by Draeger (1992) who examined the utilization of nurses. The intention in both of these studies was to decrease the throughput time of patients in emergency departments.

Doctors were studied by Chin & Fleisher (1998). Their main objective was to examine patients' waiting times and doctors' idle time. They showed that by making the doctors more effective (by increasing utilization) in the ED, it was possible to decrease both the patients' average throughput time as well as their long throughput times. Rossetti, et al. (1999) focused in their study on doctor resources as well. Their results show that by adding an extra doctor on the shift from 10.00 am to 18.00 pm decreases the throughput time by 14.5 minutes per patient. In addition, the number of patients staying long in the ED is reduced.

Centeno, et al. (2003) concentrated also on the resource allocation but approached the problem from a slightly different point of view to that of the previous researches. They developed a tool where simulation and optimization are combined. In that tool the simulation model defines the need of resources for a certain period of time, and also specifies all the special condition requirements and operation times. The results of the simulation model are fed into an optimization model which defines the optimal resources (nurses) for a given period of time. The simulation model and the optimization model were integrated by using VBA (Visual Basic for Applications).

All the studies above focused on finding solutions on resource allocation. The other way to approach the problem is through processes. From the processes point of view there are quite a many studies in the literature as well. We will have a look at those studies in the next chapter.

3.1.2 Improving the operation of the Emergency Department by using processes as the main decision variable

When the development is undetaken from the processes point of view, the main objective is to find solutions which would have a positive effect on the selected target variables (reduced waiting times, LOS, etc.). Blake & Cater (1996) have been working on this area of research. These two researchers examined patients' waiting times in the ED and noticed that there were two things which had a major effect on the selected target variables. These things were the accessibility of doctors and teaching. If the doctors were always available, without having to spend so much time on teaching younger doctors, the waiting time of patients would decrease.

Usually when bottlenecks are located, it is the time to start searching for answers as to the reasons for them. There are many ways to do that, one of the most popular being reconsideration of the processes. Work along these lines has been done for example by McGuire (1994) and Freedman (1995). Both of these researchers' main objective was to decrease throughput time for patients in the emergency department by changing the operation and selecting the most effective scenarios for implementation.

While McGuire and Freedman took all the processes under examination, Centano, et al. (1995), Lange (1997) and Conolly & Bair (2004) concentrated only on certain solutions. These specific solutions were the fast-track solution and the triage definition. Centeno, et al. focused only on the fast-track solution and showed that this solution would decrease the total average throughput time for patients by 25 %. Lange, for his part, took the triage definition under examination. The results of his model indicate that when the triage-method is used, the number of patient visits would decrease by 20 %. Besides that, the waiting times would decrease by 40 %. Conolly & Bair took both of these aspects under study in their research. Their results show that the triage-method decreases bottlenecks in X-ray services and operation times for high priority patient, but at the same time substantially increases operation times for patients whose priority is lower.

Besides process descriptions and resource allocation there are some other entities which can be selected as decision variables as well. This kind of entity can consist, for example, of the amount of beds. Studies, where the number of beds was used as a decision variable, have been examined in the study of Bagust, et al. (1999) and Brailsford, et al. (2005). Bagust, et al. considered bed demand caused by patients who are transferred to hospital and risks of inadequate bed capacity for patients who require immediate admittance. The results of the simulation run indicated that risks exist if the bed occupancy is over 85 % and a patient's treatment can be endangered if the bed occupancy exceeds 90 %. Brailsford, et al. for their part studied the same problem by using analytical method in addition to simulation. The model showed that the final placement of patients had a major effect on the patient's throughput time.

A study similar to that of Brailsford et al., considering static and dynamic combination, was conducted by Martinez-Garcia & Mendez-Olague (2005). The results of their study show that a combination of static and dynamic modeling can be used effectively in improving the operations of ED. They used this mixed technique in testing the triax-method where a nurse and a doctor were in the same team. This solution reduces the total throughput time of patients in the ED. They also found out that by increasing space in the way that the bed occupancy could be arranged better improve the operation of the ED as well.

Gonzales, et al. (1997) used a so-called mixed-technique in their research as well. Their main intention was to show that by using the concept of TQM (Total Quality Management) and simulation animation, the quality of an emergency department can be improved. The results showed that the ways of action were not standardized, a doctor formed a bottleneck, and there were not enough resources (nurses and instruments) and room for the patients in the ED.

The operation of the ED can be examined from other viewpoints besides efficiency. Glick, et al. (2000) did their study from the point of view of cost, which is one of the target variables. They developed an expanded simulation model which measures the expenses of an operation of the ED. The aim was to perform Activity-Based-Costing by using simulation. The results indicate that by using simulation it is possible to do quite a realistic cost analysis.

The main objective of the study is not always to collect information on the effects of the performed activities on certain target variables. The objective can consist of related software development as well. This was the case in the studies of Alvarez & Centeno (1999) and Sinreich & Marmor (2004). The purpose of the study of Alvarez & Centeno was to develop an efficient simulation tool. As a result they developed a tool which includes a database, a specific library for the translation routines and specific data files. Sinreich and Marmor for their part concentrated on developing a tool which could be used as a decision support tool in an emergency department. The tool was based on the general process description of the ED. A user interface was developed as well in order to make it possible to enter data into the model.

3.2 Simulation studies of other health care units

After examining simulation studies performed in emergency departments, it is good to expand our view and take a look at how simulation has been used to model other health care units and systems, i.e., hospitals, clinics, laboratories, X-ray units, etc.

Simulation has been used for improving the operations of other health care units in the same way as in the emergency department. Operations have been examined from the processes point of view, resources point of view and costs point of view. In addition, simulation has been used as a decision support tool.

Resources have been used as the main decision variable in several studies. In these studies, the patient numbers have been under close examination on every shift, and the resources have been allocated as effectively as possible proportioned to the number of patients. This type of research was conducted by Vissers (1995), Richard (1997) and Merkle (2005) in their studies. In addition to resources Merkle investigated the processes as well. By using these new process descriptions and different resource scenarios the optimal amount of resources was defined.

Resources have been, to some extent, investigated in Huangs & Lees (1996), Hashimotos & Bells (1996) and Benneyans (1997) studies as well. Huang & Lee focused on resource utilization, throughput times and queue lengths in an outpatient clinic. They studied how a simulation model can be used to examine the changes in resources, appointments and different service units. Benneyan concentrated in his study on resource utilization as well. He took under examination the effects of different services and operations on the appointments, delays of waiting rooms and calling service. Hashimoto & Bells conducted the same kind of research in an appointment-based clinic.

Centeno, et al. (2001) and Hendershott (1995) have examined the operation of health care units from the resources point of view as well, but the focus of their studies has been only on a certain location or a certain process phase at a time. Centeno, et al. conducted their study in two different locations. Under examination in their study were operation rooms and a single radiology room. They investigated the effects of different resource scenarios, schedule scenarios and constructional changes on the operation of the radiology department. The results indicate that one of the resource scenarios would improve the operation. Hendershott for his part concentrated on resource allocation in operation rooms. Clinical laboratory was subjected to particularly close attention in his study.

Although resources play an important role in different health care units, all the problems cannot be solved just by reallocating them. This is the case especially if the costs need to be kept under control as well. The other possible way for improving the operation is to examine the processes and try to reorganize them. Research, using this point of view, appears in studies by Everett (2002), van Merode, et al. (2002) and El-Darzi, et al. (1998).

Everett described the development of a simulation model which helps to schedule patients who wait for their admittance to the surgery. Van-Merode et al. studied sytostatic treatment of chemotherapy patients at the hospital in Holland. They developed a simulation model which was used to examine the medicine ordering process. The main aim was to find the best combination of different patients and medicine types in order to minimize waiting time and costs. El-Darzi, et al. (1998) focused on processes at the geriatric ward of a London hospital. They studied the effects of congestion on the patient's throughput times.

Taylor & Kuljis (2001) conducted research on processes at a basic level as well. Their intention was to improve the operation of the general ward at a Leeds hospital. The results of their study show that by staggering patient's appointments, arrival of personnel and consultations and by other administrative changes the operation could be improved. The queues for reception, test rooms and doctor shorten as a result of these actions.

Ramis, et al. (2001) studied the operation of a new ambulatory surgery center where patients would arrive and be discharged during the same day. Their main objective was to examine the operation conditions which would maximize the throughput of patients during one day. The results show that the maximum number of surgeries (10) can be achieved by allocating beds as effectively as possible and by following a certain rule (the most difficult surgery first).

All the research above was conducted at the basic level, which means that the researcher's attention was centered on a certain health care unit in each case. However, the operations can be studied in a larger or a smaller scale as well. The operations have been studied, from a larger perspective, by Blasak, et al. (2003), Edwards, et al. (1994), Baesler & Sepulveda (2001), Elbeyli & Krishnan (2000) and Morrison, et al. (2003).

Blasak, et al. investigated two different health care units. These units were the first aid unit and a telemetry unit. The aim of their research was to simulate the operation of these units and study how their operations affect each other. By examining the operations, the bottlenecks of the process between these two units were located. Subsequently, the developed simulation model was resorted to in order to resolve them. Edwards, et al. did same kind of work. They examined the time and role revision of consultation and waiting times by using different queue systems (serial queue system and parallel queue system). In a serial queue system patient waits in a certain queue, whereas in a parallel queue system patients are guided to the shortest queue in order to control the patient flows in the clinic.

Elbeyli and Krishnan studied patient flows in a large hospital. The main goal was to locate the bottlenecks and study the effects of bed availability on waiting times. In order to model patient flows completely, the operations of telemetry, ICU and other units had to be modeled as well. Morrison, et al. studied an ambulatory unit and the methodology used in it. Their main aim was to locate bottlenecks in the entire hospital. Under examination were the Step-Down unit, Medical unit, Surgical unit, Oncology unit and Orthopedic unit. The results indicate that the Step-Down unit was a bottleneck and more beds were needed in that unit. An increase of beds in M/S/O/O unit improved the operation as well. It decreased waiting times in the emergency department by 64 %.

Research in a smaller scale has been conducted by Groothuis, et al. (2005) and Cote (1999). They concentrated in their studies on modeling only a certain operation in the process. Groothuis, et al. used simulation in designing operations of a catheterizing room. The main goal was to study how to model patients scheduling. Cote, for his part, focused on finding solutions for the problems in the hospital by modeling the way doctors operate. He developed a simulation model of a doctor's office. He used the developed model to examine the effects of operation room's capacity and patient flow.

Studies modeling outpatient clinics have been done also by Huebner & Miller (1996), Iskander & Carter (1991), Kalton, et al. (1997), Watford & Owen (1989) and Aharonson-Daniel, et al. (1996).

In all the studies above the focus has been on waiting times, throughput times and queue lengths, the most common target variables to measure operation. However, other target variables can be used effectively to examine the operation as well. One of the most effective variables is cost. Research from this point of view has been conducted by Weng & Houshmand (1999), Vemuri (1994) and Tanaka, et al. (2004).

Weng & Houshmand developed a simulation model where costs were the main target variable. They developed three different scenarios, the intention of which was to improve the operation by changing the amounts of resources. The best scenario was selected based on its cost effect. Vemuri used costs as the main target variable in his work as well. He modeled the operation of a pharmacy and examined cost effects of different scenarios which would reduce waiting times. Tanaka, et al. focused also on costs. They did not examine the actual patient process but created a simulation model of hospital administration. The model was based on costs of different illnesses in several university hospitals in Japan.

Ratcliffe, et al. (2001) took costs under a closer look as well but that was not the only target variable in their research. They studied cost effectiveness of liver transplant process, so time-based target variables were used as well. They evaluated the effects of different procedures on the process and found factors which should be taken into account in improving the cost effectiveness.

Delfoi (2003), a consultation company, performed one of the few simulation studies in Finland. They examined the operation of a laboratory center at the University Hospital of Tampere. The main objective of the research was to centralize different kinds of laboratory tests in the same place and in that way to change the operations of the laboratory center to serve more widely regional needs around Tampere. Their investigation dealt with present operation, resource changes, amounts of tests and equipment.

Riley (1999) used simulation as a decision support tool in designing a new health care facility and its operation. In the process Riley found a new operation model for appointments and reception of patients. Earlier patients had been received in no particular order. The new operation model decreased waiting times of patients who had reserved an appointment. In addition, doctors' working time was reduced as well, although the number of patients remained the same.

Applied simulation as a decision support tool has been discussed, at a general level, also by Moreno, et al. (1999), and, as focused on resources, by Allen, et al. (1987), Arthur & Ravindran (1981) and Wilt & Goddin (1989). Simulation as a decision support tool from the waiting times point of view was performed by Benneyan, et al. (1994), Mahachek (1992), Lowery (1996) and Groothuis, et al. (2004).

Erdem, et al. (2005) modeled the operation of an outpatient clinic. Their main objective was to develop and implement an efficient appointment system with the help of simulation. They wanted to minimize or eliminate totally all the errors which might occur in the system. They used the model in studying the effects of small changes (increase in the number of patients) and big changes (shutting down the entire unit and transporting personnel and material resources to another unit). Their attention was caught by the fact that it was possible to make quite an accurate prediction as far as small changes are concerned but when it came to bigger changes more data was needed. Their recommendations include development of a so-called cost analysis engine as well.

Besides research which has concentrated on improving the operations of different health care units by using certain target variables, there are also contributions in the literature which have studied the suitability of simulation for modeling health care operations in general. These contributions include work by Triola and Holzman (2004). They examined the feasibility of using simulation for modeling the operation of Medical Intensive Care Unit (MICU) and found it very useful for that kind of work. Andersson & Andersson (2005) studied for their part the suitability of simulation for examining the advantages of a computer-based physician order entry system.

Although a lot of work has been done for improving these kinds of operations, there are also contributions which have concentrated on developing new simulation tools for examining health care operations. This research includes the studies by Cooper, et al. (2002) and Pitt (1997). Cooper, et al. developed a low price, discrete event and general simulation model. The model was developed to serve the personnel, who could modify it for their own needs. Pitt's research falls in the same category. Pitt participated in the PRISM project, the main objective of which was to develop a general tool for examining the economy of hospitals, the use of space and the connections between hospitals and other health care units.

4 THE DEVELOPMENT OF A SIMULATION MODEL FOR AN EMERGENCY DEPARTMENT

A simulation project usually includes many different phases and follows a certain hierarchy. These phases are shown in Figure 5.

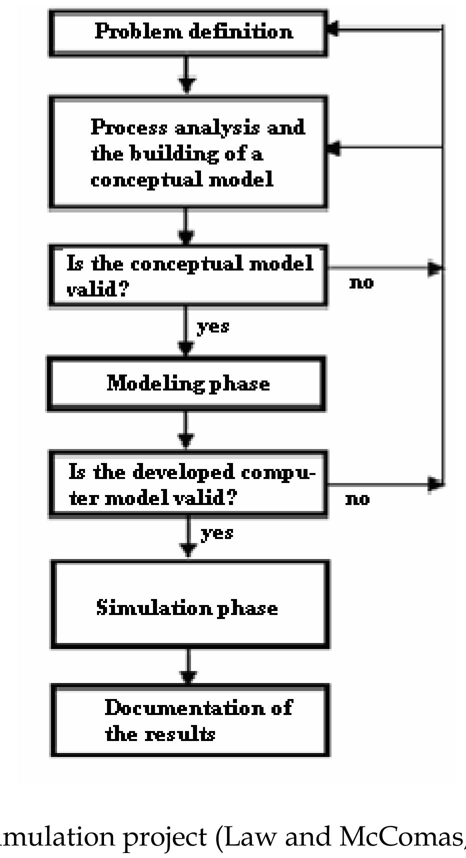


FIGURE 5 Phases of a simulation project (Law and McComas, 2001)

4.1 Problem definition

A simulation project starts with a problem definition. This phase is the most important and essential phase in the project. However, usually this phase is ignored and the starting point is considered to be the actual modeling phase. This may lead to difficulties when the project advances, especially in the data collection part. If the problem definition is incomplete and it is not known where the answers could be searched for, the collection of correct data is not possible.

In this work the problem definition was done carefully right at the beginning. General research objectives were defined, target variables were selected and the accuracy of the model was decided. All the resources and time limits were defined as well.

The main objective of this study is to improve the operation of emergency departments. Waiting times are too long and patients have to spend too much time in the process before they are discharged or forwarded. This presents a problem which has to be solved. Because the main objective is to make the operation more effective, the main target variables are selected to be the length of stay and waiting times of patients. These variables are the best indicators of effectiveness. In order to make it possible to find solutions which would be appropriate for all emergency departments, the accuracy of the model is restricted to concern mainly the main process. However, there are phases in the process which are quite essential for patients' advancement in the process and the model is enlarged for these parts. For example, the operation of a clinical laboratory is such a project phase.

4.2 Process analysis

The process analysis phase is a part of preparation of the actual technical simulation. The purpose of this phase is to define the structure of the system being modeled and find out how it works in practice (logic). In this phase, events, their operation, and certain branching points under certain circumstances with certain parameters, are defined. The intention is not to use any simulation language or software at this point but to form a conceptual model of the operation of the modeled system on paper or computer. The conceptual model doesn't have to be an exact presentation of the system; it can be simplified and only necessary points for the simulation need to be selected.

In this study the information on the patient process was gathered from the Emergency Department at the Central Hospital of Jyväskylä, Finland, and the process was modeled on paper. All essential phases of the processes are included in the conceptual model. All the routing possibilities from a certain phase to another are described as well.

The process starts with the patient arrival. After registration the patient goes to the reception where a secretary collects the patient's basic information.

Besides basic information, the special field is defined as well. After these operations the patient is guided to the correct waiting area.

The patient is then seen by a specialized nurse, who defines the urgency (triage), interviews the patient, takes the basic tests (blood pressure measurement, etc.), and then decides where to send the patient next. There are three possibilities regarding where the patient can be guided to after being seen by the nurse. The patient can be seen by a doctor for the first time in which case the doctor examines the patient and orders the necessary tests. The second option is to order the tests without seeing a doctor and send the patient directly to the laboratory or X-ray unit. The last option is to send the patient to the doctor for a final diagnosis if there is no need for tests.

If the patient is guided to the doctor for the first time, the route from there takes the patient either to the laboratory or to the X-ray unit, depending on the tests ordered. If only laboratory tests are ordered, the patient goes to the laboratory; if X-ray tests are ordered, the patient goes to the X-ray unit.

Once all the tests have been taken and the results are ready, the patient is seen by the doctor for a final diagnosis. After the diagnosis has been made, the patient goes either home and leaves the ED of Special Health Care, or to the waiting area for their case history. If the patient goes home that is the end of the process, but if the patient is transported to the ward or some other welfare institution, the case history must be ready and the patient has to wait for that. After the case history is documented, the patient is ready to leave the system. The initial process flow is shown in Figure 6.

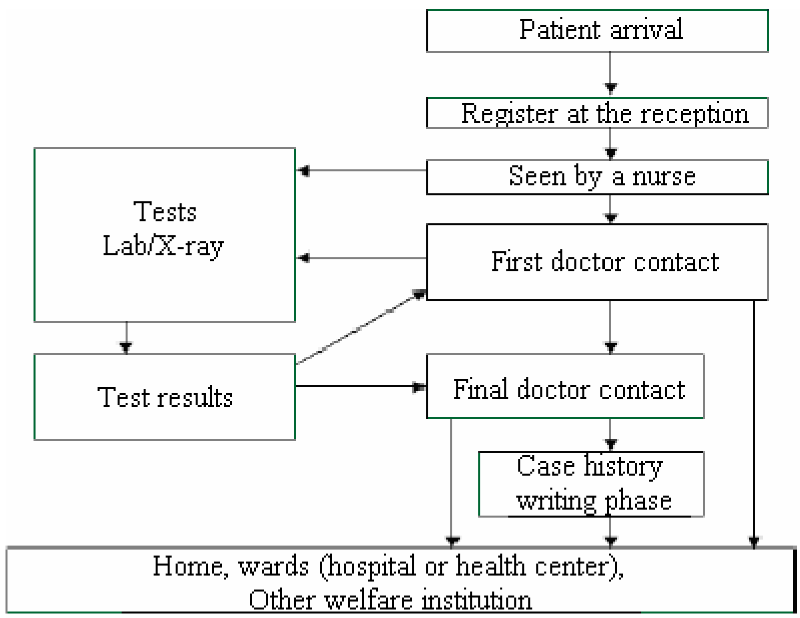


FIGURE 6 Process flow in the emergency department

4.3 Validation of the conceptual model

After the process description phase, it is very important to revise it. The main objective in this phase is to define whether the theories and assumptions are correct and whether the structure of the model and the parameters in the model are valid. These things have to be checked in order to make it possible to find solutions for the right problems.

Besides universal examination, it is recommended to check the core processes and the backup processes separately. In the examination the necessity, appropriateness and accuracy level of each process are evaluated in order to make sure that all the processes produce a desired result. It is also useful to describe the relations between different processes. This will help in making the model work in a desired way.

4.4 Modeling phase

Modeling phase is a technical phase of the project and usually regarded as the actual simulation. There are several elements which should be taken into account in this phase before the model creation. These are:

- Selection of the type of modeling (discrete or continuous)
- Data collection
- Selection of simulation software

Selection of the type of modeling
Operations in the emergency department and in health care in general are quite complex and contain many random features. This means that simulation in health care is mostly clearly discrete, stochastic and process-oriented. Continuous simulation models do not suit well for modeling complex and uncertain environments, where the interest is in several different events and their durations. That is why discrete event modeling was selected for this study.

Data collection
Data has an important role to play in simulation. However, sometimes it may not be very easy to gather the data, and this could become a real problem in some occasions. This is the situation especially in health care, where parts of the information systems are quite old. They were not designed for simulation, which means that the information is not necessarily in the right form and cannot be used directly in modeling and simulation. A good example of this is patient visit information in hospitals. Although there is a lot of information on the patient, the information on the operation times is usually hard to find or missing.

One solution for the problem is to collect real-time data manually by observing patients for a certain period of time. The use of real-time data is appropriate for certain simulations and gives a clear view of the system. The longer the system is observed and data collected the more realistic is the view obtained of the system operation.

Data for this work was collected in August 2004 by observing patients in the Emergency Department at the Central Hospital of Jyväskylä, Finland, during two weeks. The patients were observed 24 hours a day and seven days a week. In addition, observation data from earlier research, conducted a half a year earlier, was also used in this project. Altogether there were six weeks' data available. The total number of patients' visits was a little under 4000.

In both cases the data was collected using a special form which was created for the project. The form included information, among other things, on the patient's arrival (how they had arrived), symptoms, urgency (triage), and process times.

Data collection was performed by specialized nurses and secretaries, who filled the form as the patient went through the process. The form was among the patient's other documents and thus followed the patient from one point of the process to another. After the patient had left the emergency department, the data on the form was entered into an Access database and processed with the SPSS and Stat:: Fit statistical software.

Selection of the simulation software

The actual simulation model is built, based on a certain modeling philosophy, with a selected simulation language or software by using defined process descriptions, theories and assumptions related to the processes and by exploiting the collected data. The model to be built should be an exact abstraction of the real system, in order to get the desired results.

In health care the models are usually too complex and described at too detailed a level. As a consequence, no additional value is gained and both time and resources are wasted. The complexity of the model is usually proportional to the duration of the simulation process. The most important thing in simulation is to develop as simple a model as possible, a model which still can meet the challenges and can be used to find solutions to the problems found. If it is necessary to describe the operation in a more detailed level at a later time, that can be easily added into the existing model.

Once all the preparations have been performed, the actual development of the model can begin. The development consists of many different phases, the number of the phases depending on the qualities of the simulation software. Usually simulation software which possesses the necessary capabilities for graphical as well as numerical simulation requires more definitions. In this work the definitions are affected by this consideration. The model here was created with the MedModel (www.promodel.com) graphical software, but the definitions used are also valid for software with no graphical capability. The phases of the model development are:

- Background definitions
- Location definitions
- Path network definitions
- Entity definitions
- Resource definitions
- Attribute definitions
- Shift definitions
- Data handling
- Logic definitions
- Arrival definitions
- Empirical distribution definitions

As can be seen, the model development consists of many different phases, where each phase is essential in order to create a valid model.

4.4.1 Background definitions

Background definitions are an important part of the model development, if all capabilities and qualities of visualization (animation) are to be used in the most efficient way. Background definitions form a graphical framework for the animation. It is very important to consider all the necessary background definitions; this will make it possible to describe the modeled phenomenon as clearly and understandably as possible.

A background can be constructed manually or by using the actual layout of the system. In the case of manual construction the layout for the system being modeled is created by using the graphical elements available. All the locations and their elements are situated in the desired places. In a software of this kind there should be an editor for this type of definition. It is normally also possible to use the actual layout of the system or some other graphical view of the system as a background. It can be imported into the software in a certain file format. This sort of background can be referred to as automatically constructed background. It includes all the locations exactly in the order and in positions corresponding to the real system.

Whether it is better to define the background manually or automatically by using the actual layout depends on the nature of the system being modeled. If the modeled construction is small, the actual layout doesn't necessarily offer any additional value for the modeling (for example in the case of modeling a certain operation in a certain location), but because the operation of a system can be described with the help of different graphical elements (like chairs, beds, tables, etc.) it can provide a better understanding of the operation. However, if the modeled system is quite large, the use of the actual layout provides real added value for the modeling. This is the case for example in systems which consist of many processes and location definitions.

In this work the modeled system is quite large (the whole Emergency Department), which is why the actual layout was used as a background (Figure 7).

This was done partially because we had graphical simulation software in our possession and partially because it was much easier to present the operation of the Emergency Department of Special Health Care to managers and to the staff by using a graphical view.

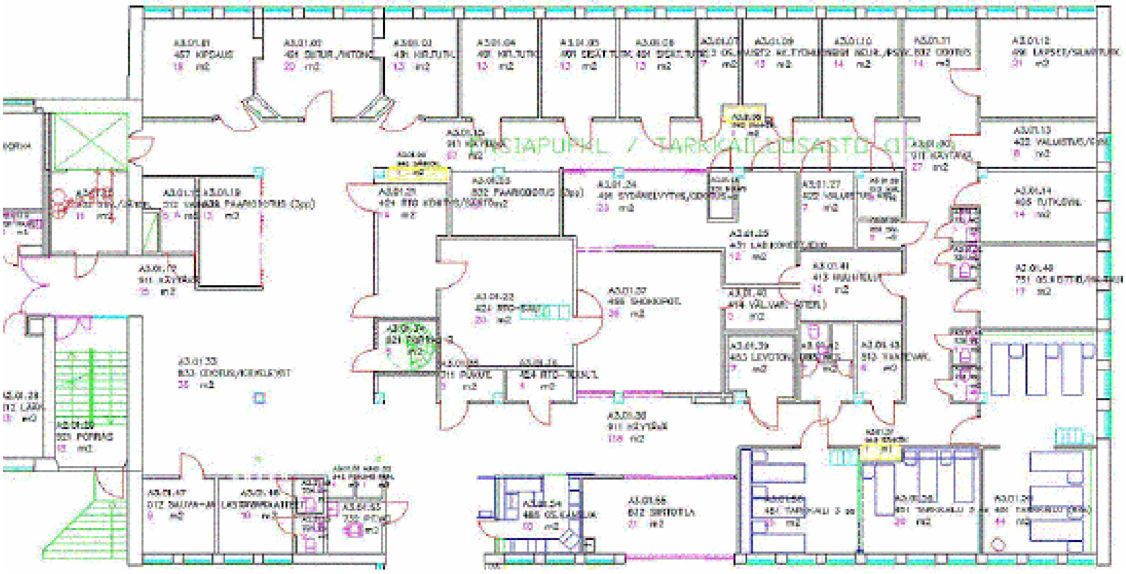


FIGURE 7 A layout for the simulation model

Background definition is the first step for the model development. It forms a graphical framework for the model and the actual structural and functional definitions are easy to start with after this on the layout. The first structural definitions which are necessary, especially for graphical simulation tools, are the location definitions.

4.4.2 Location definitions

The main objective of location definitions is to define places and areas in the system (in this case in the ED) where entities (patients, blood test samples, lab test results) are possibly routed for a certain activity, decision making or storage. If these definitions are not made, it is impossible to define the movement of entities in the layout and the model cannot function.

Before the locations can be defined, it is important to specify all the areas and places which are essential for the model and which are relevant for the process. This forms the base for location definitions. In the Emergency Department of Special Health Care the relevant places and areas were:

- Entrance area: a place where the patient is created in the model (common for all specialties)
- Reception area: a place where the patient registers (common for all patients)

- Doctors' offices: a place where patients are examined and diagnosed (Every specialty has its own place)
- Nurse area: a place where the patient is seen and interviewed by a specialized nurse (every specialty has its own area)
- X-ray unit: a place where X-rays are taken (common for all patients)
- Laboratory: a place where all the laboratory tests are handled and analyzed (common for all patients and blood sample tests)
- Secretariat: a place where the case history is written (common for all patients and their documents)
- Waiting areas: places where the patients are waiting in the process
- Laboratory test result tables: places where the results from the laboratory are sent to (common for all patients)
- Sampling area: a place where all the blood test samples in the model are taken to (common for all patients)
- Exit: a place where the patient is removed from the model

Location definitions themselves are normally created by using graphical libraries or by making one's own graphical definitions and tools for placing them in the layout. The exact operations vary between different tools but the idea is the same. The graphical definitions and layout of our study were made with the MedModel software and are shown in Figure 8.

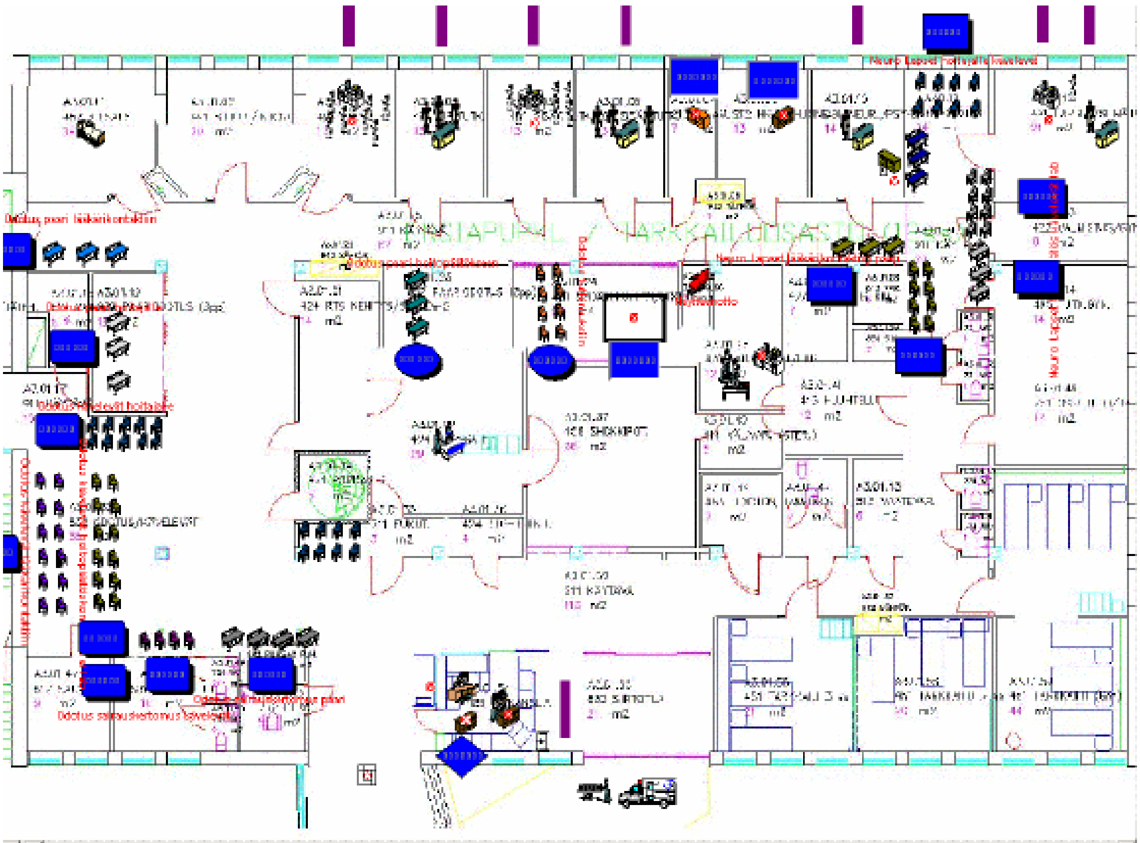


FIGURE 8 The graphical view of the model

However, the graphical definitions alone do not make the locations functional. They have to be activated, and all the attributes for each location need to be defined in order to make them operate in the right way. In our model seven different definitions were made. These definitions were:

- Icon
- Name
- Capacity
- Units
- Downtimes
- Statistics
- Rules

Icon is used to select a representation for a certain location in the model. It is not a functional definition and not an obligatory specification in every tool. In our work the first graphic selected for a location was shown in this definition field.

Name definitions on the other hand are crucial for the model. They identify different locations in the process and they are used in the processing logic. Name definitions of locations are very important especially for the operation and routing logic. In the operation logic these names are used to define where a certain operation for the patient is done and in the routing logic the areas where the patient is guided after a certain operation is specified. Without the name definitions it would be impossible to make the model functional and describe the process flow accurately. In the model of the emergency department the locations were named in the same way they were named in the layout. In this way a clear understanding on the structure of the model was accomplished.

Capacity is an important functional definition as well. It specifies how many entities the location can hold or process at the same time. In order to create a valid model, which truly represents the real system, these definitions should be taken under close examination. In our model the definitions were made as follows: in doctors' offices there was room for only one patient at once, which is the case in the real system as well. These definitions were made for each specialty individually. If these locations were defined to process more than one patient at a time, there would be more than one doctor at that location processing the patients. The same definitions (only one entity at a time) were made also for the sampling area, for the reception and for the office where the case history was written. In waiting areas the number of patients is not restricted. The situation is the same with the case history desk where the patient's documents are brought, as well as with the lab test result's desk where the results from the lab are sent. There can be an infinite number of entities at these locations.

After the capacity definitions, the number of units at a location should be specified. If there are several locations where a certain operation for the patient in the process can be performed, they have to be defined. In our model there were no need to create any multi-unit locations so this definition was the same for all the locations in the model.

Next statistic collection was specified. There were three different levels of data collection available in our case:

- None: No statistic will be collected
- Basic: Only average time and utilization in certain locations is collected
- Time Series: Basic statistic is collected and time series tracking the contents of a certain location over time are done.

The definition for our model was the time series option. It gave all the information needed. All the other choices would have given too little information on the locations for our use.

The last definition was the rule definition. It was used to define how a location selects the next incoming entity to enter that location, how multiple entities queue for output and which unit of a multi-unit location is selected by an incoming entity. In our model there were two different kinds of definitions. These were “oldest by priority” and “lowest attribute value - triage”. All the locations with the capacity of one were ordered to select the incoming entity by “lowest attribute value” which was the trige attribute. The urgency levels were stored in this attribute and the lowest value meant the highest priority. All the other areas like waiting areas were defined to use the “oldest by priority” definition. Because there were now restrictions for the number of entities in these areas, it was the most appropriate choice for routing rules for these locations. All the location definitions of the model of the ED are shown in Table 1.

TABLE 1 Location definitions of the model of an emergency department

Name	Capacity	Units	Downtimes	Rules
Waiting areas	infinite	1	None	Oldest by priority
Doctor's offices	1	1	none	Lowest attribute value
Case history office	1	1	none	Lowest attribute value
Case history desk	infinite	1	none	Oldest by priority
Lab test results desks	infinite	1	none	Oldest by priority

4.4.3 Path network definitions

In the model, resources and entities are modeled as dynamic units which travel between defined locations. To enable them to move from one location to another, it is necessary to specify the paths between different locations. All the defined paths together form a path network which the resources and entities can follow during the simulation. Because the movement in the model can only occur along the defined paths, special attention should be paid to them.

The way the path definitions are made in the model depends on the software. If a graphical modeling environment is available, as we had in our research, this type of definition is very easy to do. In cases like this the paths can be drawn directly in the layout and in that way give a clear understanding of the paths for every entity and resource. The graphical view of the path network definitions of the emergency department is shown in Figure 9.

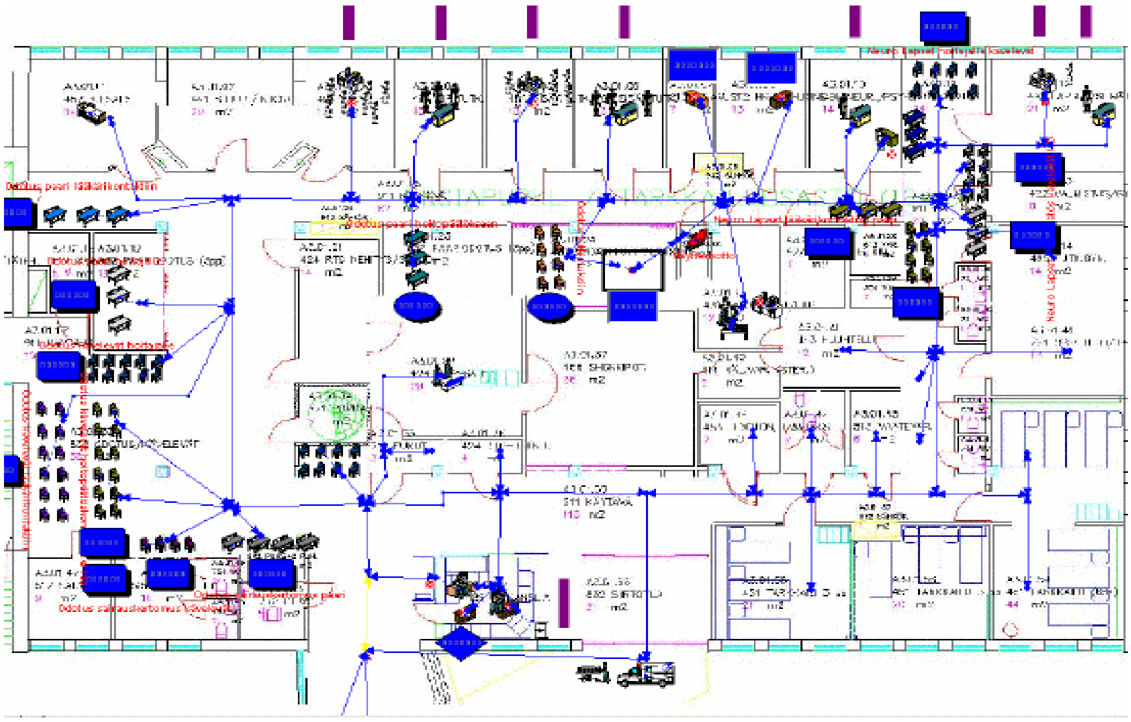


FIGURE 9 Graphical path definitions of the model

However, connecting the locations visually does not make the path network active. It requires many definitions before it is functional. The exact requirements may differ depending on what software is in use, but at least the following definitions should be made, especially if animation is going to be used:

- Graphic
- Name
- Type
- Time/Speed
- Paths
- Interfaces
- Mappings

Graphic definitions

Graphic definition is not very crucial for the model operation but it can be used to define whether or not the defined path network will be visible at run time. This is purely a definition for animation and does not have an influence on the functional part of the model. Because we had a graphical simulation tool in our use and we wanted to make the animation as real as possible, it was decided that the graphical view of the path network should be kept invisible.

Name definitions
Name definition is more important for the model operation. It defines the name that identifies the path network. The defined name is used in the model's move logic. In our model the path network was named Emergency Department, a natural and obvious name choice for the model of an ED.

Type definitions
Type definition is a functional definition. It is used to choose whether the entities and resources are allowed to pass each other. There are two choices available, i.e., Passing and Non-Passing. The Passing definition enables entities and resources to pass each other while the Non-Passing definition does not. In the Non-Passing mode entities may not pass each other even if an entity is moving faster that the other entity in front of it. Because in the real world patients and staff members can travel at different speeds, the Passing mode is a clear and appropriate definition for our model.

Movement measuring definitions
Movement measuring is an important definition and can be done in two different ways. Travel along the network can be measured in time or in speed and distance. If travel along the network is measured in time, all entities and resources take the same time to travel it, regardless of their speed. If travel along the network is measured in terms of speed and distance, the length of the segment has to be defined. Travel time along the path is then determined by the length of the segment in conjunction with the speed of an entity or a resource.

In our model travel was measured in time, because we did not have any accurate information on the length of segments. The time information definitions were easy to make and simple to use.

Path definitions
In order to make the paths in the model functional, node-to-node connections have to be specified. These node-to-node connections make up a path network and they also define how it works and how the entities should be handled in the model when they are traveling along a certain path. There are several definitions which have to be done to enable this. These definitions are:

- Starting point definition
- Destination definition
- Direction definition
- Movement measurement definition

The beginning node of the path segment is very crucial to define. The same thing goes for the ending node, because with these two definitions a certain path is identified in the model. However, in order to model the system as accurately as possible, a direction and movement measuring for the path has to be specified as well.

Traffic in the modeled system can occur either in only one direction or in both directions. This has to be taken into account in the model as well. In our model the traffic was defined to be bi-directional. All paths were paths where traffic can flow in both directions.

The last important definition for paths is the movement measuring for which there were two possibilities. Although the selection for the movement measuring was made in an earlier phase, the values still needed to be specified for this phase. When the measurement unit used is time, the time value required for a resource or entity to travel a certain path segment needs to be given. When the measurement unit is speed and distance, the length of a certain segment needs to be specified at this point. Because in our model travel along the network is measured in time, the time values for every path segment were given.

Interface definitions

Interfaces are links between locations and nodes and they are necessary for guiding a patient to the correct location in the model. When an entity is picked up or dropped off at a particular location by a certain resource, that specific location has to be connected to a node. If these interface definitions were not made, it would be impossible to route a patient to a certain operation area, as the right path that would lead the patient to the wanted location would not be known.

In our model there were quite many interface definitions, which means that there were many active locations where patients could be routed during the process as well. The connections between nodes and locations were made by numbering all the nodes and by connecting locations by their name to those numbered nodes. Altogether they were 46 different interface definitions in the model of the emergency department. This number was quite small compared to the number of all existing nodes in the model, but it has to be remembered that only the nodes which were situated in the operational areas, i.e., in locations, were linked and defined here. An example of these definitions is shown in Table 2.

TABLE 2 Interface definitions of the simulation model

Node (number)	Location (name)
1	Entrance
3	Reception
6	Waiting area for the nurse contact (bed patients)
8	Waiting area for the final doctor contact (walking patients)
14	Doctor's office (SurgeryTraumaGE)
19	Doctor's office (Internal Disease)
22	Laboratory
x	y
x	y
x	y

Mapping definitions

Mapping definitions are not necessarily needed but they can be useful in some situations. Usually if there are several paths emanating from a certain node to another node, the path selection is based on the shortest distance (speed and distance networks) or the least number of nodes (time based networks). However, if the mapping definitions are not appropriate, they can be overridden by explicitly mapping certain destination nodes to specific branches. An entity or a resource can then use these when traveling out of a starting point node.

In our model there was no need to do any extra definitions to specify any branches. The least number of nodes was a sufficient and accurate base for our model.

All the definitions above were needed to develop a functional path network in the model. There were definitions which were needed for animation and definitions which were purely needed for the computational part of the model. All the definitions for the path network are shown in Table 3.

TABLE 3 Functional path specifications of the model

Graphic	Name	Type	Movement Measuring	Paths	Interfaces	Mapping
none	Emergnecy Department	Passing	Time	88	46	none

From	To	Direction	Time (min)
N1	N2	Bi-directional	0.1
N2	N3	Bi-directional	0.1
N2	N4	Bi-directional	0.1
N4	N5	Bi-directional	0.1
N5	N6	Bi-directional	0.1
N5	N7	Bi-directional	0.1
N7	N8	Bi-directional	0.1
N7	N9	Bi-directional	0.1
N9	N10	Bi-directional	0.1
N9	N11	Bi-directional	0.1

Node (number)	Location (name)
1	Entrance
3	Reception
6	Waiting area for the nurse contact (bed patients)
8	Waiting area for the final doctor contact (walking patients)
14	Doctor's office (SurgeryTraumaGE)
19	Doctor's office (Internal Disease)
22	Laboratory
x	y
x	y
x	y

4.4.4 Entity definitions

Entity is one of the key elements in a simulation model. Anything that the model processes is called an entity. It can be, for example, a human being, document, sample, etc. It depends on the system being modeled. Entities can be treated as a single unit or as a group. The way they are handled in the model depends on the desired accuracy level. There could be, for example, a certain patient group (small and restricted) possessing the same symptoms defined in the model. In this case all the patients having the same symptoms are created, in the model, with the same qualities. This kind of definition is at a very detailed level. To build the whole model using the same accuracy would require numerous group definitions.

Usually it is more useful to handle entities, such as patients, in larger groups. It simplifies the structure of the model and still provides all the information wanted and desired. In such cases patients are grouped, for example, by their specialty needs. Patients in the group may possess different symptoms but they are all treated in the same way, depending on their specialty needs. This kind of definition does not need as extensive group definitions and logic descriptions as the more accurate model. The accuracy chosen is case related and is based on the desired results and used target variables.

In our research, patients, lab test results, case history documents and blood test samples were defined as entities. The main target variables were selected to be the waiting times and the length of stay in the ED. Therefore patients were grouped by their specialty needs as follows:

- SurgeryTrauma
- SurgeryGE
- Internal Medicine
- Pediatric
- Neurology

This kind of accuracy was sufficient, because all the wanted information on the whole operation of the ED was possible to gather by these definitions. Besides patients, there were other entities in the model as well. These other entities were:

- Laboratory test results
- Blood test samples
- Case history documents

In order to form these entity groups in the model, there were certain specifications which had to be made. In order to make both the numerical part of the model and the graphical part of the model functional, the following attributes were defined for every entity group individually:

- Icon
- Name
- Speed
- Statistics

Icon definitions
Icon definitions are very important to make, in order to get the animation to look as real as possible. A graphic icon represents the entity during the animation, which is why special attention should be paid to the selection of these representations. In our model these icons were selected from the graphical library of the MedModel software. Representations were available for doctors, nurses and patients as well as for documents and blood test samples for use in the animation view. Although in our software the graphic libraries were available, this may not be the case with every simulation tool. These graphical definitions, which may vary between different tools, are very important variables when using visualization in addition to numerical processing.

Name definitions
The second definition for entities was the name definition. It is used to identify entities in the model. Entity names are used in the processing logic (both in operation and routing logic) to define which entities are processed at which location at what time. In this model all different patient groups were named after

their specialty needs, the blood test sample was called sample and the documents were named based on their purpose (case history was referred to as case history document and the test results of lab tests were known as test results).

Speed definitions
Speed definition can be applied to self-moving entities such as patients. The speed of such entities can be defined in meters or feet per minute and it can be used for any of the entity's movement along the path network. In our model we used the metric system and the default value of the software was considered to be the most realistic definition. This default value was 50 mpm (meters per minute) which is roughly the speed of a human walking in the real world (for healthy people).

Statistic definitions
Statistic was the last obligatory definition before the entities could be activated and used in the model. There were three different levels of statistical detail to collect for each entity type. These options were None, Basic, or Time Series. In the model of the ED, Time Series statistics was selected to be the best choice for providing appropriate information on each patient group.

With the help of all these definitions the entities were created in the model. These entity definitions in the model of the emergency department are shown in Table 4.

TABLE 4 Entity definitions of the developed model

Icon	Name	Speed (mpm)	Statistics
Selected icon	Internal Medicine	50	Time Series
Selected icon	SurgeryTrauma	50	Time Series
Selected icon	SurgeryGE	50	Time Series
Selected icon	Neurology	50	Time Series
Selected icon	Pediatric	50	Time Series
Selected icon	Case history document	50	Time Series
Selected icon	Sample	50	Time Series
Selected icon	Lab test results	50	Time Series

Although the structure and the entities that we are interested in had now been developed in the model, there were still some more definitions to make before the model could be run and the results from the operation of the ED could be made available. Specifications for the resources which can handle patients in the model were needed also. The logic of the patient treatment and routing in the model had to be defined as well.

4.4.5 Resource definitions

A resource in the simulation model can be a person, equipment or some other item which belongs to the process and transport entities, performs maintenance on a certain location(s), or assists in operations on entities. Resources consist of one or more units. A unit may be, for example, a doctor, nurse, secretary, etc.

There are three different resource groups defined in our model. These groups consist of doctors, nurses and secretaries. Doctors and nurses were defined individually for each specialty, because there were different resources in the real system for each specialty. Secretaries were seen as common resources, and they were defined to serve all the patients in the model.

In order to make it possible to create resources in the model and make both the numerical part of the model and the graphical part of the model (animation) functional, the following attributes had to be defined for each resource group individually:

- Icon
- Name
- Units
- Statistics
- Specs
- Search
    - Work search
    - Park search
- Pts

Icon definitions
Icon definition was the first definition which was made. These icons were animation definitions to be used to represent the entities in animation. They were selected from the graphical library of the MedModel software. They could have been defined manually as well, had there not been appropriate representations already available in the library.

Name definitions
The first functional definition used was name definition, which is a very important specification for the model logic, because it identifies the resources in the model. Identification of the resources makes it possible for entities to call them in the operation logic and move logic as well as through macros. Resources were named after their names in the real system. This kind of naming methodology allowed the model become an even more accurate abstraction of the real system.

Unit definitions
Units are the number of resources available in the model and they can not be changed during the simulation. Unit definitions were made by defining the total amount of a certain resource around the clock (24 hours). This means that if there are three shifts in the emergency department and for example one resource unit on a shift at a time, the total number of resources is three. This was the case for example with doctors in our model. The number of resources in our

model by shift is shown in Table 5. Data for this definition was collected in the Emergency Department at the Central Hospital of Jyväskylä, Finland.

TABLE 5 Resources of the model

Surgery (trauma + GE)	Morning shift	Evening shift	Night shift
Nurse	3	3	2
Doctor	1	1	1
Neurology			
Nurse	1	2	1
Doctor	1	1	1
Internal Medicine			
Nurse	2	2	2
Doctor	1	1	1
Children's Medicine			
Nurse	0	1	0
Doctor	0	1	1
Shared resources			
Secretary	2	2	2
Lab staff	1	1	1
X-ray staff	1	1	1

Units were defined in the model by using special macros instead of directly entering the number of resources as pure numbers. This makes it possible to easily change the amounts of resources and perform efficient resource allocation with optimization in the future.

Statistics definitions

It is also important to define how to gather the desired statistics for the resource. There were two possibilities for us in this respect. The statistics could have been collected as a summary report over all units or individually for each unit of a resource. We chose to gather the information as a summary, because we did not need to know the individual statistics. It would not have given us any more information than the summary of all resource units.

Specs definitions

Specs definitions here are actual functional definitions. These include the following specifications:

- A path network assignment for the resources
- Setting a speed for the resources,
- Defining methods for entity search
- Specifying all necessary nodes for the resource (home node, break node, off shift node, etc.).

Path network was defined to be the ED path network described and developed earlier. Resources' speed was defined to be the average human walking speed, i.e., 50 meters per minute, just like the speed of entities. Entities for their part were defined to be searched based on their triage classification. The patients were treated in the order of urgency.

Search routine definitions

Besides speed and network definitions there was a need for other activating definitions as well. One of these definitions concerned search routines for the resources. These routines refer to the instructions a dynamic resource is going to follow after being released at a path node where a search routine was defined. In this case there are three options for defining the search routines. These are "work search", "park search" and "no search".

Work search is a definition which lists all the locations where entities may be waiting for a resource. It can be specified in two different ways. The locations can be either limited or the resource may be programmed to check for work at certain locations first, and then move on to others. If there is no work found at a certain time of the process, the resource will either park at the node listed, go to the home node, or become idle until work is available.

Park search for its part is used to send a resource to the next most likely place for work, or to get a resource off the main path segment. A park search is defined as a list of nodes to which a resource may be sent to park if no work is waiting at the work or default search locations.

In our model no search routines were used. There was no need for search routines, because resources were situated in their locations permanently and were requested by entities when needed.

Pts definitions

The last definition was a definition for the resource point. Resource points are the layout coordinates of the resource graphic. This definition is important for animation, because it defines where a certain resource will appear and in that way prevents resources from appearing on top of each other. The resource point definitions were made in our model by defining the places for resources one by one in the graphical layout.

After all the resources (every single unit) were placed in the model, the resource definitions were ready and the model, for that part, was functional. All the definitions of different resources are summarized in Table 6.

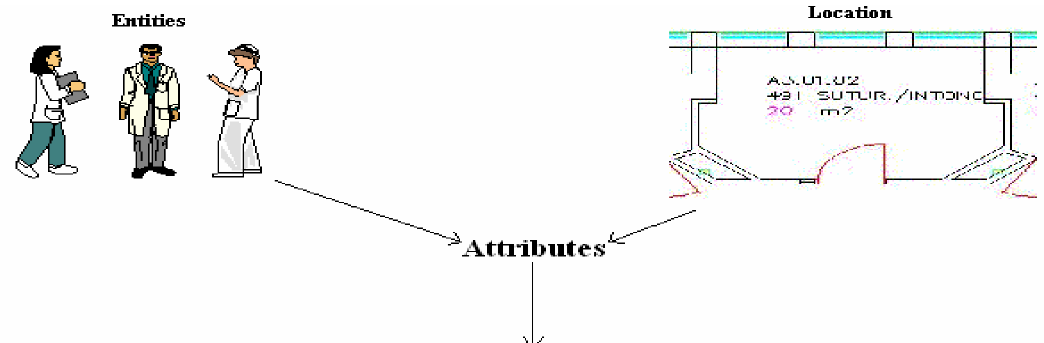
TABLE 6 Functional resource definitions in the model of an emergency department

Name	Units	Statistic	Specs	Search
Nurse_Internal_Disease	Macro	Summary	Operational definitions	None
Nurse_SurgeryTrauma + GE	Macro	Summary	Operational definitions	None
Nurse_Neurology	Macro	Summary	Operational definitions	None
Nurse_Pediatric	Macro	Summary	Operational definitions	None
			Operational definitions	
Doctor_Internal_Disease	Macro	Summary	Operational definitions	None
Doctor_SurgeryTrauma + GE	Macro	Summary	Operational definitions	None
Doctor_Neurology	Macro	Summary	Operational definitions	None
Doctor_Pediatric	Macro	Summary	Operational definitions	None
			Operational definitions	
Office_Secrate1	Macro	Summary	Operational definitions	None
Office_Secrate2	Macro	Summary	Operational definitions	None
			Operational definitions	
X-ray personnel	Macro	Summary	Operational definitions	None
Laboratory personnel	Macro	Summary	Operational definitions	None

Path Network	Resource	Speed	Home node	Off Shift node	Entity search
Emergency Department	Nurse_Internal_Disease	50 mpm (meters per minute)	N17	N59	None
Emergency Department	Nurse_SurgeryTrauma + GE	50 mpm (meters per minute)	N12	N59	None
Emergency Department	Nurse_Neurology	50 mpm (meters per minute)	N31	N59	None
Emergency Department	Nurse_Pediatric	50 mpm (meters per minute)	N75	N59	None
					None
Emergency Department	Doctor_Internal_Disease	50 mpm (meters per minute)	N19	N59	None
Emergency Department	Doctor_SurgeryTrauma + GE	50 mpm (meters per minute)	N14	N59	None
Emergency Department	Doctor_Neurology	50 mpm (meters per minute)	N26	N59	None
Emergency Department	Doctor_Pediatric	50 mpm (meters per minute)	N32	N59	None
					None
Emergency Department	Office_Secrate1	50 mpm (meters per minute)	N3	N59	None
Emergency Department	Office_Secrate2	50 mpm (meters per minute)	N54	N59	None
					None
Emergency Department	X-ray personnel	50 mpm (meters per minute)	N58	N59	None
Emergency Department	Laboratory personnel	50 mpm (meters per minute)	N22	N59	None

4.4.6 Attribute definitions

An attribute is in all its simplicity a tag (numeric tag) which can be attached to either an entity or a location. It is a place holder similar to a variable but is attached to a specific entity and location and normally contains information about them. They can be real numbers or integers. The relations between entities/locations and attributes as well as the definitions of attributes are shown in Figure 10.



ID	Type	Classification
Name of the attribute 1	Real or Integer	Entity or Location
Name of the attribute 2	Real or Integer	Entity or Location
Name of the attribute 3	Real or Integer	Entity or Location
Name of the attribute 4	Real or Integer	Entity or Location
Name of the attribute 5	Real or Integer	Entity or Location

FIGURE 10 Required definitions for entities' and locations' attributes in the model

In our model there were many situations where specific attributes were needed both for patients and locations. This was because the model contained many different entities and locations (five different patient groups, blood tests samples, documents and operational areas). Attributes defined for entities and locations were used in several occasions. These situations were:

- Arrival definitions
- Operation logic
- Moving logic
- Route definitions

Attribute definitions were made in two ways. There were generic attributes in the model which all the entities were able to use, but there were also attributes which had to be defined for each entity group individually. This kind of differentiation had to be made in order to avoid any overlapping (for example among different patient groups). Because there were common process phases for every group, the use of the same attribute (same name identification) at the same phase of the process could have given the same value for each group. This could have made the individualization of a certain treatment for the patient very difficult afterwards.

Although the processing logic is covered in more detail later on, it may be useful to give a rough idea of the problem definition at this point. Let's think about a situation where the patient sees the doctor for a final diagnosis. In this phase it is decided whether the patient is going to be discharged immediately afterward (the patient can go home) or whether the patient should be guided to some other hospital or ward. In the latter case the patient is sent to the waiting area where the patient has to wait until the case history is written. We should keep in mind that there are different resources for each group, and different groups are treated in parallel. In the final diagnosis phase the case history documents for the patient are created. Both the patient and the case history documents are given the same ID (numerical value) in order to make it possible to interlink them afterwards in the waiting area after the case history documents are ready. If this given ID value is now increased (whether it is location or entity related) by one at a time, at some point we will end up with a situation where members from two or more different patient groups will have the same value (depending on the number of patients and their arrival frequency). This is because every attribute is initialized first to zero for each group and the values are increasing side by side. This would lead to inoperability of the model. To solve this problem, we used individual attributes instead of common attributes wherever necessary.

Attributes in the model were constructed by using three different kinds of definitions. All of these definitions were crucial and made it possible to use them in the model's processing logic (code). The definitions used to create the attributes in the model were:

- ID: defines the name of the attribute and is unique
- Type: Defines whether the value of the attribute is an integer or a real number
- Classification: Defines whether the attribute is related to an entity or to a certain location

In our model there were altogether 36 different attributes used. All of these attributes had important roles to play at the different phases of the process. They are shown in Table 7.

TABLE 7 Attribute definitions of the simulation model

ATTRIBUTES		
ID	**Type**	**Classification**
Triage	Integer	Entity
Total time	Integer	Entity
Total_time2	Integer	Entity
After_nurse_contact	Integer	Entity
Doctor	Integer	Entity
Lab	Integer	Entity
X-ray	Integer	Entity
FDC	Integer	Entity
Tests	Integer	Entity
Case_History_ID_Internal_Disease	Integer	Location
Case_History_ID_SurgeryTrauma	Integer	Location
Case_History_ID_SurgeryGE	Integer	Location
Case_History_ID_Neurology	Integer	Location
Case_History_ID_Pediatric	Integer	Location
ID_Internal_Disease	Integer	Entity
ID_SurgeryTrauma	Integer	Entity
ID_SurgeryGE	Integer	Entity
ID_Neurology	Integer	Entity
ID_Pediatric	Integer	Entity
Sample_Internal_Disease	Integer	Location
Sample_SurgeryTrauma	Integer	Location
Sample_SurgeryGE	Integer	Location
Sample_Neurology	Integer	Location
Sample_Pediatric	Integer	Location
Sample_ID_Internal_Disease	Integer	Entity
Sample_ID_SurgeryTrauma	Integer	Entity
Sample_ID_SurgeryGE	Integer	Entity
Sample_ID_Neurology	Integer	Entity
Sample_ID_Pediatric	Integer	Entity
Operation_time_Lab	Integer	Entity
Operation_time_Rtg	Integer	Entity
Operation_time_Doctor	Integer	Entity
Operation_time_Nurse	Integer	Entity
Time_till_First_Doctor_contact	Integer	Entity
Time_till_Final_Doctor_contact	Integer	Entity
Time_till_Case_History_writing	Integer	Entity

In order to provide a clear understanding of how the model works, it is important to explain how the attributes were used and the purpose of each attribute in our model. Let's examine the attributes shown in Table 7. First we look at the attributes which all the entities can exploit and after that attributes which are entity-specific.

Common attributes in the model

There were several attributes in the model which all the entities were able to use for storing their own data (individual values) at different phases of the process. These attributes were defined only once and all the entities were then able to use them with their own logic for their own purposes. This was possible, because these attributes were defined to be entity-specific. These attributes were:

- Triage
- Total time
- After_Nurse_contact
- Lab
- X-ray
- Tests
- FDC

Triage is an attribute which is needed right at the beginning of the process. It is used to define the urgency of patients. The urgency, for its part, specifies how the patient is routed and processed in the model. Triage is divided into four levels, which means that the triage attribute can get four different values. These values and levels are as follows:

- ***Triage1***: The treatment has to be started immediately. The patient possessing this value in the model is treated before anyone else.
- ***Triage2***: The treatment has to be started in less than 10 minutes. The patient possessing this value is treated before patients who possess lower values.
- ***Triage3***: The treatment has to be started in less than an hour. The patient possessing this value is treated before patients possessing a lower value.
- ***Triage4***: The treatment has to be started in less than two hours. The patient possessing this value is not deemed urgent and will be treated after all the other patients.

The *Total time* attribute is a placeholder for time information. It is used to store patients' length of stay (throughput time) in the developed model. The attribute operates as follows: When the patient enters the model the attribute is initialized as zero. After that, the time from arrival to exit is recorded in the defined time units (in our case minutes) and stored into the attribute. When the patient exits the model, the value of the attribute reveals how long the patient stayed in the process. In other words, it shows the throughput time for the patient.

The *After_nurse_contact* attribute is used in routing logic to define where the patient is to be routed after having been seen by a nurse. The analysis of the collected data shows that there are three different possibilities for patient's routing in that case. The patient can be seen by a doctor for a first time, or for the last time, or the patient is guided directly to the tests without seeing the doctor first. Because there were three different route options in the process, there had to be three different values for the attribute as well.

The values for the attribute were defined by using a special macro and empirical distribution. Value 1 meant that the patient is seen by a doctor for the first time after having been seen by a nurse. Value 2 meant that the patient is guided directly to the tests after the nurse contact. Value 3, for its part, meant that the patient is sent to the doctor for a final diagnosis.

The *Lab* attribute was used to define whether the patient had had laboratory tests or not and whether blood tests had been taken from the patient or not. It was used as a flag, and only two different values were used. These possible values were 1 and 0 and were given to the patients right in the beginning of the process. Value 1 meant that the patient would have laboratory tests during the process, and value zero meant that the patient would not have any tests during the process. As long as the value remained 1 it meant that the patient had to be routed to the tests at some point of the process. When the patient finally enters the sampling area, the value of the attribute is changed to 0, which means that the tests will have been taken. By using this attribute it is possible to route the patient always to the right place and phase in the process.

The *X-ray* attribute is similar to the lab attribute and is used exactly the same way. The possible values for the attribute are either 1 or 0, which define whether the X-ray tests of the patient have been taken or not.

The *Tests* attribute is used to specify the information on patient's tests. There are three possible values for this attribute, because there can be three different combinations of tests for the patient in the model. These values are 1, 2 or 3 and they are used as follows: Value 1 means that only laboratory tests are ordered for the patient. Value 2 means that only X-ray tests are ordered for the patient. Value 3 three says that both laboratory and X-ray tests have been taken from the patient during the process. These values are entered into the attribute by using a special macro and empirical distribution.

Individual attributes in the model

All the attributes in the model can not be defined as common attributes, and often they have to be defined individually. There are situations where a change in the value of a certain attribute is based on the location. This is the case, for example, in the sampling area, where a specific ID is created to interlink a patient and a sample taken from the patient later in the process. If the common attributes were used in these situations, patients from the different specialties might get the same ID number which would lead to inoperability of the simulation model.

The individual attributes in the model were defined as follows:

- Case_History_ID
- ID
- Sample
- Sample_ID

The *Case_History_ID* attribute is a location-specific attribute, which is used to interlink the patient with the patient's case history documents after the dictation has been transcribed. A value for the attribute is created in the final doctor contact phase. The attribute is initialized first as zero and it is increased by one each time a patient enters the final doctor contact phase. When the values is increased by one each time, it eliminates the possibility of giving overlapping values for patients and assures a valid operation of the model during the simulation run.

However, it is not enough that the patient gets the ID number for the case history writing phase. The documents and the ID for them have to be created as well. The use of the documents' ID attribute is explained later (see the next attribute definition), but the main idea is to place the value of the Case_History_ID in the documents' ID attribute. In this way the same value for both the patient and patient's documents can be assured.

The *ID* attribute for the patient's case history documents is created in the final doctor contact phase (as briefly mentioned earlier). To ensure that the patient and the patient's documents have the same value, the value of the earlier defined Case_History_ID is placed in the ID attribute. This makes it possible to interlink the documents with the right patient in the waiting area.

The *Sample* attribute is similar to the Case_History_ID attribute. The main idea is to create a connective ID (value) for the patient and for the samples taken from the patient. It is used later in the process to interlink the test results with the right patient. This value is stored in the patient's Sample attribute and for samples in the Sample_ID attribute.

The *Sample_ID* attribute is created for the samples taken from the patient (as mentioned before). It is a placeholder for the ID created for both the patient and the samples.

4.4.7 Shift definitions

Shift definitions are very important for the model, especially if the aim is to allocate the resources as efficiently as possible. Shift definitions make the model more accurate and create better abstraction of the system being modeled. This is because in the real world there are different amounts of resources on different shifts in the emergency department. In the night time the resources employed are smaller than for example in the evening.

In order to create as accurate a model as possible, different shifts were constructed in the model. There were three shifts in the real system and these shifts were defined in the model by using three different specifications. These specifications were:

- Location
- Resource
- Shift

First a location for the shift assignment was defined. In this way it was possible to form different shifts for different locations. The second definition was a resource definition which was used to specify a certain resource for a certain location. In addition to resource definition (selecting a resource), the amount of the resource needed to be specified as well. The last definition was a time definition which was used to specify a period of time for a certain shift (duration). All these definitions are shown in Table 8.

TABLE 8 Required definitions for shifts in the model

Location	Resource	Shift	Logic
Name of the location 1	Name of the resource 1; amount	Period of time	Control definitions if any
Name of the location 2	Name of the resource 2; amount	Period of time	Control definitions if any
Name of the location 3	Name of the resource 3; amount	Period of time	Control definitions if any
Name of the location 4	Name of the resource 4; amount	Period of time	Control definitions if any
Name of the location 5	Name of the resource 5; amount	Period of time	Control definitions if any

In our model the specifications above were defined as follows: locations as well as resources were selected from the lists of created locations and resources. The amount of resources for every shift was created with the help of macros in order to enable optimization in resource allocation in the future. Data (presented in the resource definition chapter (4.4.5)) for the amount of resources were gathered from the Emergency Department at the Central Hospital of Jyväskylä. Duration for each shift was defined just as in the real system. In the real system there were three different shifts:

- Morning shift: 07.00am-15.00 pm
- Evening shift: 15.00pm-22.00pm
- Night shift: 22.00pm-07.00am

4.4.8 Data handling and distribution definitions

Data was collected by observing patients in the Emergency Department for two weeks in August 2004. The patients were observed 24 hours a day and seven days a week. In addition, the observation data from the earlier research, which was conducted half a year earlier, was also available and was used in this project. Altogether there were six weeks' data available. The total number of patients' visits was a little under 4000.

In both cases the data was collected with a special form created for this project. The form included information, among other things, on the patient's arrival (how the patient had arrived), symptoms, urgency (triage), and process times.

Data collection was done by specialized nurses and secretaries, who filled the form as the patient went through the process. The form was among the patient's other documents and thus followed the patient from one point of the process to another. After the patient had left the emergency department, the data on the form was entered into an Access database and processed with SPSS and Stat: Fit statistical software.

The most important definition of these concerns the information on durations of different events and activities (process times):

- Reception phase
- Nurse contact
- Specialist contact
- X-ray
- Blood test samples analysis
- Final doctor contact (final diagnosis)
- Case history writing

In simulation the waiting times of different phases are based on the durations of different operations and activities in the process. Because in our study only the starting times for every phase were written down, it was necessary to define the ending times of different operations by analyzing the collected data. If the ending times had not been separately defined, i.e., had the duration of different operations been considered to be the time between different phases (previous operation ends when the next operation begins), it would have led to wrong operation of the model. This is because the time between different phases includes both the actual operation time and the waiting time for the next operation. It should not be assumed that the duration of a doctor contact ends only when the patient is admitted to the next phase (X-ray, blood sample test, etc.). In the real world the duration of a doctor contact ends when the patient leaves the doctors' office. This should be the case in the model as well. This is why it was important to define the exact duration for every operation. The definitions of the durations of different operations are explained next.

Defining the duration of a nurse contact from the collected data

A nurse takes care of the patient throughout the process so the duration of the nurse contact might be thought of as the duration of the whole patient process. But when thinking about the operation of an emergency department as a process which advances from the patient's arrival to the patient's departure and which includes different phases, a nurse contact is better defined as a phase which includes the interview of the patient and the first treatments, after which the patient is guided forward in the process.

However, because the duration of the operations was not gathered from the process by using the starting points and ending points, they had to be defined from the data in some other way. The starting point was not the problem, because it was noted down during the observation process. The problem was in defining the ending point for the operation. The answer was found by examining the way nurses operate.

After a nurse has interviewed the patient, performed the first tests (measured the blood pressure, etc.) and defined the urgency, s/he possibly orders some tests for the patient. This is the case at least with the laboratory tests. Because at this point the patient is guided forward in the process and the nurse will not see another patient before the tests are ordered, it is assumed that the tests ordering point is the end of the nurse contact.

By using the definition above, the distributions for nurse contact were defined for each patient group separately. This was done with two special statistical tools. The distributions were put in the order of best fit, and the best distribution was selected to represent the duration of the nurse contact. The durations and distributions for each group were:

- SurgeryGE: Weibull(1., 1.4, 15.2)
- SurgeryTrauma: Exponential(2., 8.24)
- Neurology: Weibull(1., 1.63, 14)
- Pediatric: Weibull(5., 2.44, 13.9)
- Internal Medicine Weibull(3.3, 3.16)

In each case, the first number specifies the random number stream sampled.

Defining the duration of the first doctor contact from the collected data

The definitions employed for the nurse contact phase were used for the doctor contact phase as well. The exact operation time with the patient should be defined as accurately as possible in order to get the waiting times in the model specified correctly. A differentiation should be made between the first doctor contact and the final doctor contact in the model as well. In the real world it is usually thought that a doctor contact starts when the patient is seen for the first time by a doctor and ends when the final diagnosis is made, but from the process point of view they are two separate phases and should be differentiated.

Doctor contact was defined by analyzing the gathered data and by getting acquainted with the operation. Just as in the case of the nurse contact phase the starting time was available but the ending time was unclear and had to be defined some other way. After analyzing the process and the data available we concluded that the best point to represent the ending of the doctor contact phase was the ordering of the tests, especially x-ray tests. A doctor usually first examines the patient and then orders any necessary tests before seeing another patient. Particularly x-ray tests were selected to represent the ending point, because only doctors can order those tests. By using these definitions the operation times for the first doctor contact for each patient group were defined as follows:

- SurgeryGE: Lognormal(1., 1.79, 11)
- SurgeryTrauma: Inverse Gaussian(1., 10.2, 11.2)
- Neurology: Weibull(2., 1.66, 12.8)
- Pediatric: Exponential(1., 5., 9.03)
- Internal Medicine: Inverse Gaussian(1., 11.2, 9.57)

Defining the duration of the final doctor contact from the collected data
As in other phases, the starting time was already known in this phase as well, but the ending time once again remained unclear. By analyzing the operation and collected data, it was possible to define the end of the final doctor contact. The operation which described the end of the final doctor contact best was the delivery of the dictation tape to the secretaries' office for transcription. The doctor can not see another patient before the dictation is ready and fetched from the doctor's office.

The distributions for each patient group were defined by using statistical tools (Stat:Fit, SPSS), and the distribution which was the best (number one in the ranking) was selected to represent the duration of the first doctor contact. The distributions were:

- SurgeryGE: Weibull(1., 1.42, 13.8)
- SurgeryTrauma: Weibull(1., 1.44, 17.9)
- Neurology: Erlang(1., 6., 2.69)
- Pediatric: Triangular(4., 46.9, 4)
- Internal Medicine: Pearson5(4.15, 55.7)

Defining the duration of the case history writing from the collected data
The duration for the case history writing differed from the other definitions, because both the starting time and the ending time were available. These were written down on the form during the observation. In this case, the only thing which had to be done was to define distributions for each group. A statistical analysis defined the following distributions for representing the duration of the case history phase:

- SurgeryGE: Exponential(3, 20.7)
- SurgeryTrauma: Lognormal(1., 2.69, 0.795)
- Neurology: Pearson 6(3., 32.3, 2.5, 4.88)
- Pediatric: Exponential(5., 13.1)
- Internal Medicine: Inverse Gaussian(3., 49.9, 26.8)

Defining the duration of the laboratory operation from the collected data
The operation of the clinical laboratory was defined in more detail than initially thought possible. On the observation form there was only information on times when the test had been ordered and when the results were ready. This kind of examination was too approximate, because the collaboration with the clinical laboratory consisted of many different phases and those phases needed to be studied more closely.

In order to examine the operation in more detail, more accurate data was needed. The information on operations and durations of operations were received from the clinical laboratory. The time information on every phase of the collaboration between a clinical laboratory and an emergency department had been collected in these observations. This data was then used to define all the necessary distributions for the model.

The process was divided into four different phases. This kind of division was accurate enough for enabling the examination which was needed for this study. The first phase of the process consisted of the nurse's walk to the ED after a request for tests had been receipted in the clinical laboratory. There were well-defined time stamps for that definition. After the nurse had arrived in the emergency department, blood samples were taken from the patients. This was the second phase of the laboratory process. However, data for this phase of the process was not directly available, so it was estimated by the staff. The last two phases after the actual sampling action were the delivery of the samples to the laboratory and analysis. These two phases were combined and the time for this combined operation was statistically defined from the collected data.

The laboratory process was common for all patient groups so there was no need to define the laboratory operation for all groups individually. Therefore, it was specified to be the same for all the groups. The durations for every phase of the process were defined from the collected data as follows:

- Walking to the ED: Exponential(3,7.74) min
- The sampling action: Uniform(3,1) min
- Delivering the samples to the laboratory and analysis: Weibull(1.89,58.5)

Defining the duration of the X-ray operation

Originally the X-ray operation was defined just like the laboratory operation, on a very coarse level. On the form there was only information on the time when the imaging services were ordered and when the results were ready. However, from the processes point of view as well as from the animation point of view this kind of specification was not accurate enough and would have led to a distortion in the graphical presentation. There was a need to separate waiting from the actual operation, and from the time before the results would be ready for a doctor's examination.

When the examination of the process is conducted on a coarse level as it originally was in this study, valuable information may be lost on the operation of the modeled system. For example, our study would not have allowed a possibility to study the queues, because the time between an order and the results would have included the waiting as well as the actual operation time. This means that there would have been just a single location where the patients would have been situated in parallel with each other for a particular period of time.

The definitions of the X-ray process were much easier to do than the definitions of the clinical laboratory. This was because the only corrective which needed to be made was the information on the actual imaging phase. In the laboratory process there were more specific definitions, such as information on the amounts of patients and samples during one round.

Because the information on the actual operation was not directly available from the collected data, the duration definitions were estimated by the X-ray staff. The definitions were made for each group separately, because different patients and symptoms required different amounts of treatment. The durations were estimated as follows:

- SurgeryTrauma: The operation was estimated to last 10 minutes on average. Because there is always some dispersion in times, half range was defined to be 2 minutes and uniform distribution was selected to be the best representation of the duration (U(10,2)). It means that the minimum value is 8 minutes and the maximum value is 12 minutes and all the values between these limits are equally possible.
- SurgeryGE: The estimation for the duration and the grounds for estimation were the same as they were for SurgeryTrauma.
- Neurology: The duration for neurology patients is slightly longer due to symptoms. In their case the duration was estimated to be 20 minutes and half range was defined to be 2 minutes. Uniform distribution was selected to be the best distribution for describing the duration. The definition in the model was U(20,2).
- Pediatric: The estimation by the staff was the same as it was with the Surgery patients. Under these circumstances the definition in the model was U(10,2).
- Internal Medicine: The estimation in the case of internal medicine was 15 minutes. Dispersion was defined to be 2 minutes as was the case with all the other specialties as well. The definition in the model was hence U(15,2).

The process times for each phase of the process in each patient group separately are summarized in Table 9.

TABLE 9 Process times for each phase of the process

Surgery (trauma) patient	Time (min)		Surgery (GE) patient	Time (min)
Reception time	N(5,1)		Reception time	N(5,1)
Nurse contact	E(8.24)		Nurse contact	W(1.4, 15.2)
First doctor contact	IG(10.2, 11.2)		First doctor contact	L(1.79, 11)
Blood test	U(3,1)		Blood test	U(3,1)
Walking to the ED	E(3,7.74)		Walking to the ED	E(3,7.74)
Walking to the laboratory and analysis	W(1.78,47.1)		Walking to the laboratory and analysis	W(1.78,47.1)
X-ray	U(15,2)		X-ray	U(15,2)
Final doctor contact	W(1.44, 17.9)		Final doctor contact	W(1.42, 13.8)
Writing case history	L(2.69, 0.795)		Writing case history	E(20.7)
Neurology patient	**Time (min)**		**Internal medicine patient**	**Time (min)**
Reception time	N(5,1)		Reception time	N(5,1)
Nurse contact	W(1.63, 14)		Nurse contact	W(3.3,3.16)
First doctor contact	W(1.66, 12.8)		First doctor contact	IG(11.2,9.57)
Blood test	U(3,1)		Blood test	U(3,1)
Walking to the ED	E(3,7.74)		Walking to the ED	E(3,7.74)
Walking to the laboratory and analysis	W(1.78,47.1)		Walking to the laboratory and analysis	W(1.78,47.1)
X-ray	U(23,3)		X-ray	U(15,2)
Final doctor contact	ER(6, 2.69)		Final doctor contact	P5(4.15,55.7)
Writing case history	L(2.7, 0.846)		Writing case history	IG(49.9,26.8)
Children patient	**Time (min)**			
Reception time	N(5,1)			
Nurse contact	W(2.44,13.9)			
First doctor contact	E(9.03)			
Blood test	U(3,1)			
Walking to the ED	E(3,7.74)			
Walking to the laboratory and analysis	W(1.78,47.1)			
X-ray	U(10,2)			
Final doctor contact	T(4,4,46.9)			
Writing case history	E(13.1)			

4.4.9 Processing definitions of the simulation model

Processing logic defines the routing of entities (patients, blood test samples, lab test results and other documents in this model) through the system and the operations to which the patients are subjected at each location. Routing definitions specify how and to where the patient is guided from a certain location. Operational definitions for their part specify everything that happens to the patients at each location until they exit the system. In other words, processing definitions make the model functional.

However, before the processing logic building is possible, all the locations and the entities (patients, documents, resources, samples, etc.) to be referred in the processing have to be defined. If these definitions have not been made, it is impossible to reference them, which makes it difficult to specify activities in the model and build the logic.

This phase of the process is the most crucial phase for making the model functional. This is the phase where the whole operation of the model is defined for every entity, location and resource. The conceptual models are now translated into a computing language. The gathered and processed data are entered in the model as well. In this phase the modeler has to be very careful in order to get the model work just like the real system.

Processing logic definition consists of two different phases. In the first phase the operational definitions are made. This phase includes three different specifications which all are important. First the entity type for which the process is defined needs to be specified. After this a location where the process occurs is selected and defined. The last and the actual functional part of the operational definition is to establish all the actions to which the specified patient at that specified location is subjected. This is done by coding, using some programming language. Usually at least the amount of the time the entity spends at the location needs to be defined. If the entity needs a resource to process it, it is normally specified here as well. The operational definition requirements are shown in Table 10.

TABLE 10 The operational definitions required for the processing logic in the model

Entity	Location	Operation
Internal Disease	Operation area	Code
SurgeryTrauma	Operation area	Code
SurgeryGE	Operation area	Code
Neurology	Operation area	Code
Pediatric	Operation area	Code

In order to move the entity forward in the process, the routing specification has to be made. This is done after the operation logic is specified. Routing definitions guide the entity to the next location in the process. These four necessary specifications are shown in Table 11.

TABLE 11 Required routing definitions for the processing logic in the model

Output	Destination	Rule	Move Logic
Entity name	Operation area	Rules for destination selection	Moving method and logic
Entity name	Operation area	Rules for destination selection	Moving method and logic
Entity name	Operation area	Rules for destination selection	Moving method and logic
Entity name	Operation area	Rules for destination selection	Moving method and logic
Entity name	Operation area	Rules for destination selection	Moving method and logic

Routing definitions start by specifying the name of the entity resulting from the operation. The name can be the same as it was when the entity entered the location, or it may be some other name, or there can be even several names for the entity leaving that location. After the name definition, the location where the entity is about to move to after the operation is complete is specified. These are the basic elements for routing.

However, these output and destination definitions tell only where to guide the entity next. It is also important to know how they are routed there and in which order. That is why the rule and move logic definitions need to be made. This is the case especially for tools with animation capabilities.

The rules definition may contain several different features which extend the operation of the model. Rules are basically used for the selection of the next location (if there are for example multiple locations for a certain operation). In our model the following definitions were possible:

- First available
- By turn

- If join request
- If send
- Until full
- Probability
- User condition
- Most available
- Random
- If load request
- Longest unoccupied
- If empty

These rule definitions may vary with different tools, but in principle at least a few options on how to select an appropriate location after another are needed.

The move logic allows defining the method of movement for the entity. Any other logic to be executed during the movement can be defined as well. This was an important definition in our case because of the animation and the resource reservation involved. This is the place where it can be specified whether the entity can move all by itself or whether transportation to move it to another location is required.

Now when all the basic principles are clear, it is time to have a closer look on the processing definitions of the emergency department. There are locations and operations which are universal for all patient groups but there are also certain locations and operations which must be specified for each patient group individually. We will proceed, from here on, phase by phase starting with the patient arrival and advancing until the patient exits the model. This will provide us with a clear understanding of how the model in this study was developed and how it should be developed.

Definitions for the patient entering the model (entrance)

When the patient is created in the model, there are several definitions which have to be made in order to define the right order for treatment and to enable collection of time information on the patients at different locations. In this model there are two important definitions which needed to be made. These definitions are the triage definition and the time attributes definition. The triage definition specifies the urgency of the patients in the model. It was made with the help of the empirical distribution processed from the collected data.

The empirical distribution definition in the model is based on four important specifications. The distributions were first identified. In other words, they were given names in order to identify and include them in the code used. Then there was the selection to determine whether the distribution would be continuous or discrete. For the purpose of this study, discrete distributions were preferred. There was also information on cumulativeness and, most importantly, on percentages of each urgency level. These definitions are shown in Table 12:

TABLE 12 The empirical distribution for the triage definition

ID	Type	Cumulative	Table
Urgecy_Internal disease	Discrete	No	Defined
Urgency_SurgeryTrauma	Discrete	No	Defined
Urgency_SurgeryGE	Discrete	No	Defined
Urgency_Neurology	Discrete	No	Defined
Urgency_Pediatric	Discrete	No	Defined

Percentage	Value
9,3	1
10,6	2
34,6	3
45,5	4

Percentage	Value
3,7	1
4,9	2
25,4	3
66	4

Percentage	Value
3,7	1
8	2
42,6	3
45,7	4

Percentage	Value
6,1	1
6,1	2
39,5	3
48,3	4

Percentage	Value
7,2	1
12,5	2
57,1	3
23,2	4

Time definitions in the model were made to enable validation. They measure time between the arrival and a certain operation (for example how long the patient had been in the process until seen by a doctor for the first time, for the last time, etc.). To save the time information at different points, certain attributes needed to be defined (for storing the information). There were also many other attribute definitions, which will be explained in more detail later. In this work time was measured at three different phases of the process:

- Time when the patient was seen by a doctor for the first time
- Time when the patient was seen by a doctor for the last time (final diagnosis)
- Time when the patient exited the system.

At each location the time information was gathered and stored in the defined attribute. These time stamps were then used in the model validation.

After the entrance all the patients are routed to the reception. This definition was the same for each patient group. The whole processing logic definition at the entrance phase is shown in Table 13.

TABLE 13 Processing logic definitions of the entrance phase

Operation logic

Entity	Location	Operation
Internal Disease	Operation area	Triage=Urgency_distribution() Doctor_contact_time=clock() Doctor_contact2_time=clock() If triage = 1 or triage = 2 then graphic 2 else graphic 1 Length_of_Stay=clock() Length_of_Stay2=clock()
SurgeryTrauma	Operation area	
SurgeryGE	Operation area	
Neurology	Operation area	
Pediatric	Operation area	

Routing logic

Output	Destination	Rule	Move logic
Urgecy_Internal disease	Reception	First Available	Move on the ED model
Urgency_SurgeryTrauma	Reception	First Available	Move on the ED model
Urgency_SurgeryGE	Reception	First Available	Move on the ED model
Urgency_Neurology	Reception	First Available	Move on the ED model
Urgency_Pediatric	Reception	First Available	Move on the ED model

Operations for the patient at the reception

The next phase of the process after entrance is reception. This is a common phase for each patient group so there was no need to differentiate the action between these groups at this point. The duration of this phase was evaluated to be approximately five minutes, and, therefore, normal distribution was used to describe the duration of this operation in the model. The average value was 5 minutes and the variance 1 minute. These definitions were entered in the model logic by coding. In our software there was a certain function which made it possible to reserve the resource for a certain period of time. This function was used to specify the duration of the reception operation and to reserve a resource for the patient for that time.

When the patient had spent the defined time at the reception, the routing definitions were needed again. In this model the routing was based on the triage definition. There were different waiting areas for different triage patients. Level 1 and level 2 patients were acute patients, and they were routed to the waiting area for bed patients. Level 3 and level 4 patients were not as acute cases, and they had their own waiting area (chairs). In other words, the patients were divided into two groups based on the acuteness of their condition and on whether they were able to walk or not. The processing definitions of the reception phase are shown in Table 14.

TABLE 14 Processing definitions of the reception phase

Operation logic

Entity	Location	Operation
Internal Disease	Reception	USE 1 Receptionist for N(5,1) if Triage = 1 or Triage = 2 then route 1 //level 1 and 2 patients else route 2 //level 3 and 4 patients
SurgeryTrauma	Reception	
SurgeryGE	Reception	
Neurology	Reception	
Pediatric	Reception	

Routing logic

Output	Destination	Rule	Move logic

Urgecy_Internal disease	Waiting area for level 1,2 or 3,4	First Available	graphic x
			If Triage = 1 or Triage = 2 then begin
			MOVE WITH nurse THEN FREE
			end
			else if Triage = 3 or Triage = 4 then
			{
			graphic x
			MOVE ON ED
			}

Urgency_SurgeryTrauma	Waiting area for level 1,2 or 3,4	First Available	
Urgency_SurgeryGE	Waiting area for level 1,2 or 3,4	First Available	
Urgency_Neurology	Waiting area for level 1,2 or 3,4	First Available	
Urgency_Pediatric	Waiting area for level 1,2 or 3,4	First Available	

Waiting area definitions

Waiting areas in the model were divided in accordance to the different phases of the process. There are waiting areas for the nurse contact, first doctor contact, final doctor contact, sampling, X-ray and case history writing. In this way it is easier to follow and observe queues and the numbers of patients at different phases of the process more closely than when using only one waiting area. Let's first consider the waiting area of the nurse contact and its definitions. This phase had many more definitions than the previous operation areas. In addition to operational definitions there were more options for the advancement of the patient as well.

The operational definitions contain a lot of information which guides the patient to the next phase of the process. To make the operation of the model easier to understand, especially the operation of its logic part, macros were used to execute bigger functional groups in the process logic.

A macro is a placeholder for a set of statements and functions that might be used in an expression or logic field. It needs to be typed only once and can be called anywhere in the model by its name. Macros are used in this model at different phases. At this point it is essential to examine the macro definitions used in the waiting area of nurse contact.

In the waiting area operation, logic of the nurse contact macros was used to define the routes forward and the distributions of lab and X-ray tests for the patients, who were guided directly to the tests after the nurse contact (without seeing the doctor first). The distributions for the routes and for the tests were created manually (empirical distributions) and coded into the macros. In addition to test distributions, there was also a definition about whether the patients who were guided directly to the tests were seen by the doctor between the tests or not. This definition was made by using the empirical distribution and it was embedded in the macro code as well.

Because there were five different patient groups in the model and their behavior was quite different from each other, it was essential to make these definitions for each group individually. An example of a macro definition is shown in Figure 11. In that figure, macro definitions for internal medicine patients have been described. The same definitions were made for other patient groups as well, but since the logic in them is similar, differing only in percentage proportions and attributes, there is no need to show them all here.

```
After_Nurse_contact = Route_after_Nurse_contact()
if After_Nurse_contact = 1 then route 1

if After_Nurse_contact = 2 then
{
Test_Internal_Disease_macro
if Tests = 1 then route 2
if Tests = 2 then route 3
if tests = 3 then route 4
}

if After_Nurse_contact = 3 then route 5
```

```
Tests = Test_Internal_disease()
if Tests = 1 then begin
First_Doctor_contact = First_doctor_contact_after_lab()
if First_Doctor_contact = 1 then
{
Lab = 1
Rtg = 1
}
else
{
Lab = 1
Rtg = 0
}
end

if Tests = 2 then begin
First_Doctor_contact = First_doctor_contact_after_x-ray()
if First_Doctor_contact = 1 then
{
Lab = 1
X-ray = 1
}
else
{
Lab = 0
Rtg = 0
}
end

if Tests = 3 then begin
First_Doctor_contact = First_Doctor_contact_bothTests()
Lab = 1
X-Ray = 1
end
```

FIGURE 11 An example macro in the nurse contact phase (Internal medicine)

Three different route options for the patients after the nurse contact emerged from the gathered data. It is possible for patients to go either directly to the tests without seeing a doctor first, they could be guided to the doctor's office for the first time, or they could be seen by a doctor for the final diagnosis. These routing specifications were made in the model based on the processed data and by using the empirical distribution definitions. These definitions were placed into the macros to be called in the operation logic code. The processing definitions of the nurse contact phase are shown in Table 15.

TABLE 15 Processing definitions of the nurse contact phase

Operation logic

Entity	Location	Operation
Internal Disease	Waiting area (nurse contact)	GET 1 Nurse_Internal_disease WAIT Nurse_contact_Internal Disease FREE Nurse_Internal_disease First_route_after _nurse_macro
SurgeryTrauma	Waiting area (nurse contact)	
SurgeryGE	Waiting area (nurse contact)	
Neurology	Waiting area (nurse contact)	
Pediatric	Waiting area (nurse contact)	

Routing logic

Output	Destination	Rule	Move logic

Urgecy_Internal disease	Lab, X-ray, Doctor 1, Doctor 2	First Available	graphic x
			if Triage = 1 or Triage = 2 then begin
			MOVE WITH nurse THEN FREE
			end
			else if Triage = 3 or Triage = 4 then
			{
			graphic x
			MOVE ON ED
			}

Urgency_SurgeryTrauma	Lab, X-ray, Doctor 1, Doctor 3	First Available	
Urgency_SurgeryGE	Lab, X-ray, Doctor 1, Doctor 4	First Available	
Urgency_Neurology	Lab, X-ray, Doctor 1, Doctor 5	First Available	
Urgency_Pediatric	Lab, X-ray, Doctor 1, Doctor 6	First Available	

Definitions for the waiting area of doctor contact

The waiting area of doctor contact did not need any extensive specifications, because in this area the patients just waited for their turn to enter the doctor’s office. The only definition which had to be made (if the animation was wanted to be as accurate as possible) was the graphical definition. Because we were using software which possessed the capabilities of visualization, these definitions were also made.

The waiting area of doctor contact, just like the other waiting areas, was divided into two parts based on the acuteness (triage) of the patient's condition. It was important to make the graphical definitions in the model based on whether the patient was lying on the bed or sitting in a chair. Otherwise the animation would not have given a right picture of the process. Apart from the graphical definitions, no other definition was needed.

The routing definitions were very simple as well. In the model, there was only one destination available for patients leaving this phase, thus only one destination definition was required. This was, of course, the doctor’s office.

Doctor contact definitions

Both the first doctor contact and the final doctor contact (diagnosis) took place in the same area, in the doctor’s office. Because two different operations had to be defined for the same area and the amount of data was quite large, two different macros were used. There were separate macro definitions for the first doctor contact and for the final doctor contact. This was the only way to differentiate whether the patient was entering the first doctor contact phase or the final doctor contact phase and to define how the patient should be treated.

The decision whether the first doctor contact macro or the final diagnosis macro would be called in the logic was made with the help of two different attributes. These special attributes were the After_Nurse_contact attribute and the First_Doctor_contact attribute. The values of these attributes were defined in the earlier nurse contact phase. If the value of the After_Nurse_contact was one, or the value was two and the value of First_Doctor_contact was two, macro for the first doctor contact phase was called and the patient entered the first doctor contact phase. Otherwise the patient would enter the final diagnosis phase. Besides the macro definitions there were certain definitions for the graphical representations and time collection in the logic as well.

When the patient leaves the doctor's office there are several options where the patient could be routed. If the patient were in the first doctor contact phase, s/he could either go to the lab or to the X-ray unit. On the other hand, if the patient were in the final diagnosis phase, the options would be either to go home or advance to the case history writing phase. The operation logic and routing definitions are shown in Table 16.

TABLE 16 Processing definitions of the doctor contact phase

Operation logic

Entity	Location	Operation
Internal Disease	Doctor's office	graphic x if After_Nurse_contact = 1 OR (After_Nurse_contact = 2 AND First_doctor_contact = 1) then begin LOG "First doctor contact_Internal disease", Doctor_contact_time First_doctor_contact_Internal_disease_macro end else begin Final_doctor_contact_macro end
SurgeryTrauma	Doctor's office	
SurgeryGE	Doctor's office	
Neurology	Doctor's office	
Pediatric	Doctor's office	

Routing logic

Output	Destination	Rule	Move logic

Urgecy_Internal disease	Lab, X-ray, Case history writing, exit	First Available	graphic x
			if Triage = 1 or Triage = 2 then begin
			MOVE WITH nurse THEN FREE
			end
			else if Triage = 3 or Triage = 4 then
			{
			graphic x
			MOVE ON ED
			}

Urgency_SurgeryTrauma	Lab, X-ray, Case history writing, exit	First Available	
Urgency_SurgeryGE	Lab, X-ray, Case history writing, exit	First Available	
Urgency_Neurology	Lab, X-ray, Case history writing, exit	First Available	
Urgency_Pediatric	Lab, X-ray, Case history writing, exit	First Available	

The actual code for both phases was created using macros as described earlier. These macro definitions were made for each patient group individually, because there were certain differences in the distributions regarding how the patients were routed forward in the model and how they were guided to the tests (blood tests samples and X-ray). The duration of these phases (first doctor contact and final diagnosis contact) differed as well. Because there were five different patient groups, it is not necessary to demonstrate the definitions for all of those groups individually but just to give an example of one special field. This helps us to see how the macro definitions were made in this model. The macro definitions of the internal medicine are shown in Figure 12.

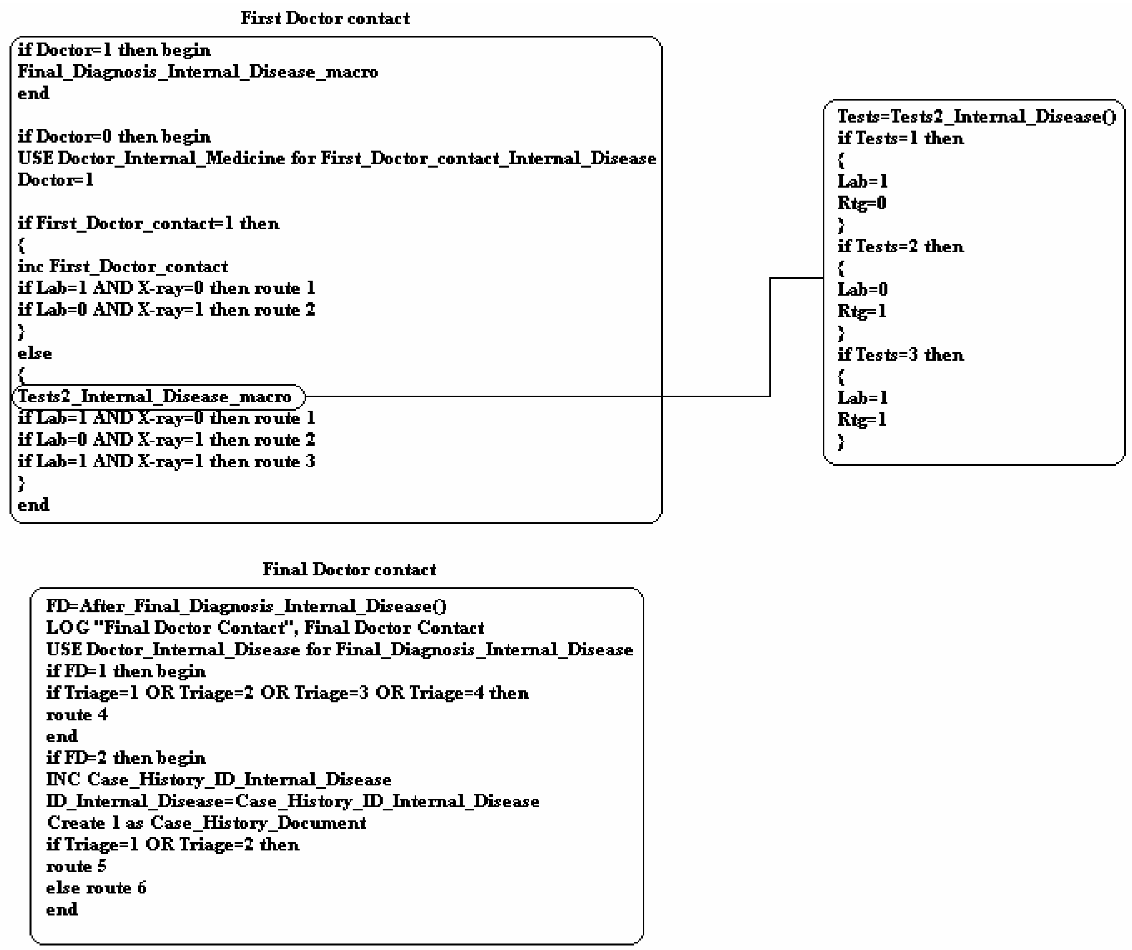


FIGURE 12 Macro definitions of the internal medicine

Definitions for the waiting area of laboratory operations

The waiting areas have not contained many functional definitions so far, because the routes from the waiting areas have been mostly straightforward or otherwise simple. However, in the case of the laboratory the situation is a little bit different. When examining the operation in a more detailed way than just as a duration between the test orders and lab results, the valid operation of the emergency department has to be taken into account more carefully.

In the real operation a nurse starts the round from the laboratory to the ED as soon as the orders are received. The number of the test requests depends on how many requests have arrived at the laboratory while the nurse has been on the round. The number of requests is directly related to the number of patients and the number of tests needed (which, in turn, depend on the symptoms of the patient).

The probable number of patients during one round was obtained by analyzing the gathered data from the Emergency Department at the Central Hospital of Jyväskylä. The probabilities for different amounts of patients during one round are shown in Figure 13.

Portions

- 1 patient per visit - 27,3 %
- 2 patients per visit – 33,5 %
- 3 patients per visit – 17,0 %
- 4 patients per visit – 7,2 %
- 5 patients per visit - 6,4 %
- 6 patients per visit – 3,1 %
- 7 patients per visit – 3,6 %

FIGURE 13 The probabilities of the number of patients visiting the waiting area of laboratory operations

The probabilities shown in Figure 30 were defined in the model by using empirical distributions. The values of these distributions were stored in the attribute called the "patient group". The value of this attribute was used to gather a certain number of patients in the waiting area and group them together. These patients were then moved to the waiting area for the sampling action. The operation logic in the waiting area of the sampling action is shown in Table 17.

TABLE 17 The operation logic in the waiting area of the sampling action

Entity	Location	Operation
Internal Disease	Waiting area of the sampling action	graphic x NoP=NoP_during_one_round() GROUP NoP AS OneRoundPatients
SurgeryTrauma	Waiting area of the sampling action	
SurgeryGE	Waiting area of the sampling action	
Neurology	Waiting area of the sampling action	
Pediatric	Waiting area of the sampling action	

The route from the waiting area leads to the area where the grouped patients are ungrouped. They are then forwarded to another area, where a nurse takes blood samples from them one by one. Because there is only one route option for the group, no special definitions had to be made. There was only one entity group to be routed from the actual waiting area. These definitions were very simple and they do not need to be demonstrated here.

The definitions of the sampling action phase

Laboratory process starts in the sampling action phase. In this phase a nurse comes and takes the blood test samples from the patients one by one and delivers them to the clinical laboratory for analysis. As mentioned earlier, the sampling action phase is the first phase of the laboratory process. In that phase the graphic definitions are made, ID:s which link the patient and certain samples together are created, and the use of resources as well as routing attribute definitions are configured. These definitions are coded in the model (operation logic) as shown in Table 18.

TABLE 18 The operation logic of the blood test samples analysis phase

Opearation logic

<table>
<tr><th>Entity</th><th>Location</th><th>Operation</th></tr>
<tr><td>Internal Disease</td><td>X-ray</td><td rowspan="5">graphic 4
Operation_time_X-ray=clock()
USE 1 X-ray_technician for U(15,2)
dec Rtg

if After_Nurse_contact=2 AND First Doctor contact=1 then begin
if Triage=1 OR Triage=2 then
route 1
else route 2
end

else begin
if Rtg=0 AND Lab=1 then
route 3

if Rtg=0 AND Lab=0 then
{
if (Tests =1 OR Tests =3) AND (Triage=3 OR Triage=4) then route 4
else if (Tests =1 OR Tests =3) AND (Triage=1 OR Triage=2) then route
6
else if Tests =2 AND First_Doctor_contact=2 AND (Triage=3 OR Triage=4)
then route 4
else if Tests =2 AND First_Doctor_contact=0 AND (Triage=3 OR Triage=4)
then route 5
else if Tests =2 AND First_Doctor_contact=0 AND (Triage=1 OR Triage=2)
then route 7
}
end</td></tr>
<tr><td>SurgeryTrauma</td><td>X-ray</td></tr>
<tr><td>SurgeryGE</td><td>X-ray</td></tr>
<tr><td>Neurology</td><td>X-ray</td></tr>
<tr><td>Pediatric</td><td>X-ray</td></tr>
</table>

Because there were two types of entities in this phase at the same time and they were routed to different locations, the routing definitions had to be made for both entities separately (as was the case with the operation logic also). Documents were routed to the waiting area and patients were routed forward in the process. The routing definition for both entities is shown in Table 19.

TABLE 19 Routing logic of the sampling action phase

Output	Destination	Rule	Move logic
Blood test sample	Laboratory	First Available	Move with nurse then free
Urgecy_Internal disease	Waiting area for the first doctor contact (stretcher)	First Available	Move on the ED model
Urgency_SurgeryTrauma	Waiting area for the first doctor contact (walking)	First Available	Move on the ED model
Urgency_SurgeryGE	Waiting area for X-ray	First Available	Move on the ED model
Urgency_Neurology	Waiting area for the final doctor contact (walking)	First Available	Move on the ED model
Urgency_Pediatric	Waiting area for the final doctor contact (stretcher)	First Available	Move on the ED model

The definitions of the analysis phase of the blood test samples

The blood test samples from the sampling action area were delivered directly to the laboratory by a nurse. The operation of the analysis phase was not analyzed very closely at this phase, only the duration for the whole operation of a laboratory was defined. It included both the actual analysis time and the walking time from the emergency department to the laboratory. The results are shown in Table 20.

TABLE 20 The processing logic of the blood test sample analysis phase

Operation logic

Entity	Location	Operation
Internal Disease	Laboratory	USE 1 Analyzer for W(1.89,58.5)
SurgeryTrauma	Laboratory	
SurgeryGE	Laboratory	
Neurology	Laboratory	
Pediatric	Laboratory	

Route logic

Output	Destination	Rule	Move logic
Blood test sample	The results desk	First Available	Move on the ED

The definitions of the X-ray process

There were specific areas for waiting to be X-rayed and for the actual X-ray process in the model. In the waiting area patients waited for their admittance to the X-ray, and they entered the room, where the actual imaging took place, one by one. The amount of resources performing the imaging was defined to be one. The durations of operations, which have been defined earlier in this work, were coded into the operation logic at this point as well. By using these two definitions, patient's treatment and the duration of the treatment could be handled in the model.

Besides operational logic, the routes after the X-ray needed to be defined as well. The route definitions were based on five different attributes and their values:

- Lab attribute: includes information about whether the lab tests have been taken (if ordered). If the value of the attribute is 1, then the blood test samples have not been taken from the patient yet. If the value is 0, then the patient has been in the sampling area and does not need to be routed there any more.
- X-ray attribute: is used in the same way as the lab attribute. The possible values are either 1 or 0.
- Triage attribute: is used to define whether the patient is a bed patient or a walking patient. There are different waiting areas for both of these urgency types in the model, so the value of this attribute was quite important for routing. There were four possible values for this attribute. Values 1 and 2 meant that the patient is a bed patient and values 3 and 4 meant that they are independent (able to walk, do not need any assistance).
- Tests attribute: holds the value which tells whether only a lab test or only an X-ray test or both have been ordered for the patient
- First_doctor_contact attribute: defines whether the first doctor contact is before the lab test/X-ray test/both tests or between them.

All the possible situations and the phase where the patient was when the X-ray was taken were defined in the operation logic. Based on those definitions the routes forward in the process were specified. The processing logic as a whole is shown in Table 21.

TABLE 21 The processing logic of the X-ray phase in the model

Opearation logic

<table>
<tr><th>Entity</th><th>Location</th><th>Operation</th></tr>
<tr><td>Internal Disease</td><td>X-ray</td><td rowspan="5">graphic 4
Operointiaika_Rtg=clock()
USE 1 Röntgenhenkilökunta for U(15,2)
dec Rtg

if Hoitajakontaktin_jälkeen=2 AND EkaLääkärikontakti=1 then begin
if Triage=1 OR Triage=2 then
route 1
else route 2
end

else begin
if Rtg=0 AND Lab=1 then
route 3

if Rtg=0 AND Lab=0 then
{
if (Tutkimukset=1 OR Tutkimukset=3) AND (Triage=3 OR Triage=4) then route 4
else if (Tutkimukset=1 OR Tutkimukset=3) AND (Triage=1 OR Triage=2) then route 6
else if Tutkimukset=2 AND EkaLääkärikontakti=2 AND (Triage=3 OR Triage=4) then route 4
else if Tutkimukset=2 AND EkaLääkärikontakti=0 AND (Triage=3 OR Triage=4) then route 5
else if Tutkimukset=2 AND EkaLääkärikontakti=0 AND (Triage=1 OR Triage=2) then route 7
}
end</td></tr>
<tr><td>SurgeryTrauma</td><td>X-ray</td></tr>
<tr><td>SurgeryGE</td><td>X-ray</td></tr>
<tr><td>Neurology</td><td>X-ray</td></tr>
<tr><td>Pediatric</td><td>X-ray</td></tr>
</table>

Route logic

<table>
<tr><th>Output</th><th>Destination</th><th>Rule</th><th>Move logic</th></tr>
<tr><td>Internal disease</td><td rowspan="5">Waiting area for first doctor contact (stretcher)
Waiting area for first doctor contact (walking)
Waiting area for final doctor contact (stretcher)
Waiting area for final doctor contact (walking)
Waiting area for samplin action</td><td rowspan="5">First Available</td><td rowspan="5">if Triage=1 OR Triage=2 then begin
graphic x
MOVE WITH Nurse_Internal_disease THEN FREE
end
else if Triage=3 OR Triage=4 then
{
graphic y
MOVE ON Emergency Department
}</td></tr>
<tr><td>SurgeryTrauma</td></tr>
<tr><td>SurgeryGE</td></tr>
<tr><td>Neurology</td></tr>
<tr><td>Pediatric</td></tr>
</table>

The definitions of the case history writing phase

This phase of the process is only for patients who are transferred to some other institution for treatment after the emergency department. The case history documents for patients who are discharged are written after they have left the hospital. For them this phase does not need to be examined because they do not load the system like the patients who are transferred further for treatment.

The process of case history writing in our model was quite similar to the blood test sample action phase. The patient and the actual document (tape) were both guided to the different locations. The patient was guided to the waiting area where s/he waited until the documents were ready and the dictation tape was delivered to the secretaries' office where the secretary transcribed it. After the tape was transcribed the documents were delivered to the waiting area where the patient was, and the patient could be transferred forward. The patients and documents were interlinked in the model by using special ID definitions. In this way it was possible to make sure that the right documents were delivered to the right patient, which, for its part, took care of the validity of the model.

Because the operations for the patient and for patients' documents were done in different places, the operation logic had to be built for them separately as well. For the patient the logic was quite simple, because the operation in the waiting area consisted basically of waiting. The only definition which had to be made was the request for the case history document. This request was made by using an ID which was defined both for the patient and the tape in the final doctor contact phase. The definitions for the tape required a bit more code and logic. There had to be a definition for the duration of the writing operation and, of course, definitions for requesting a certain resource to perform the operation. The operation logic is shown in Table 22.

TABLE 22 The operation logic of the case history writing phase

Operation logic

Entity	Location	Operation
Case history document	Secretaries' office	USE 1 Secretary for Case_historydocuments_Internal_Disease MATCH ID_Internal Disease
Internal Disease	Waiting area for case history writing	graphic x MATCH ID_Internal_Disease JOIN 1 Case_historydocuments
SurgeryTrauma	Waiting area for case history writing	
SurgeryGE	Waiting area for case history writing	
Neurology	Waiting area for case history writing	
Pediatric	Waiting area for case history writing	

Routing definitions had to be made for both entities separately just as in the case of the operation logic. The routing took place in two phases. First the documents were routed to the waiting area, and after that the patient was routed forward in the process. Although this phase was the last phase in the actual patient process of the ED, in the model there was still one phase for the patients to go through. This phase made it possible for the patients to leave the system, so that the data needed could be collected. The routing definition for both entities is shown in Table 23.

TABLE 23 The routing definitions of the case history writing phase

Route logic

Output	Destination	Rule	Move logic
Case history documents	Waiting area	Join	MOVE WITH Nurse_Internal_disease THEN FREE

Internal disease	Exit	First Available	if Triage=1 OR Triage=2 then begin
			graphic x
			MOVE WITH Nurse_Internal_disease THEN FREE
			end
			else if Triage=3 OR Triage=4 then
			{
			graphic y
			MOVE ON Emergency Department
			}

SurgeryTrauma	Exit	First Available	
SurgeryGE	Exit	First Available	
Neurology	Exit	First Available	
Pediatric	Exit	First Available	

Exit definitions

The last phase of the process in the model was the exit phase. In this phase there was no need for any other operational definitions except for data collection definitions. There was a special attribute in the beginning of the process in the entrance phase which was defined to be the storage for the time information. Value of the elapsed simulation time in minutes was stored in that attribute. In the beginning it was initialized to zero, and the end value stored in the exit phase showed thus the total length of stay of patients in the ED.

4.4.10 Arrival definitions

Any time new entities are created into the model, it is called an arrival. Arrival definitions are in a very important role in the simulation process, because they have a big effect on the patient numbers at different phases of the process and on the formation of queues. To create arrivals into the model, a few definitions have to be made. These definitions are:

- Location of the arrival
- Frequency of the arrivals
- Total occurrence of the arrival
- Number of new entities per arrival

In this study there were five different patient groups, and the definitions above were specified for each group individually. This was done because each patient group in the model was operated separately and routed differently. The arrival definitions for our model are shown in Table 24.

TABLE 24 The required definitions for the arrivals in the model of an emergency department

Entity	Location	Quantity each	First time	Occurences	Frequency
Internal Disease	Entrance	26; cycle	0	5	24 h
SurgeryTrauma	Entrance	22; cycle	0	5	24 h
SurgeryGE	Entrance	7; cycle	0	5	24 h
Neurology	Entrance	15; cucle	0	5	24 h
Pediatric	Entrance	10; cycle	0	5	24 h

The "Quantity each" field is the definition which differentiates the groups from each other and makes the arrival process functional. In that field the number of entities in the group as well as the arrival cycle for the group are defined. There are different possibilities for defining the arrival cycle. The definition can be made with statistical distributions or by defining the cycle as a pattern of individual arrivals which occur over a certain time period. If none of the statistical distributions is directly appropriate, it is best to define it manually. In such a case the following definitions have to be made:

- Quantity/Per cent
- Cumulative
- Table

The Quantity/Per cent definition specifies the total number of patient arrivals per cycle occurrence. There are two options, quantity and per cent, just as the name of the definition implies. In this study the per cent option was selected as the basis for arrivals.

The Cumulative definition is used to specify the format of the Quantity/Per cent values. It can be either cumulative or non-cumulative. Which should be used depends on the case and the system being modeled. In our case we used non-cumulative format for per cent values.

The Table definition is used to specify the cycle parameters. The cycle data is entered into the table using two definitions. These definitions are *time* and format for the cycle (*quantity or per cent*). Because the data was expressed in terms of percentages, percent values were selected as the basis for the cycle in this study.

The starting time for simulation in the model is defined to be 07.00 am and the end 07.00 in the next morning. It means that the time interval is 24 hours. The day in the arrival cycle is divided as follows:

- 07.00-12.00 (these are the first five hours defined in the table)
- 12.00-16.00 (these are the next four hours in the cycle table)
- 16.00-20.00 (these are the next four hours in the table)
- 20.00-24.00 (these are the next four hours in the table)
- 00.00-07.00 (these are the last seven hours in the cycle table)

All the arrival definitions of the model of an emergency department are shown in Table 25.

TABLE 25 The functional arrival definitions of the model of an emergency department

Entity	Location	Quantity each	First time	Occurences	Frequency
Internal Disease	Entrance	26; cycle	0	5	24 h
SurgeryTrauma	Entrance	22; cycle	0	5	24 h
SurgeryGE	Entrance	7; cycle	0	5	24 h
Neurology	Entrance	15; cucle	0	5	24 h
Pediatric	Entrance	10; cycle	0	5	24 h

Entity	Quantity/Per cent	Cumulative	Table
Internal Disease	Per cent	No	Defined
SurgeryTrauma	Per cent	No	Defined
SurgeryGE	Per cent	No	Defined
Neurology	Per cent	No	Defined
Pediatric	Per cent	No	Defined

Internal Disease

Time (Hours)	Quantity/Per cent
5	23,6
9	37,9
13	18,6
17	11,3
24	8,6

SurgeryTrauma

Time (Hours)	Quantity/Per cent
5	25,4
9	33,6
13	23,4
17	13,1
24	4,5

Neurology

Time (Hours)	Quantity/Per cent
5	27,9
9	28,6
13	22,4
17	12,2
24	8,9

Pediatric

Time (Hours)	Quantity/Per cent
5	7,1
9	21,4
13	41,1
17	26,8
24	3,6

Time (Hours)	Quantity/Per cent
5	30,9
9	18,5
13	22,8
17	13,6
24	14,2

SurgeryGE

4.5 Validation of the programmed model

It is crucial to check the operation of the programmed model before advancing in the process. The main objective is to examine whether the programmed model, based on the conceptual model, works as it should. In other words, is the operation of the model valid and can it be trusted? The validation phase consists of two parts. These parts are the static revision phase and the dynamic revision phase.

In the static revision phase the model is analyzed by going through it phase by phase. This way it is possible to find out any mistakes in the models' structure. In the dynamic revision phase the model is run under differing conditions: different input parameters are used in order to see whether the model produces desired and realistic results or not.

The model was verified and validated using its visual and numerical information. The structure of the model was examined via animation and then discussed with the staff (nurses and doctors). The logic of the model was presented phase by phase and compared to the conceptual model.

The model was validated by carrying out a confidence interval examination concentrating on the patients' average throughput time. Each patient group had some of their own resources and process routes, and also shared resources and process routes. Thus, the average throughput time of all patients was the best target variable. The average throughput time included all the individual and shared processes and described how the ED of Special Health Care operates:

$$\text{The average length of stay} = \frac{1}{n} \sum_{i=1}^{n} p(t)i,$$

where p(t)i = time of the patient i in the system

All the other specifications were made when the target variable for validation was selected. The most important definition is the margin of error of the simulation model. To make the model work as accurately as possible, the acceptable margin of error was defined to be 5 %. With this kind of error margin, the results of the real system and the results of the simulation model will not differ significantly from each other.

Besides common definitions, some run-time definitions had to be made before the actual simulation run (validation run) as well. Run-time definitions are very important for the model reliability. They will be examined next.

Runtime definitions of different scenarios

In order to get reliable results, some important run-time definitions were required for the model. The following definitions needed to be made:

- The length of the warm-up period
- The length of the actual simulation run
- Number of replications

Warm-up period is a one of the most important definitions to make in order to get reliable results. In a steady-state simulation the simulation run starts out empty, which means that it usually takes some time before it reaches steady state. The time it takes to reach steady state may vary considerably. For some models, steady state might be reached only after several hundred hours while some models need only a few hours to reach steady-state. In simulating steady-state behavior the problem is in determining when a model reaches steady-state, and this is why it is important to use the warm-up period. The warm-up time defines the period of time which is allowed to elapse before the gathering of statistics is started. This way it is possible to eliminate any bias due to observations taken during the transient state of the model.

The danger in simulation is in underestimating the warm-up period instead of overestimating it. To make sure that the warm-up period would be long enough for our study, it was defined to be a whole week. This way the system would have enough time to reach steady-state.

After the warm-up period had been determined, the length of the actual simulation run was defined. With independent replications, the usual recommendation is to run the simulation for a sufficient number of times to allow every type of event (also the rare ones) happen at least a few times if not several hundred. The longer the run is, the more reliably the results will represent a steady-state behavior. In our model, the length of the simulation run was defined to be one week. This was an appropriate period of time for each type of event to take place at least a few times.

Number of replications was the last required run-time definition which had to be made in our model. It is an important definition, because if there are random features in the real system, the results of the simulation will be random in nature as well. Multiple replications are needed, because the results of a single run give only one possible outcome, even though there might be several possible outcomes. Multiple replications make it possible to test the reproducibility of the results and to avoid the possibility that a decision might be made based on a fluke outcome, or on an outcome which is not representative.

The simulation run was replicated 30 times. Every replication was independent, which meant that the starting value (seed value) for each random stream was different for each replication. This ensured that the random numbers generated from replication to replication were really independent.

Once all the run-time definitions were made, the next phase was the actual simulation run. The simulation run and the results are considered next.

Simulation (validation) run and the results

Since the length of the warm-up period and the actual simulation run were both defined to be one week, the actual run was performed as follows: before the statistics collection, the model was run for one week in order to allow it to reach steady-state. After that the statistics collection was started and the model was run for another week. The simulation run was replicated 30 times. The average values of those runs were then calculated and presented as results. The results are shown in Figure 14.

REPLICATION ANALYSIS (Sample size 30)

Statistic	Avg	Median	Min	Max	Std Dev
Length Of Stay - Average Value	255.07	256.25	199.34	307.21	28.22
Length Of Stay - Maximum Value	843.20	859.50	559.00	1275.00	139.89
Length Of Stay - Minimum Value	11.83	11.50	6.00	20.00	3.53
Length Of Stay - Number Of Observations	543.56	543	538	550	3.53

FIGURE 14 The results of the validation run of the developed model

After the simulation run, the analysis phase of the results followed. The results themselves do not tell anything unless they are analyzed. How the results were analyzed in this study and how they should be analyzed in order to get meaningful information is explained next.

Analysis of the simulation results

Analyzing the differences between the results of real data and the results of the simulation model can be performed by comparing the average results of a selected target variable through several replications. If the results are close to each other or if the decision requires greater precision, hypothesis testing should be used. In such testing, first a hypothesis is formulated. The usual assumption is that the real system and the model both result in the same throughput time. After the hypothesis formulation a test is made to see whether the results of the simulation lead to the rejection of the hypothesis or not.

Comparing different outcomes requires a careful and accurate analysis to ensure that differences being observed are caused by the actual differences instead of statistical variation. This is where running multiple replications may prove very helpful. More replications usually give more accurate results, because after several runs there are more results from which to calculate the average mean. The more observations there are in the analysis phase, the more accurately the average mean can be defined.

The basic analysis was made by comparing the results of the simulation run with the results analyzed statistically from the real data. The hypothesis was that there is no difference between the results. The collected observation information was analyzed by using the SPSS statistical software. The following value was obtained:

Patient's average length of stay in the emergency department = 255,19 minutes

As can be seen in Figure 40, the result of the simulation was almost the same as the result analyzed from the real system. As the acceptable error of margin had been defined to be at most 5 %, and the errors between simulation results and the real system results were less than one per cent, it was clear that there was no significant error between the real system and the simulation model. The hypothesis was thus accepted. The model was found valid and working in the same way as the real system.

However, because there is always randomness in the model which is a consequence of the randomness of the real system, it was desirable to determine a confidence interval for the output as well. This had to be done because, due to randomness, the mean is not the same for each simulation run. A confidence interval is a range where the true mean can be expected to fall with a certain level of confidence. In order to find out the upper and lower limits, the confidence level has to be defined. It can be, for example, 90 %, 95 % or 99 %. If the confidence level is selected to be 95 % then we would be able to say that there is a 95 % probability that the true mean of the modeled system lies between the calculated limits.

The confidence interval is defined by using a certain equation. If the confidence level is 95 %, then

$x = p \pm 1{,}96 * S,$

where p is the average value of patient's length of stay and S refers to standard error of the mean. The value 1,96 comes from normal distribution.

However, in order to solve the equation, standard error of the mean need to be calculated as well. The standard error of the mean is obtained from the equation:

$S = s/\sqrt{n},$

where s is the standard deviation and n is the number of replications

The confidence level in our study was selected to be 95% and the confidence interval was defined by using the equation $p \pm 1{,}96 * S$. In order to solve the equation, the standard error of the mean needed to be calculated first. It was defined as follows:

In the simulation run s = 28,22 (shown in Figure 40) and n = 30 (number of replications). These values are substituted in the equation of standard error of the mean, S = 5,15. When the standard error of the mean is known, it is possible to calculate the 95 % confidence interval for the simulation results as follows:

Confidence interval = $255{,}07 \pm 1{,}96 * 5{,}15 = 255{,}07 \pm 10{,}1 = 244{,}97 - 265{,}08$.

Now because the value 255,19 calculated from the real data settles within the confidence interval, the conclusion is that the calculated value does not differ significantly, with 95 percent confidence, from the value of the simulation model.

To make sure that there really was no significant difference between the model and real system, the confidence interval for the real data was calculated as well. The results are shown in Table 26.

TABLE 26 Analysis of the real data

Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Length of stay	912	255,19	180,070	5,963	243,49	266,89	5	2055

As can be seen in Figure 40, the confidence interval for mean in the real data was 243,99 - 266,89 and in the simulation model 244,97 - 265,08, which means that they are very close to each other. Also from this point of view there is no significant difference between the results. The only difference is in the standard deviation. This is a consequence of the artificial operation time definitions in the model. Because there were no specific ending times available in the real data, they had to be created artificially. This artificial operation time formation led to too long operation times at certain phases of the process (for example in nurse contact), which caused errors in the model. That is why the data in the simulation model had to be manipulated before the distributions were defined. This means that excessively long operation times were deleted in order to get the model work properly.

Despite the variation in standard deviation the simulation model is accurate and therefore valid, because the average values are very close to each other. Thus the model can be used as a decision support tool, and its results can be trusted.

4.6 Simulation

Simulation phase is the actual functional phase of the process. Its main objective is to give information on the efficiency and behavior of the system with certain parameters. Before the simulation phase the system exists only on paper, and both the operation of the system and the progression of the events can be evaluated only conceptually, on a coarse level. When the model is transferred to the computer, it is possible to define a big set of variables and events the interaction of which, during a certain period of time, gives a more accurate view of the operation. This makes it easier to locate the problems and the bottlenecks within the model.

The simulation phase, just like many other phases of the process, includes several sub-phases. These sub-phases are:

- Definition of the input parameters
- Duration of simulation
- Duration of the warm-up period
- Replications

Based on the given definitions the simulation is started. During and after the simulation run, better understanding of the behavior of the system being modeled develops. All the possible problems and bottlenecks are revealed as well.

The last part of the simulation phase is the analysis phase. It is performed from the point of view of questions and problems set before the simulation run. Normally under analysis are the resource allocation, queuing and locating the bottlenecks. This is the case especially in health care.

Very often simulation can offer information which will reveal the problems of the system or at least locate the symptoms of the problems. However, it may not necessarily be able to find the cause of the problem or offer enough information on the nature of it. This is the difficulty of the analysis: in order to solve a problem, the cause of it should be located first. To get closer to a problem eluding solution, the model should be enlarged and its measuring accuracy increased.

4.7 Documentation

This is the last phase in the simulation process and belongs outside the actual technical simulation area. In this phase the results of all the phases are collected and they are documented carefully. Documentation is very important to allow the exploitation of the results later in the development of new models or in the refinement of the created model.

Each phase of the process produces different and important results. In the first phase of the process the so-called project description and problems identification is formulated. The resulting document gives information about where the model answers can be found. The conceptual model developed in the process analysis phase provides information on test points and describes the operation of the system being modeled. The actual modeling phase, for its part, defines the structure of the model and gives information on variables used in the model. The results indicate solutions for the problems. A good documentation speeds up the design and development of new simulation models and makes it easier.

5 CREATING A UNIVERSAL WAY OF ACTION FOR THE EMERGENCY DEPARTMENT BY USING A SIMULATION MODEL

In this work the simulation model developed was used as a decision support tool. It was used to test alternative scenarios which would improve the operation of an emergency department. However, before the simulation model was fit to be used as a testing tool, it was essential to define the most crucial problems contributing to the inefficient operation of the ED. The problems and bottlenecks of the process were located with the help of statistical analysis and the simulation model. Altogether four larger problems were defined:

- Patients had to wait too long before they were seen by a doctor for the first time.
- Late order of X-ray tests delayed the process (caused by a late first doctor contact).
- Laboratory tests were ordered at different phases of the process. First a nurse could order certain tests based on the symptoms and then a doctor could order more tests. This led to increased waiting times.
- Taking and delivering the blood test samples took too much time. During one shift it was found that a nurse had to walk almost 16 kilometers. This kind of manual delivery and numerous back and forth trips caused delays to the process.
- Doctors were the most critical resource in the ED because the patients had to be seen at least two times during the process. Because there was

only one doctor on each shift, waiting time for a doctor contact could easily arise. Solutions for automating doctor's operation were needed.

Once the biggest problems were located, it was time to start developing alternative solution proposals for the problems found. Because there were certain protocols in the emergency department and the quality of care was to be maintained at least on the existing level, the solutions had to be developed with good care.

In order to comply with the protocols, the development of alternative scenarios, with the help of the hospital personnel who best knew the way of actions in the ED, was required. Only in this way it was possible to ensure that all the developed solution scenarios would be appropriate for the operation of the ED.

However, this was not enough; good quality of care needed to be secured as well. This aspect was taken into account by ignoring the actual contact phases with the patient, i.e., operations when the patient was treated (when they were in the doctor's office, in the X-ray unit, seen by a nurse, etc.) were not considered in this context. Only the phases where nothing was done directly to the patient and where the resources were employed for something else were put under examination and made subject to efficiency improvements. Solutions were sought by reorganizing processes, reallocating resources and employing technology. Some solutions which would improve the operation of an ED were indeed found. These were:

- The triage-team method
- A pneumatic tube delivery system
- A speech recognition system

The triage-team method was developed to solve three of the problems defined earlier. It is a solution which changes the structure of the patient process and allocates the resources differently. A long waiting before the first doctor contact can be eliminated and X-ray tests as well as all the laboratory tests can be ordered right in the beginning of the process.

A pneumatic tube delivery system for its part solves the problem of blood test samples delivery. It provides an automated solution for the co-operation between a clinical laboratory and an emergency department. It eliminates the nurses' time-consuming back-and-forth trips and makes it possible to start the analysis phase for the samples much earlier than before.

A speech recognition system was tested in order to find solutions on how to improve the efficiency of patient discharge after the final doctor contact. It was noticed that there were work phases in the ED which partially overlapped. This applied specifically to the case history writing phase. First a doctor dictated the treatment instructions on the tape and then a secretary transcribed it. A speech recognition system was tested to find out whether the transcribing phase could be eliminated from the process.

The examination of different scenarios

All the solution proposals mentioned above were tested with the simulation model. They were coded into the model one by one, as new scenarios and the results were compared with the original model (a validated model for the present operation).

The run-time definitions were the same as they were for the validation phase. The warm-up period as well as the length of the actual simulation run was defined to be one week, and the simulation run was replicated 30 times.

The analysis of different scenarios differed a little from the analysis of the validation run. In the validation phase the results of the developed model were compared with the data from the real system, but in this phase the comparison was made between different scenarios. The evaluation of alternative configurations was performed by comparing the average result of several replications.

5.1 Description of the triage-team method

Triage has been studied in few contributions. Martinez-Garcia & Mendez-Olague (2005) discovered in their study that the person who classifies emergencies in a hospital is a medical assistant without much medical training. They felt a need for a more experienced person to do the evaluation. Subsequently, they created a new role in the reception area to make it an area with a physician and a nurse. In that way an emergency could be much more accurately defined. Mahaputra, et al. (2003) presented a new ESI 5 level triage system. Levels 1 and 2 dealt with the acuteness of the patient's condition, and levels 3, 4 and 5 dealt with predicted resource needs.

The triage-team method developed in this study differs from the above by altering the structure of the patient process and by allocating the resources differently. Earlier, the process started at the reception, where the receptionist documented all the patient's basic information and then guided the patient to the correct waiting area. The patient was next seen by a specialized nurse, who defined the triage, made the first examinations (measured blood pressure, etc.) and ordered the tests that nurses could order without consulting a doctor. The general protocol in the ED deems that a nurse cannot order X-ray tests, which is why they are ordered after the patient has seen the doctor. This has been the factor that has increased the throughput time of the patient, resulting in a high degree of utilization of the specialists. The triage-team method offers a solution to this problem. The purpose of the group is to reduce the utilization of the specialists and enable the ordering of all the tests the patient needs right after arrival, and in that way speed up the referral to treatment.

The triage-team consists of three staff members, who, regardless of their special field, are to receive all patients. There is a receptionist, a nurse and a doctor, whom the patient will see first after arriving at the ED of Special Health Care. First the team defines the urgency (triage). The urgency includes four different levels: A, B, C and D. A means that the treatment has to start immediately, B means that the treatment has to begin in less than 10 minutes, C means that the treatment has to begin in less than one hour and D means that the treatment has to begin in less than two hours.

After defining the urgency, the patient is interviewed (basic information), the symptoms are defined, all necessary tests are ordered, and the patient is sent to the next phase depending on the definitions made.

The most influential activity in the triage-phase is the laboratory tests ordering protocol. Earlier the tests were ordered one by one in different phases of the process and by different staff members. First a nurse might order certain tests and then a doctor might decide to order some more tests later in the process. This increased patients' waiting times, because they had to wait, in separate times, for their blood tests to be analyzed. In the triage-team method the tests are ordered as packages based on the symptoms. These packages were formed by analyzing the collected data and defining which tests were ordered for which symptoms during the whole process.

Extra tests mean extra costs and that is why their effect on the total amount of tests ordered had to be studied carefully. This was done by comparing the present operation with the package operation. The total amount of tests was not allowed to increase as a result of employing the packages.

The study was made using the collected data. First the number of patients and the number of blood tests samples during a certain period of time were defined. This information was based on the present operation. Once the amounts of the present operation were known, the definitions for the future operation could be made. In order to find out the number of blood tests samples in the case where certain packages were in use, quite a few definitions had to be made. The same period of time and the same number of patients were used to make these definitions.

In order to get started it was essential to define the percentage of patients with certain symptoms. This was done by analyzing statistically the collected data. However, this kind of a definition was not accurate enough; it was important to specify the number of patients who had laboratory tests as well. This had to be defined for each symptom group individually. When the information on the number of patients who had laboratory tests in each group was defined, the next thing was to find out how many tests were included in each symptom group. Once these parameters were known they were multiplied with each other and the results of different symptoms were summed up. The results between the present operation and the future operation (laboratory packages) were then compared with each other. The results indicated that there would not be any increase in laboratory tests. The results are shown in Table 27.

TABLE 27 The results of the laboratory packages test

Lab observation	
Patients	**558**
Samples	**8996**
Tubes	**2447**

Symptoms	Basic information of distributions			Test sample	Tubes					
	Frequency	Lab orders	Proportion	Number of patients	Number of tubes	Hitachi/ Roche	ACL	ADVia	Radiometer	Clinitek
Symptom 1	25	24	0,037	20	82	20,4	20,4	20,4	20,4	
Symptom 2	63	63	0,096	54	107	53,6		53,6		
Symptom 3	43	43	0,066	37	110	36,6	36,6	36,6		
•	23	20	0,030	17	85	17,0		17,0	17,0	
•	36	34	0,052	29	87	28,9	28,9	28,9		
•	39	38	0,058	32	162	32,3		32,3		32,3
•	72	67	0,102	57	191					
•	26	25	0,038	21	64	21,3		21,3		
•	30	30	0,046	26	77	25,5	25,5	25,5		
•	5	5	0,008	4	30	8,5	4,3	4,3	4,3	
•	28	24	0,037	20	41	20,4		20,4		
•	29	26	0,040	22	44	22,1		22,1		
•	29	20	0,030	17	46					
•	33	6	0,009	5	36	10,2		5,1	5,1	5,1
•	28	20	0,030	17	119	34,0		17,0	17,0	17,0
•	75	11	0,017	9	65	18,7		9,4	9,4	9,4
•	25	17	0,026	14	101	28,9		14,5	14,5	14,5
•	10	4	0,006	3	24	6,8		3,4	3,4	3,4
•	1		0,000	0	0	0,0		0,0	0,0	0,0
•	72	37	0,056	31	220	62,9		31,5	31,5	31,5
•	114	105	0,160	89	268	89,3		89,3		89,3
•	13	13	0,020	11	55	11,1		11,1		11,1
Symptom 23	35	24	0,037	20	66					
Total	854	656	1,000	558	**2079**	548,6	115,7	463,6	122,5	213,5
Fat				54	108					
Likvor				67	269					
Total					**2456**					

	Tubes/Equipments
Internal Medicine other	3,3468468
SurgeryGe other	3,220339
Neurology other	2,7272727

When all the activities in the triage-team method had been defined, it was time to test the method with the simulation model. The operation of this method and its effect on the overall operation were studied from two different perspectives. The efficiency was first examined. It was very important to define how fast the team should work in order to make the operation more effective. It was essential to find out the general time limits, because without that information it was very hard to define what tasks to include in the operation of the triage team and what operations should be handled with the help of the specialized nurses.

The second perspective dealt with defining how many exceptional patients the team could process without slowing down the whole operation of the ED. Exceptional patients are patients who need more attention from the triage-team (for example level A patient), therefore making the other patients wait longer.

In both cases the process times were defined using uniform distribution. Because the standard deviation and the other parameters were not known beforehand, it was assumed that any value within the defined range of variation was possible. That variation was regarded as quite small by the staff.

5.1.1 Experiments and results

The triage-team method was tested using several alternative process time scenarios. The staff estimated that the process time would be somewhere between 4-6 minutes, if everything went well. Because it was just an estimate, several different scenarios were taken under examination. It was also very important to find out how long the operation could take before it would have a negative effect on the operation of the ED. The different process scenarios developed using uniform distribution are shown in table 28.

TABLE 28 Different process time scenarios for the triage-team

Scenarios	Distribution
Process time 0.5-1.5 minutes	U(1,0.5)
Process time 1-2 minutes	U(1.5,0.5)
Process time 2-4 minutes	U(3,1)
Process time 4-6 minutes	U(5,1)
Process time 6-8 minutes	U(7,1)
Process time 8-10 minutes	U(9,1)
Process time 10-12 minutes	U(11,1)
Process time 12-14 minutes	U(13,1)

All these scenarios were tested and the results were compared with the present operation, the focus being on the average throughput time of all patients. The variation of the process time was estimated to be quite small, due to the standard procedures that the triage-team performs. For this reason the minimum and maximum values were defined as being very close to each other in these scenarios.

The results show that the operation is at its most efficient level when the operation time is between 4-6 minutes. This is also the most realistic estimation for the duration, because there are several tasks included in the Triage-team phase. These tasks require time if performed with good care. Performing the activities carefully assures a good quality of care, which is a very important factor in the development as well.

The results show that if the duration of the triage-team phase is between 4-6 minutes, it will reduce the patients' length of stay a little short of 30 %. The results also indicate that the operation becomes more effective when the process time is under 12-14 minutes. The results are shown graphically in Figure 15 and in a numerical form in Figure 16.

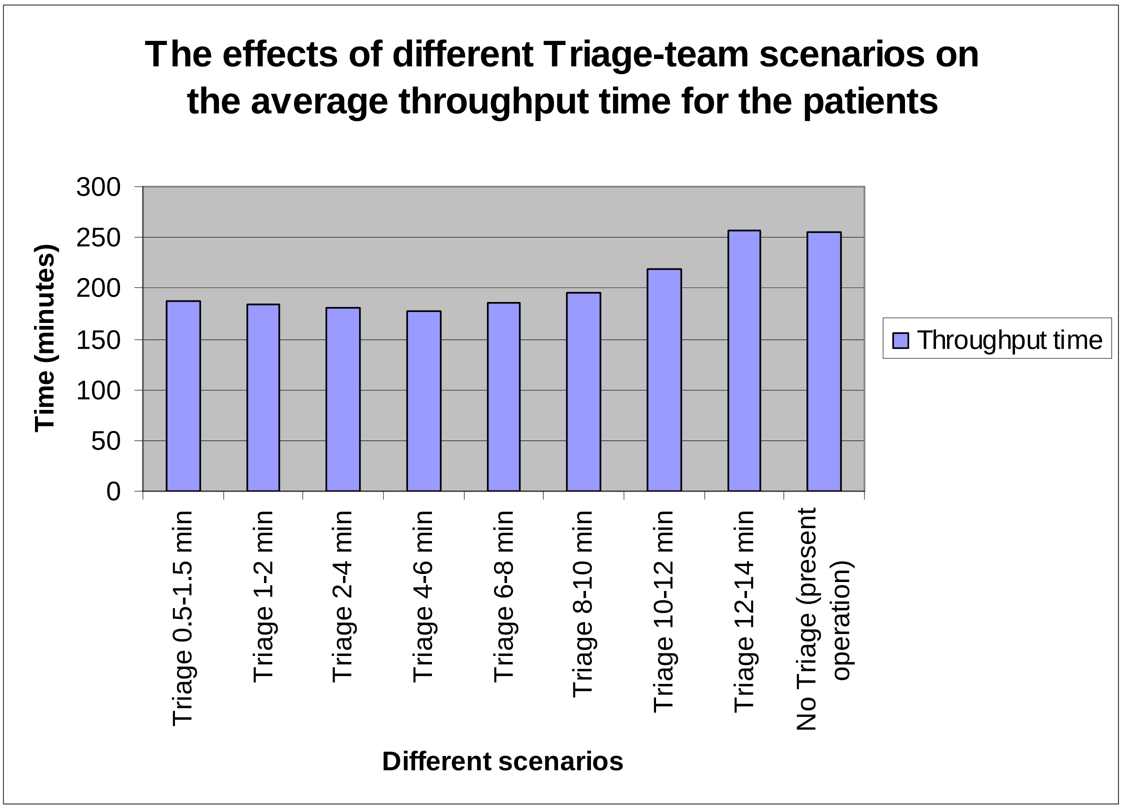


FIGURE 15 The throughput times of different scenarios in the triage-team testing phase

REPLICATION ANALYSIS (Sample size 30)

Statistic	Statistic	Avg	Median	Min	Max	Std Dev	Std Err
Length of stay - Average Value	Triage 1-2min	183.39	187.53	127.01	260.66	35.79	6.53
Length of stay - Average Value	Triage 0.5-1.5	187.31	174.76	120.37	285.60	43.83	8.00
Length of stay - Average Value	Triage 2-4	181.00	180.94	123.38	229.29	26.89	4.91
Length of stay - Average Value	Triage 4-6	178.15	169.85	117.09	322.70	43.91	8.01
Length of stay - Average Value	Triage 6-8	185.63	179.01	117.49	274.54	40.48	7.39
Length of stay - Average Value	Triage 8-10	195.93	194.99	109.73	292.23	40.94	7.47
Length of stay - Average Value	Triage 10-12	218.23	212.42	166.80	295.95	35.92	6.55
Length of stay - Average Value	Triage 12-14	256.93	255.52	184.07	339.98	41.80	7.63

FIGURE 16 The results of different scenarios in a numerical form

As mentioned before, the best results are achieved when the duration of the triage-team phase is between 4 and 6 minutes. This might seem just a little bit confusing at first, because normally it is thought that the faster the operation is the faster the patient can advance in the process before being discharged. Usually it is not thought that a fast operation in a certain phase of the process would cause long queues somewhere else in the process. In our study the fastest triage-team scenario caused longer queues for the lab and X-ray test phases as well as for the final doctor contact (specialist).

All the scenarios and their results are presented in Figure 16. The scenario where the duration was between 4 and 6 minutes gave the best results. It is also the most realistic estimation for the duration in the real world and thereby it was selected for further study.

We wanted to be 95 % confident about where the true mean falls so we defined the lower and upper limits by using the same equation we used in the model validation:

95 % CI = p ± 1,96 * S,

where p is the average value of patient's length of stay and S the standard error of the mean.

The values for the average value of a patient's length of stay and the standard error of the mean were obtained from the results of the simulation run. The results of the best scenario are shown in Figure 17.

REPLICATION ANALYSIS (Sample size 30)

Statistic	Avg	Median	Min	Max	Std Dev	Std Err
Length of stay - Average Value	178.15	169.85	117.09	322.70	43.91	8.01
Length of stay - Maximum Value	791.03	775.00	502.00	1186.00	150.22	27.42
Length of stay - Minimum Value	6.63	6.00	5.00	9.00	1.03	0.18
Length of stay - Number Of Observations	544.5	544.5	540	551	3.35	0.61

FIGURE 17 The results of the best triage-team scenario

Once all the parameters needed in the equation were known, the upper and lower limits could be calculated. The limits for the 95 % confidence interval were:

95 % CI = 178,15 ± 1,96 * 8,01 = 178,15 ± 15,7= 162,45 – 193,85.

As can be seen from the results, the difference between the triage-team method and the present operation is significant. The triage-team method improves the operation of an emergency department if it is implemented in a real environment.

5.2 Description of a speech recognition system

A speech recognition system is a system which converts speech to text in real time. In health care it is designed especially for doctors who commonly dictate their treatment instructions on tape. Currently, all doctors use tape recorders to document their instructions for treatment, and those instructions have to be typed up later. This is only one of the problems. Another problem is that tape recorder is very slow to use. Although doctors know how to use tape recorder, and may be very adept in its use, the device is still very slow to operate. If a doctor makes a mistake or forgets what s/he dictated earlier, the tape might have to be rewound and listened to and possibly re-recording of some parts would be required as well.

In a speech recognition system, the speech is converted to text in real time and the physician can see the dictation on the screen. Any mistakes can be fixed right away. The best part is that the dictation is automatically saved to be included in the electronic patient record.

5.2.1 The effects of a speech recognition system on the patient process at the ED

A speech recognition system has an automating effect on the patient process. It will eliminate one phase totally (the case history writing phase), which currently is done manually by the secretary. The manual transcription phase means extra waiting time for the patient, and this passive waiting time increases the total throughput time of the patient.

Although a speech recognition system will directly benefit patients who need to get their treatment instructions before they are discharged, it will also ease the treatment of the patients whose case histories are normally written at a later time. This is because all the information concerning the patient is immediately available in the electronic patient record. In this study we are only concentrating on the operation of the ED of Special Health Care, and only the effects at the Emergency Department are under examination. The patient process, when a speech recognition system is in use, is shown in Figure 18.

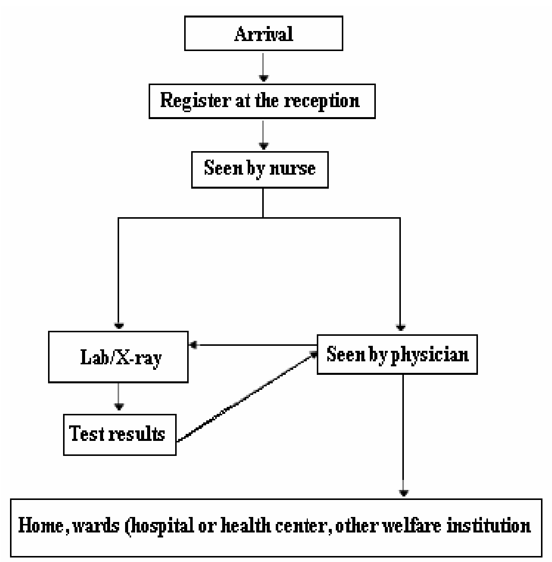


FIGURE 18 The patient process after the implementation of a speech recognition system.

5.2.2 Evaluating the effects of a speech recognition system with the help of simulation

Simulation has not been used very often to test the effects of human use of different technologies on the patient process, even though it can be used for that purpose very efficiently.

A speech recognition scenario was created in the model along the lines of the triage-team method earlier. The simulation time was one week. A warm-up time of one week was needed to reach steady state for the parameters in the system being modeled. Each scenario was replicated 30 times. The main target variable was the total average throughput time of all patients. The decision variable used was the speech recognition system.

New data for speech recognition system testing wasn't gathered, because all the data necessary for it had already been entered into the model when testing the new process scenario previously. We used the same distributions for the final specialist contact that were used earlier.

In an ideal situation no delay is going to take place in the final specialist contact. This is simply due to the automating effect of a speech recognition system. This new system is also much easier to use, although at first it may require some time before the users are totally acquainted with it.

The simulation was performed by creating several new scenarios. In these scenarios the case history writing phase was removed, and the patients were discharged right after the final specialist contact.

As mentioned earlier, in the ideal situation a speech recognition system will not affect the duration of the final specialist contact, but that possibility still remains. This is why in some scenarios the duration of the final specialist contact was extended. In that way it was possible to test how much the duration of the final specialist contact could possibly lengthen before it would make the total throughput time longer. By examining that aspect it was possible to determine the extent to which this new system could delay the specialist's operation and still make the operation more efficient. The additional amounts of time by which a speech recognition system could lengthen the final specialist contact were created by using uniform distribution.

The results of the new scenarios were then compared with the present operation, where the case history phase was still included. The average throughput time was the target variable which was compared. The present distributions of the final specialist contact and the additional times in the final contact of different scenarios are shown in Tables 29 and 30.

TABLE 29 Processing times for the final specialist contact (P5= Pearson 5, W= Weibull, ER= Erlang, T= Triangular).

Specialty	Time (min)
Internal decease	P5(4.15, 55.7)
Surgery trauma	W(1.44, 17.9)
Surgery GE	W(1.42, 13.8)
Neurology	ER(6,2.69)
Pediatrist	T(4,4,46.9)

TABLE 30 Time additions to the final specialist contact in new process scenarios.

Specialty	**Scenarios (min)**		
Internal decease	+ U(2,1)	+ U(4,1)	+ U(6,1)
Surgery trauma	+ U(2,1)	+ U(4,1)	+ U(6,1)
Surgery GE	+ U(2,1)	+ U(4,1)	+ U(6,1)
Neurology	+ U(2,1)	+ U(4,1)	+ U(6,1)
Pediatrist	+ U(2,1)	+ U(4,1)	+ U(6,1)

5.2.3 Results of the simulation

All the alternative scenarios of Table 2 were tested and the results were compared with the present process. The focus was on the total average throughput time of all patients. The results show that if the speech recognition system works in the ideal way, which means that there is no change in the duration of the final specialist contact, there will be a 8,2 % reduction in the average throughput time. The results also indicate that the operation is more effective than the present operation if there is no more than 6,5 minutes added to the final specialist contact. The results of the simulation run are shown graphically in Figure 19 and numerically in Figure 20.

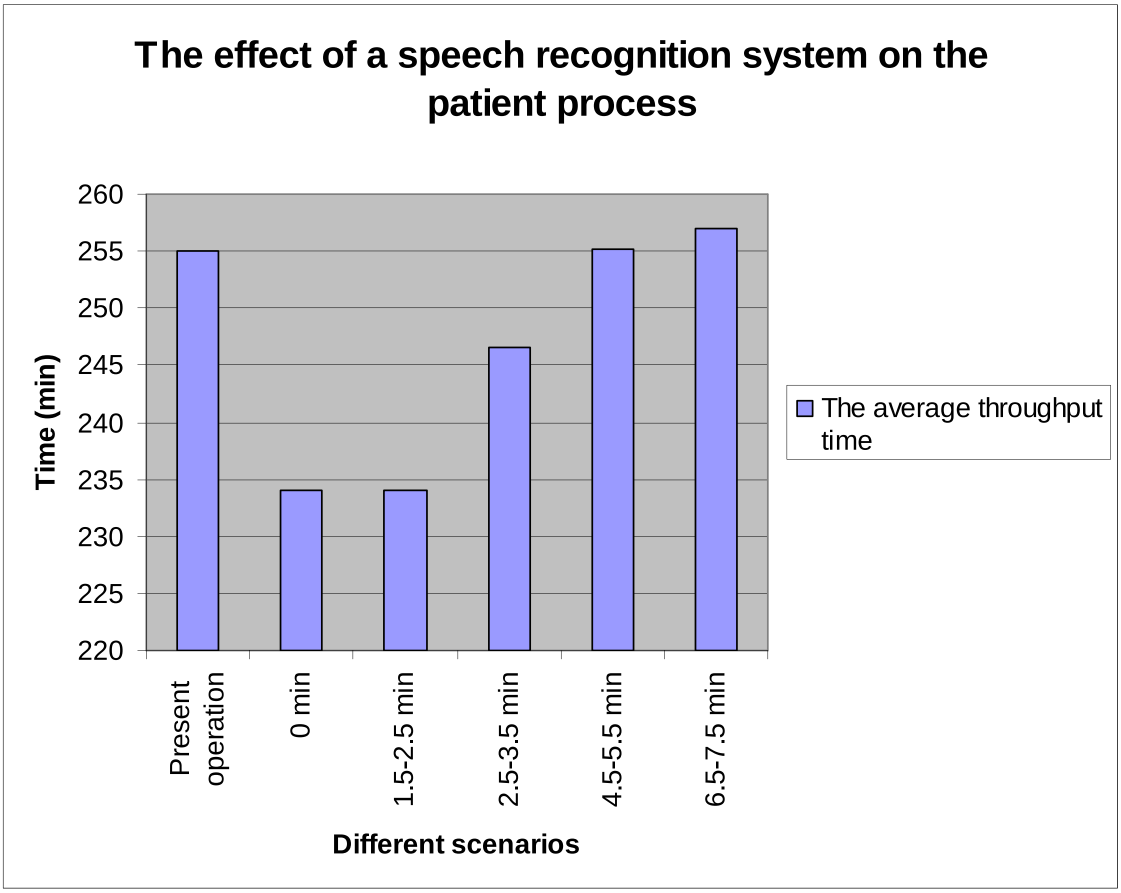


FIGURE 19 The results of different scenarios on the patient process in a graphical form

REPLICATION ANALYSIS (Sample size 30)

Statistic	Statistic	Avg	Median	Min	Max	Std Dev	Std Err
Length of stay - Average Value	Normaaliajo	234.07	229.34	169.02	364.00	38.56	7.04
Length of stay - Average Value	ExtraTime 2.5-3.35	246.64	250.05	179.43	317.22	35.06	6.40
Length of stay - Average Value	ExtraTime 4.5-5.5	255.15	253.65	192.20	325.15	34.17	6.23
Length of stay - Average Value	ExtraTime 6.5-7.5	256.77	260.78	173.90	318.53	35.98	6.56

FIGURE 20 The results of different scenarios on the patient process in a numerical form

As mentioned before and as can be seen in Figure 46 as well, the best scenario is the scenario where a speech recognition system does not add any time to the final doctor contact phase. Because we were interested in solutions closest to the ideal, this scenario was taken under more detailed examination. It was important to define the confidence interval just as we did in the case of the triage-team method. There is always randomness in simulation, and in order to define the limits where the true mean will fall with a certain probability, it is important to do the confidence interval examination. The confidence level was selected to be 95 % which was the same as in the triage-team method testing and was calculated as follows:

The average length of stay was 234,07 minutes and the standard error of the mean was 7.04. Based on these values the limits for 95 % confidence interval were:

95 % CI = 234 ± 1,96 * 7,04 = 234 ± 13,8= 220,2– 247,8.

The result shows that the true mean falls between 220,2– 247,8 with a probability of 95 %.

Although a speech recognition system will eliminate one phase totally (the case history writing phase) and in the ideal situation will reduce the average length of stay by 8,2 %, the confidence interval examination shows that there is no significant difference compared to the present operation. If this option is selected for implementation alone, it needs to be taken under closer examination.

5.3 Description of the pneumatic tube delivery system

One of the problems found in the emergency department was in its co-operation with the clinical laboratory. The patients' length of stay was increased particularly by the time-consuming back-and-forth trips of nurses when delivering blood test samples from the emergency department to the laboratory. In this chapter a solution to that problem is presented. First the current operation is described and then a new solution for the problem is presented.

5.3.1 The operation of the present specimen delivery process

A tube delivery process starts from the ED when the tests for patients are ordered. Test requests are sent via the hospital information system to the laboratory where a nurse acknowledges receipt of the request. After receiving the requests, a nurse takes the sampling equipment, walks to the ED and locates all the patients whose orders have been received. The patients are examined one by one and blood samples are taken from them. Once the patients have been examined, the nurse walks to the laboratory with a cart to deliver the blood samples. The initial process flow is shown in Figure 21.

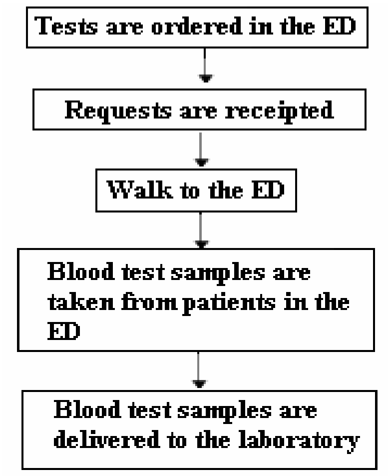


FIGURE 21 Present sampling action process in the ED

5.3.2 The operation after the implementation of the pneumatic tube delivery system

A pneumatic tube delivery system will change and automate the process as follows. A nurse, currently effecting the delivery of the specimens to the laboratory by walking, can be situated permanently in the ED. This means that the nurse does not have to walk between an emergency department and a clinical laboratory any more but he/she can send the samples to the laboratory instead. Once a nurse has collected the samples, he/she takes them to the preparation room, prepares them and places them into a duct. There is a direct connection between the laboratory and the preparation room. The transportation time in tubes is approximately 30 seconds. After the samples have arrived at the laboratory, the process continues in the same way as in the present operation. The process flow of a pneumatic tube delivery system is shown in Figure 22.

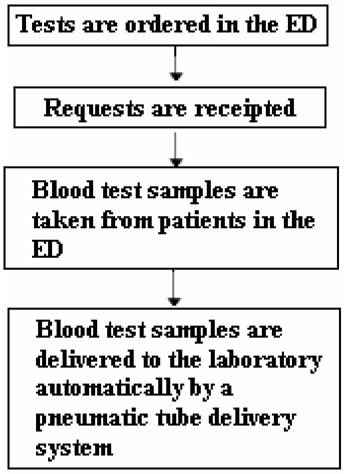


FIGURE 22 A blood test sample delivery process after installation of a pneumatic tube delivery system

5.3.3 Evaluating the effects of a pneumatic tube delivery system by using simulation

The simulation model of the Emergency Department of Special Health Care at the Central Hospital of Jyväskylä, Finland was used in evaluation. The operation of a pneumatic tube delivery system was configured into the model and the results of the scenario developed were then compared to the validated simulation model of the present operation.

The operation of the pneumatic tube delivery system was defined and examined as follows. First a certain area for the sampling action was configured into the model. Earlier, the blood samples were taken where the patient happened to be at the moment (waiting area, etc.); in this new scenario the sampling action was centralized. After the location definition, a certain resource for the sampling action was defined: the nurse, who earlier took the blood samples and delivered them to the laboratory, was placed permanently in the sampling room instead of the laboratory. These were the structural definitions of the pneumatic tube delivery system scenario.

Because the structure of the process was changed, process logic needed to be changed as well. In this new scenario, patients were routed directly to the waiting area of the sampling action room after the lab tests were ordered. There they waited for their turn and then entered the room where the blood samples were taken. After the blood test, the samples were delivered directly to the laboratory through the pneumatic tube delivery system, and the patients were routed normally to the next phase of the process.

The duration of operation for each phase of action was obtained partially from the information system and partially by observing the process. Data was analyzed with the Stat::Fit statistical software and the defined distributions were then entered into the model. Time definitions for the present operation and the pneumatic tube delivery system scenario are shown in Tables 31 and 32.

TABLE 31 Time definitions for the present operation (E= Exponential distribution, U= Uniform Distribution, W= Weibull distribution)

Activity	Duration (min)
Walking to the ED	E(3,7.74)
Sampling action	U(3,1)
Walking back and analysis	W(1.89,58.5)

TABLE 32 Time definitions for the pneumatic tube delivery system (E= Exponential distribution, U= Uniform distribution, W= Weibull distribution)

Activity	Duration (min)
Walking to the ED	E(3,7.74)
Sampling action	U(3,1)
Transportation of samples	0.5
Analysis of samples	W(1.78,47.1)

5.3.4 RESULTS

The scenario of a pneumatic tube delivery system was tested and the results were compared with the present operation. The focus was on the patient's average length of stay (throughput time), which was the main target variable in our research. The simulation time was one week and a one week's warm-up period was used. The warm-up time was needed to reach steady state for the parameters in the system being modeled. To get appropriate results, the pneumatic tube delivery system scenario was replicated 30 times. The results show that the pneumatic tube delivery system will reduce the patients' length of stay 13,2 %. The results are shown graphically in Figure 23 and numerically in Figure 24.

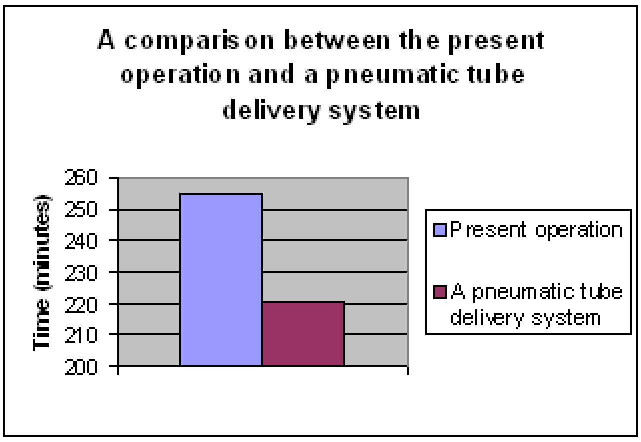


FIGURE 23 The effect of a pneumatic tube delivery system on patients' average length of stay in the ED compared with the present operation in a graphical form.

REPLICATION ANALYSIS (Sample size 30)

Statistic	Avg	Median	Min	Max	Std Dev	Std Err
Length of stay - Average Value	221.31	224.46	161.17	312.40	35.15	6.41
Length of stay - Maximum Value	739.93	708.50	579.00	983.00	106.14	19.37
Length of stay - Minimum Value	11.96	11.50	5.00	17.00	2.80	0.51
Length of stay - Number Of Observations	544.63	545	538	549	2.93	0.53

FIGURE 24 The results of a simulation run in a numerical form

Just like in the other scenarios, the confidence interval examination was performed in order to define where the true mean falls with a certain probability. The confidence level was selected to be 95 %, which was the same as in the other scenario testings and was calculated as follows:

The values for the average value of the patient's length of stay and the standard error of the mean were obtained from the results of the simulation run. As can be seen in Figure 51, the patient's average length of stay was 221,31 minutes and the standard error of the mean was 6,41

Once all the parameters needed in the equation were known, the upper and lower limits were calculated. The limits for 95 % confidence interval were:

95 % CI = 221,31 ± 1,96 * 6,41 = 221,31 ± 12,56 = 208,75 – 233,87.

The result shows that the true mean falls between 208,75 – 233,87 with a probability of 95 %.

As shown above, the collaboration between the ED and the clinical laboratory has a significant effect on the patient process and it should be taken into account when improving the operations in the ED. The use of a pneumatic tube delivery system can significantly reduce the total throughput time of patients. It also eliminates the tiring back and forth trips for nurses and makes it possible to take more blood tests and see more patients in the ED.

5.4 Creating a universal operation model for the Emergency Department by combining all the solution proposals together

In the earlier chapters all the alternative solution proposals were described and tested separately, but in order to see the effects if they are implemented together (partially or totally) they have to be tested together as well. Although all the alternative solutions improve the operation when they are implemented separately, it is difficult to validate the combined effects of two or more solutions without testing them together. In this chapter all the combinations of the developed solution proposals are tested.

A speech recognition system and a pneumatic tube delivery system together
First under examination is a combination of a speech recognition system and a pneumatic tube delivery system. This new scenario was coded in the model and then run 30 times. The results were compared with the original operation (present operation). The results indicate that if both speech recognition and the pneumatic tube delivery system are implemented together, it will reduce the throughput time by 23,1 %. The results are shown graphically in Figure 25 and numerically in Figure 26.

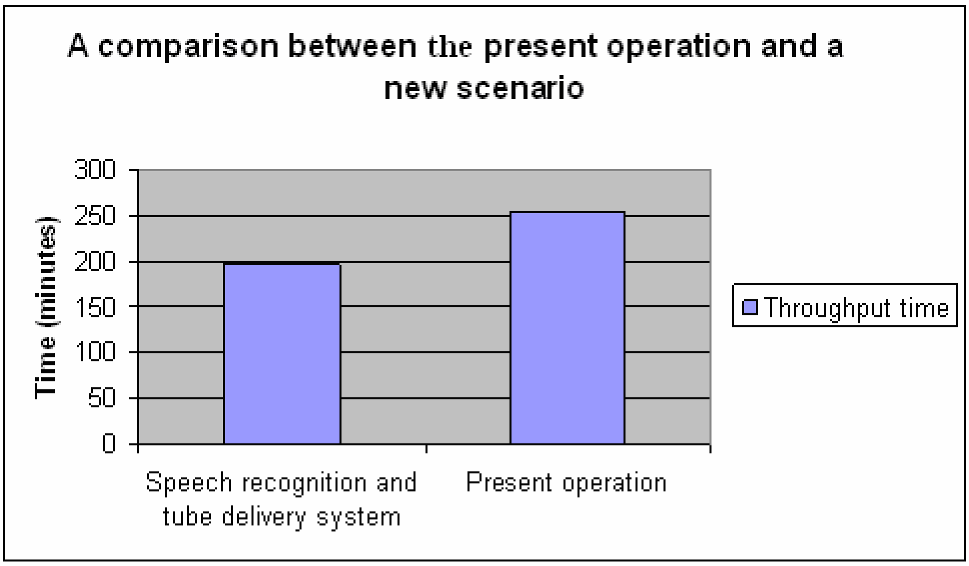


FIGURE 25 The results of a simulation run in which the present operation was compared with a scenario where a speech recognition system and a pneumatic tube delivery system were in use at the same time

REPLICATION ANALYSIS (Sample size 30)

Statistic	Avg	Median	Min	Max	Std Dev	Std Err
Length of stay - Average Value	196.13	188.44	143.40	322.30	39.24	7.16
Length of stay - Maximum Value	669.90	649.00	436.00	1005.00	129.70	23.68
Length of stay - Minimum Value	12.06	12.00	8.00	17.00	2.76	0.50
Length of stay - Number Of Observations	543.9	544	538	552	3.98	0.72

FIGURE 26 The results of the simulation run in a numerical form

The patient's average length of stay, after 30 replications, was 196,13 minutes as can be seen in Figure 50. Just like in all the other scenarios, the confidence interval examination was performed for this scenario as well. The confidence level was selected to be 95 %, which was the same as in the other scenarios. It was calculated as follows:

The average length of stay was 196,13 minutes and the standard error of the mean was 7,16 (obtained from the results of the simulation run).

Once all the parameters needed in the equation were known, the upper and lower limits were calculated. The limits for 95 % confidence interval were:

95 % CI = 196,13 ± 1,96 * 7,16 = 196,13 ± 14,03 = 182,1 – 210,16.

The result shows that the true mean falls between 182,1 – 210,16 with a probability of 95 %. As can be seen from the results, the difference between the present operation and this combined scenario is significant. However, when the results of this scenario are compared with the results of the scenario where a pneumatic tube delivery system was tested alone, the difference is not significant. The confidence intervals are partially overlapping, which causes that.

A speech recognition system and the triage-team method tested together

The second combination, which was taken under closer examination, was the triage-team method and a speech recognition system. Both of these solutions were coded in the model as a new scenario, and then the model was run 30 times. The results of this new scenario were compared with the original operation. The results show that a combination of the triage-team method and a speech recognition system would decrease the throughput time by 35,5 %. The results are shown graphically in Figure 27 and in a numerical form in Figure 28.

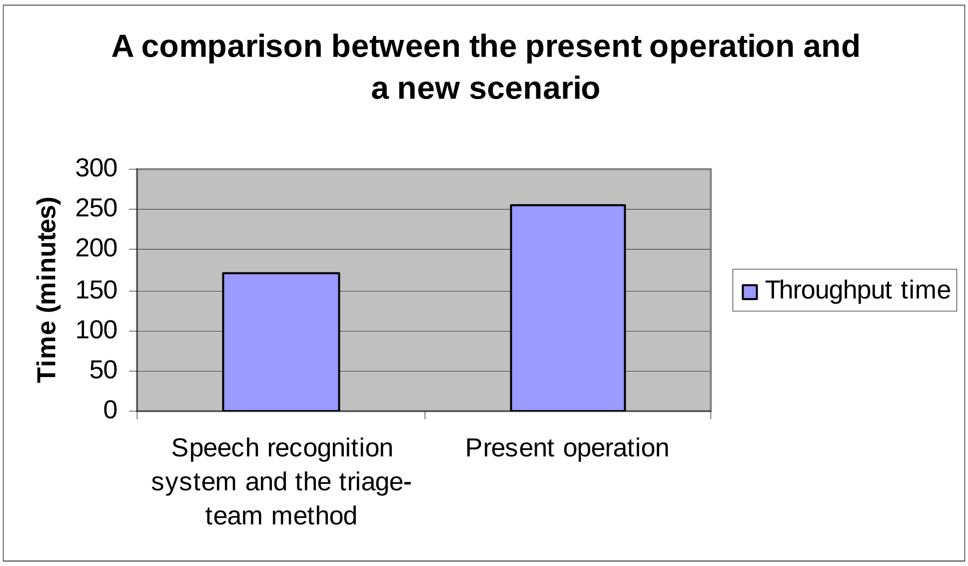


FIGURE 27 The results of the simulation run in which the present operation was compared with a scenario where a speech recognition system and the triage-team method were in use at the same time

REPLICATION ANALYSIS (Sample size 30)

Statistic	Avg	Median	Min	Max	Std Dev	Std Err
Length of stay - Average Value	164.57	165.59	88.20	230.56	34.88	6.36
Length of stay - Maximum Value	743.03	750.00	428.00	927.00	120.92	22.07
Length of stay - Minimum Value	6.03	6.00	4.00	9.00	1.09	0.20
Length of stay - Number Of Observations	543.53	543	535	555	4.71	0.86

FIGURE 28 The results of the simulation run in a numerical form

After 30 simulation run replications the results showed that the patient's average length of stay was 164.57 minutes. Once the simulation was performed, the confidence interval examination was done. The confidence level was once again selected to be 95 % and it was calculated as follows:

The values for the average value of the patient's length of stay and the standard error of the mean were obtained from the results of the simulation run. As can be seen in Figure 55, the patient's average length of stay was 164,57 minutes and the standard error of the mean was 6,36.

Once all the parameters needed in the equation were known, the upper and lower limits were calculated. The limits for 95 % confidence interval were:

95 % CI = 164,57 ± 1,96 * 6,36 = 164,57 ± 12,47 = 152,1-177,04.

The result shows that the true mean falls between 152,1 – 177,04 with a probability of 95 %. When the results are compared with the present operation, it can be seen that the difference is significant. It means that by implementing a speech recognition system and the triage-team method together, it is possible to reduce patients' length of stay and passive waiting time in an emergency department remarkably.

A comparison between this combined scenario and single scenarios (scenarios where both solutions were tested alone) is good to do as well. It reveals that the difference between a speech recognition system and combined scenario is significant but the difference between the triage-team method and this scenario is not significant.

The triage-team method and a pneumatic tube delivery system together

In the third scenario the triage-team method and a pneumatic tube delivery system were coded in the model. The developed scenario was run 30 times just like in the other scenarios. The simulation time was one week, and a one week's warm-up period was used to allow the model to become steady. The same definitions were used in the other scenarios as well. The results of the simulation run of the new scenario were compared with the original operation (present operation). The results show that by implementing the triage-team method and a pneumatic tube delivery system together, the patients' length of stay would be reduced by 34,5 %. The results are shown graphically in Figure 29 and numerically in Figure 30.

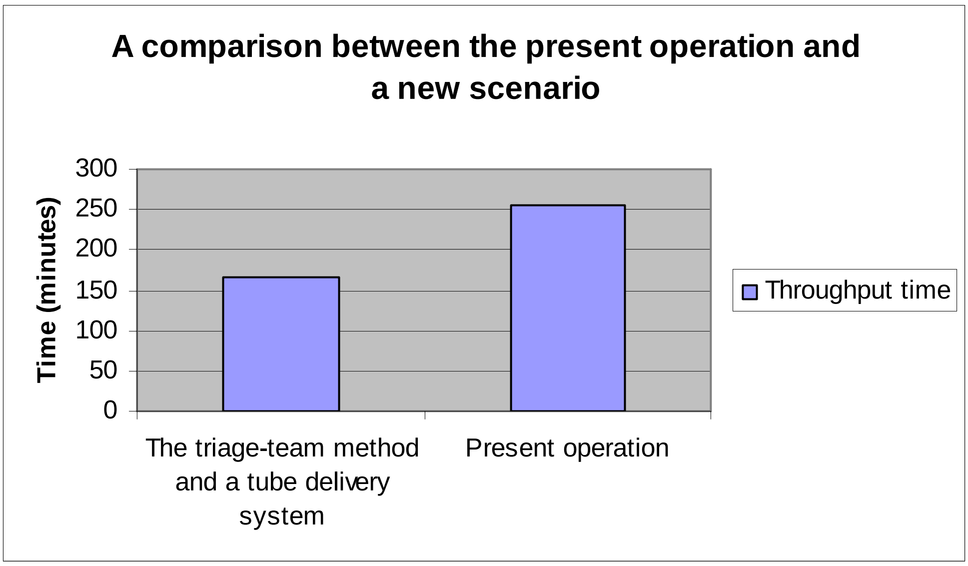


FIGURE 29 The results of a simulation run in which the present operation was compared with a scenario where the triage-team method and a pneumatic tube delivery system were in use at the same time

REPLICATION ANALYSIS (Sample size 30)

Statistic	Avg	Median	Min	Max	Std Dev	Std Err
Length of stay - Average Value	167.10	161.01	93.49	298.10	42.61	7.78
Length of stay - Maximum Value	737.00	716.50	461.00	1098.00	141.93	25.91
Length of stay - Minimum Value	6.03	6.00	4.00	8.00	0.96	0.17
Length of stay - Number Of Observations	544.5	544	541	552	3.15	0.57

FIGURE 30 The results of the simulation run in a numerical form

After 30 simulation run replications the results show that the patient's average length of stay was 167,10 minutes. When the simulation was performed, the confidence interval examination was performed as well. The confidence level was once again selected to be 95 %, and it was calculated as follows:

95 % CI = p ± 1,96 * S,

where p is the average value of the patient's length of stay and S is the standard error of the mean.

The values for the average value of the patient's length of stay and the standard error of the mean were obtained from the results of the simulation run. As can be seen in Figure 57, the patient's average length of stay was 167,10 minutes and the standard error of the mean was 7,78.

Once all the parameters needed in the equation were known, the upper and lower limits were calculated. The limits for 95 % confidence interval were:

95 % CI = 167,10 ± 1,96 * 7,78 = 167,10 ± 15,23= 151,87– 182,33.

The results show that the true mean falls between 151,87– 182,33 with a probability of 95 %. It means that the improvement compared to the present operation is significant. However, besides comparing the results only with the present operation, it is very important to compare the results with scenarios where both solutions are tested separately. This kind of examination reveals that the difference between this scenario and a pneumatic tube delivery system scenario is significant. It means that this scenario improves the operation more than a tube delivery system alone. In the case of the triage-team method scenario the situation is different. The confidence intervals of the triage-team scenario and this scenario are partially overlapping, which means that the difference is not significant.

All the solution proposals tested as one single scenario

In the last scenario all solution proposals were tested together. They were coded in the model as a single scenario and run with the same parameters as all the other scenarios. The simulation was replicated 30 times as well. The results showed that implementing all the solutions proposals at the same time would decrease the patients' length of stay by 43,4 %. The results are shown graphically in Figure 31 and in a numerical form in Figure 32.

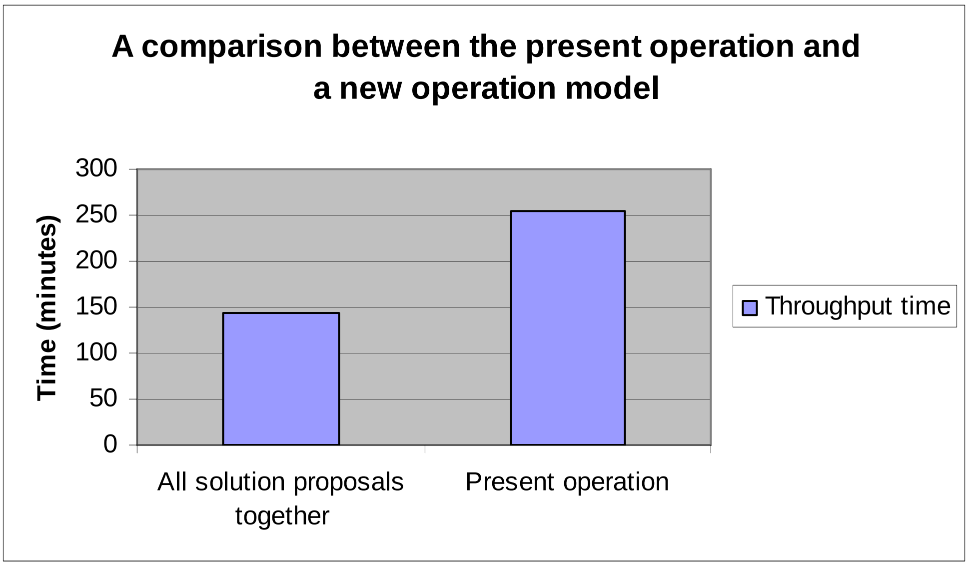


FIGURE 31 The results of a simulation run in which the present operation was compared with a scenario where all the new solution proposals were implemented together

REPLICATION ANALYSIS (Sample size 30)

Statistic	Avg	Median	Min	Max	Std Dev	Std Err
Length of stay - Average Value	144.32	139.95	95.64	198.20	25.72	4.69
Length of stay - Maximum Value	714.50	713.50	509.00	884.00	103.82	18.95
Length of stay - Minimum Value	6.06	6.00	4.00	7.00	0.73	0.13
Length of stay - Number Of Observations	543.2	543.5	536	549	4.05	0.74

FIGURE 32 The results of the simulation run in a numerical form

After 30 simulation run replications the results show that the patient's average length of stay was 144,32 minutes. When the simulation was performed, the confidence interval examination was performed as well. The confidence level was once again selected to be 95 %, and it was calculated as follows:

95 % CI = p ± 1,96 * S,

where p is the average value of the patient's length of stay and S the standard error of the mean.

The values for the average value of patient's length of stay and the standard error of the mean were obtained from the results of the simulation run. As can be seen in Figure 32, the patient's average length of stay was 144,32 minutes and the standard error of the mean was 4,69.

Once all the parameters needed in the equation were known, the upper and lower limits were calculated. The limits for 95 % confidence interval were:

95 % CI = 144,32 ± 1,96 * 4,69 = 144,32 ± 9,19= 135,13 – 153,51

The results show that the true mean falls between 135,13 – 153,51 with a probability of 95 %. As can be seen from the results, the improvement is remarkable compared to the present operation (the difference is significant). However, if the results of this scenario are compared with the two earlier scenarios (the triage-team method and a pneumatic tube delivery system; the triage-team method and a speech recognition system), the difference is not significant because the confidence intervals are partially overlapping.

All the solution proposals and their combinations have now been tested. The average values of each solution proposal as well as their confidence intervals are summarized in Figure 33.

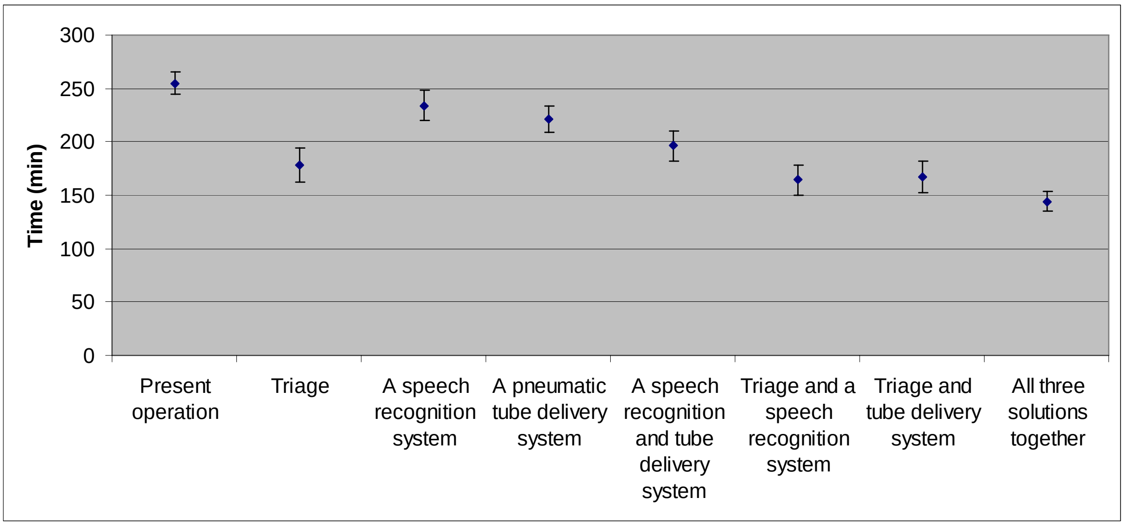


FIGURE 33 All scenarios and their confidence intervals

As can be seen from the results, the best single solution is the triage-team method which improves the operation substantially on its own. Although a pneumatic tube delivery system also improves significantly the present operation, it does not reach the same efficient level as the triage-team method. The triage-team method is significantly better than either of the other single solutions.

Although the triage-team method is the best single solution, it does not provide the best result when the combinations of different solutions proposals are taken under examination as well. The best improvement is achieved when all the solution proposals are implemented together, as can be seen from Figure

60. However, the triage-team has such a great effect on the operation that the only combination which significantly differs from it is the combination of all three solution proposals.

So far the results of different scenarios have been analyzed by comparing them with the present operation one by one. However, this kind of an approach is not the only way to analyze the results. For example, in statistics, regression analysis is widely used method for analyzing the results as well. It examines the relation of a dependent variable to specified independent variables. Next we analyze the results of simulation runs also from that point of view.

5.5 Regression analysis

Regression analysis is a statistical technique. It identifies the relationship between quantitative variables: a response variable and an explanatory variable (or variables), after a certain number of experiments (= n). The mathematical model of their relationship is the regression equation. In the case of several explanatory variables the linear regression equation is written as follows:

$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots. + \beta_k x_k + \varepsilon$,

where

- y is the value of the response variable that is being explained,
- x_k are variables which are varied in the experiment,
- β_k are constants, and
- ε is the error term

The same equation can be written in a matrix form as well. In this case the equation is written as follows:

$y = X\beta + \varepsilon$, where

$$X = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}$$

$\beta = (\beta_0, \beta_1, \beta_2, \ldots, \beta_k)$

$\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n)$

In order to efficiently evaluate the effects and possible interactions of several factors (explanatory variables) instead of evaluating one factor at the time, it is important to take design of experiments into account. The aim is to define an experiment design which is used to construct the appropriate regression model to explain the real system or simulation model. With simulation the experiment of design is quite easy to do because all the experiment parameters can be controlled, each experiment is reproducible, and the time a single experiment requires is usually quite short.

Here we are investigating the effects of several different factors on the response variable. In statistics this kind of an experiment is called a factorial experiment or 2^k factorial experiment which is basically an experiment involving k factors, each of which has two levels (+ or -). The points in two-level factorial experiment are marked with plus and minus signs (+1 and -1 regardless of true values of the factor (real, integer, logical, etc.)). In factorial experiments the effects of each factor on the response variable, as well as the effects of interactions between factors on the response variable, are under examination. The main objective is to estimate the factor effects, which indicate how each factor affects the response variable. The effect of each factor on the response variable can be a result of the interaction between the factors or due to a single factor (a main effect of the factor).

Our study deals with three factors, each having two levels. Thereby the experiment is a 2^3 factorial experiment, producing 8 factorial points. The full regression model in our case is

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{23} X_2 X_3 + \beta_{123} X_2 X_3 X_3 + \varepsilon,$$

where

- Y is the average length of stay,
- X_1 is the triage-team method,
- X_2 is a speech recognition system,
- X_3 is a pneumatic tube delivery system,
- $\beta_{0\text{-}k}$ are constants, and
- ε is the error term

To facilitate the determination of the + and – signs of the coefficients needed for calculating the effects, a matrix is constructed. It is constructed as follows: if the solution is "on", it will get a + sign. If it is "off" it will get – sign. For interaction factors, the signs of their individual factors simply need to be multiplied for each combination. The matrix of our study is shown in Table 33.

TABLE 33 Regression analysis

test	x0	x1	x2	x3	x1x2	x1x3	x2x3	x1x2x3	y
1	1	-1	-1	-1	1	1	1	-1	255,07
2	1	1	-1	-1	-1	-1	1	1	178,15
3	1	-1	1	-1	-1	1	-1	1	234,07
4	1	-1	-1	1	1	-1	-1	1	221,31
5	1	-1	1	1	-1	-1	1	-1	196,13
6	1	1	1	-1	1	-1	-1	-1	164,57
7	1	1	-1	1	-1	1	-1	-1	167,1
8	1	1	1	1	1	1	1	1	144,32
β	195,09	-31,55	-10,32	-12,88	1,23	5,05	-1,67	-0,63	

As can be seen in Figure 61 the first test describes the present operation and the last test (test 8) defines the test where all solutions are tested together (main effects and all their interactions). On the bottom row, the regression coefficient β is estimated. It describes the effects of explanatory factors on the response variable. The regression coefficient is calculated as follows:

$$\beta = (X^t X)^{-1} X^t y$$

However, in our study the matrix was orthogonal. For this reason the equation for the regression coefficient β was

$$\beta = X^t y_{/n}$$

In order to get some relevant information on the explanatory factors, the significance of beta coefficients had to be estimated. It was done by using the confidence intervals as follows:

$$95\ \%\ CI\ (\beta_i) = \beta_i \pm 1{,}96 * \sqrt{\sum_j Var(y_j)/8^2} = \beta_i \pm 4{,}62$$

95 % CI (β 1) = -31,56 ± 4,62= (-36.18,-26.94)

95 % CI (β 2) = -10,32 ± 4,62= (-14.94,-5.7)

95 % CI (β 3) = -12,88 ± 4,62= (-17.5,-8.26)

95 % CI (β 12) = 1,23 ± 4,62= (-3.39,5.85)

95 % CI (β 13) = 5,05 ± 4,62= (0.43,9.67)

95 % CI (β 23) = -1,67 ± 4,62= (-6.29,2.95)

95 % CI (β 123) = -0,63 ± 4,62= (-5.25,3.99)

The hypotheses for the significance of beta coefficients were $H_0 : \beta = 0$ and $H_1 : \beta \neq 0$. It means that if the value $\beta = 0$ is in the confidence interval, that solution has no significant effect on the dependent variable.

As can be seen from the results, the main effects are all significant. The triage-team method has the biggest effect on the operation. That effect is almost three times bigger than the effects of a pneumatic tube delivery system and a speech recognition system, which also have a significant effect on the operation of an emergency department.

The only interaction which might have effect on the response variable is between factors x1 (the triage-team method) and x3 (a pneumatic tube delivery system). All the other interactions between factors are not significant.

Regression analysis was performed in order to explain the results of the simulation run. As can be seen from the coefficient β examination, the regression analysis backs up the results obtained earlier and defines how the average length of stay has been formed.

After two different analyses of the results it can be said that the operation of an emergency department can be substantially improved by changing the processes, reallocating the resources and using technological solutions, as shown in this work. These solutions reduce the passive waiting time, which is the biggest problem in emergency departments today.

However, it should be kept in mind that these results show the most optimal situation and in the real world the situation is slightly different. It is not always possible to work in the optimal way, and it may also be that the new working models will not be adapted in the most efficient way. This leads to a situation where the level of effectiveness and improvement depends on how well the new working models can be learned.

6 SCOPE OF APPLICATIONS

This study examined the operation of an emergency department but the use of the model is not limited to this area only. The same methodology where different entities travel and queue between different locations and are operated by different resources can be used and exploited to study the operations of other health care units as well.

For example, a clinical laboratory can be such a unit. The operation of a clinical laboratory consists also of different entities and different resources although they are somewhat different from those in an emergency department. For a clinical laboratory, patients, test results, etc. can be replaced with blood samples. Also, besides nurses and other staff members, there are machines for operating the samples as well. Nevertheless, there is a certain analogy between them. The analogy between the core operation of an ED and a laboratory is shown in Figure 34.

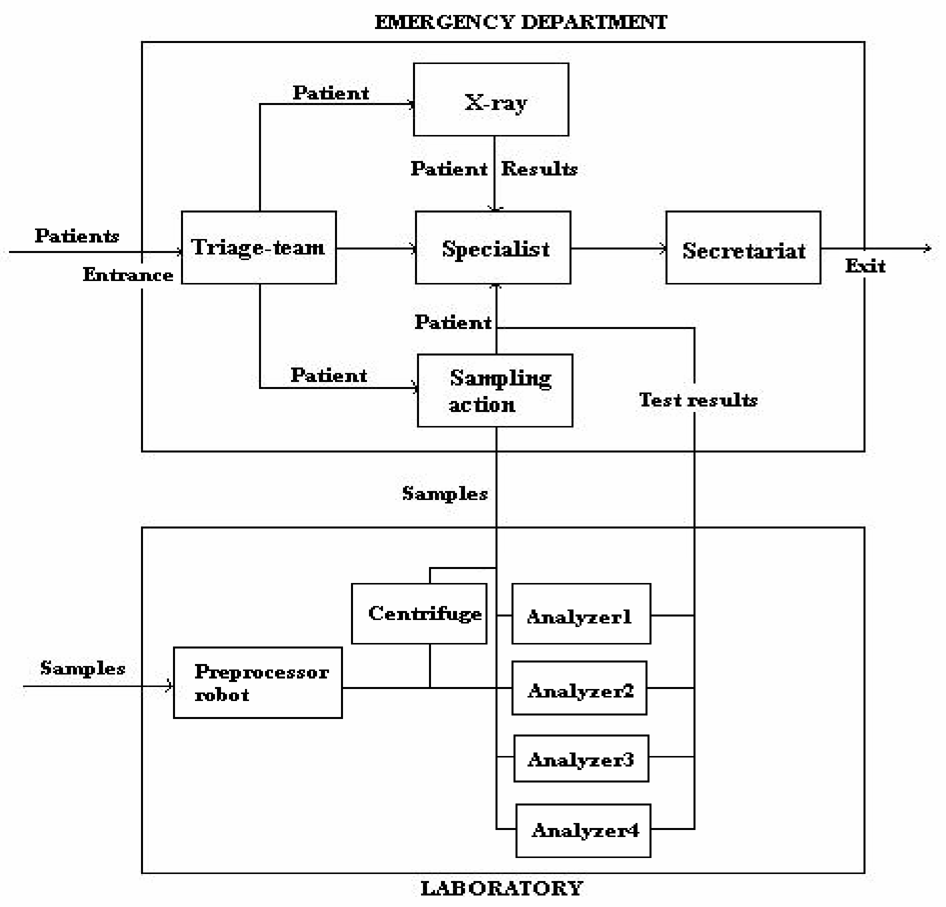


FIGURE 34 The analogy between an ED environment and a laboratory environment

A clinical laboratory is an individual unit but it is also an important part of the patient process of an ED. Because it is an individual unit, it does not receive and analyze only ED samples but samples from other health care units are analyzed by it as well. The number of samples processed during one day may be quite large, depending on the number of units which deliver their samples there.

The actual analysis phases in a laboratory are performed by certain machines, and the capacity of those machines defines how efficient the process is (how many samples it is possible to analyze within a certain period of time). If the situation changes, and some other units start to deliver their samples to the laboratory in question as well, the only way to keep the operation as efficient as it was before is to purchase new equipment with enough capacity to handle it all within certain timelines.

However, the selection of new equipment is very difficult if there are several choices with almost equal capacities. This is where a simulation model like the model described in this study can become very useful. By defining different machine candidates in the model as a resource and studying the operations (activities) around them, it is possible to arrange the different machines in order of superiority.

6.1 Simulation of a clinical laboratory

In this chapter a simulation model is used in selecting a new preprocessor robot for the laboratory. The main interest is not in the throughput time of the samples but in the amount of work done by hand around the robot. Although different robot candidates may be efficient enough to handle all samples in the required time, there may still be big differences in manual operations which need to be done around the robot in order to successfully operate the samples. This is why the main target variable in the simulation of a clinical laboratory is the amount of handwork.

6.1.1 Background and location definitions

The actual layout was used as a background and the operational areas (locations) of the process were defined in the layout by using the elements in the graphical libraries of MedModel software. Using the actual layout of the clinical laboratory in the simulation made it possible to demonstrate the operation of the model more accurately to the staff. The future changes and their effect on the process were also much easier to present and explain when the real floor plan was used in the visualization.

The processes in the laboratory are complex and include both handwork and mechanized work, and therefore the operational areas for both work phases needed to be defined separately.

After the locations had been defined, they had to be connected to each other in order to make it possible for samples and staff to move from one part of the process to another and from one area to another. Once that was done, the structure of the model was ready.

However, the structural definitions formed just a framework for the model. To make the model functional, more definitions had to be made. This required information on entities, information on resources, logic definitions (operational logic and route logic), and information on operation times.

6.1.2 Entities in the laboratory model

There were different types of specimens in the laboratory, with different priorities, so they had to be categorized into different groups.

The first division was done by priority. This partition formed two different groups: the ED specimens and the specimens from other health care units around the county. If the specimen was from the emergency department, the priority was higher than for the other specimens, and the specimen was going to be processed before the others. After that, the specimens from elsewhere were handled on an equal footing.

The second division was made for both priority classes by forming different specimen type groups. Different types of specimens were processed and analyzed partially by their own analyzers and own staff. That is why this kind of definition was important to make.

In our study, six different types of specimens for both priority classes (ED specimens and the others) were included in the model (altogether 12 groups). These six specimen groups were clinical chemistry, special chemistry, hematology, coagulation, blood type and acid-based equilibrium. Process logic, including operation logic and route definition, was defined for each specimen type individually. The entity definitions are shown in Table 34.

TABLE 34 Entities in the laboratory model

Name	Speed	Stats
Clinical chemistry sample (ED)	50	Time series
Hematology sample (ED)	50	Time series
acid-based equilibrium (ED)	50	Time series
Blood type sample (ED)	50	Time series
Coagulation sample (ED)	50	Time series
Clinical chemistry sample (Other)	50	Time series
Hematology sample (Other)	50	Time series
acid-based equilibrium (Other)	50	Time series
Blood type sample (Other)	50	Time series
Coagulation sample (Other)	50	Time series

6.1.3 Resource definitions in the laboratory model

A resource is anything that transports entities, performs maintenance on locations, assists in performing operations on entities at locations or performs maintenance on other resources. It can be a person, piece of equipment, or some other device. In this model only staff members are considered as resources. Equipment and devices are defined as location elements, because analyzers and centrifuges are machines with a high capacity and their operations are easier and simpler to define as location elements.

There are different kinds of actors at the different phases of the process, and their properties are defined individually. For example, at the beginning of the process there are various persons handling the specimens. For ED samples there is a laboratory technician who goes to the emergency department, takes the blood samples and delivers them to the laboratory. For the blood samples from elsewhere there are persons who sort the samples, put them into racks or feed the samples into centrifuges. After that all the samples are handled by the same resources (certain nurses), depending on the sample type. Altogether eight different resource groups were defined in the model. These groups are shown in figure 62.

6.1.4 Processing logic of the model

Processing defines the operations that take place at each location which are defined in the model, and it defines also the routing of entities through the system. The logic and routes are described for each sample type and both priority classes individually, because equipment and human resources for handling them may be partially different.

The samples arrive at the laboratory in two different ways. They are fetched from the emergency department by a laboratory technician or some other health care unit of Central Finland sends them to the laboratory by car. If the sample is from the ED, it possesses a higher priority than the samples from other health care units. This feature divides the samples into two different groups (priority groups) depending on from where they are delivered to the laboratory. Because there are different flows for each priority group, the arrival distributions are defined for each group individually. Also, the first few phases of the process differ between these two groups, so it is important to describe the operation logic and route definitions for each priority group separately.

Processing of the ED specimens

The process for the ED samples starts at the emergency department. There a laboratory technician takes a blood sample from the patient. The number of samples s/he takes depends on how many requests have arrived to the laboratory before s/he has started the round. After all the samples have been taken, they are delivered to the laboratory.

The first phase in the laboratory for the ED samples is receipt. All the samples have to be receipted before they can advance in the process. After the receival, the laboratory technician delivers the samples into the right processing area. Where the samples are delivered after that, depends on the sample type. There are different areas, procedures and staff for every type.

If the sample belongs to clinical chemistry, it has to be stabilized for a while before it can advance in the process and that is why the laboratory technician delivers it to the area where this is done. After the stabilization, the sample is put into the centrifuge by a nurse at the clinical chemistry. The centrifuge processes the sample for a certain time, after which it is delivered to the analyzer. The ED samples are fed into the analyzer before other samples, and do not have to wait. The analyzer processes the samples and then gives out the results. If everything is all right and there is nothing wrong with the results, they are automatically sent to the ED. If there is something wrong with the sample, it has to be checked by the nurse or reprocessed by the analyzer.

If the sample is a hematology sample, it is delivered to the hematology area by a laboratory technician, who took the sample at the ED. The sample is left on the table, where a nurse, who is working in that area, takes it to the analyzer. The samples are fed into the analyzer in their own rack. After the analyzer has processed them, the results are sent to the computer. A nurse checks the results and then sends them to the ED.

If the sample is a coagulation sample, it is delivered to the coagulation area by the same laboratory technician who takes all the samples to the ED and collects them from there. The sample is handed over to a nurse, who is working in that area. After the sample has arrived at the coagulation area, it is put into the centrifuge. The centrifuge processes the sample for a while and after that it is fed into the analyzer by a nurse. When the sample has been analyzed, the results are sent to the ED.

If the sample is a blood type sample, it is delivered to the corresponding area and fed into the blood type analyzer. The processing time is quite long and there was no accurate information available of the operation times either, so this part of the process is based on estimations.

If the sample is an acid-base equilibrium sample, it is delivered directly to its own analyzer. There is no staff dedicated to handling just these samples; any readily available staff member can put them into the analyzer and collect the results. An acid-base equilibrium sample has to be processed right away, otherwise it will be spoiled.

The above mentioned sample types are ED entities in the simulation model. The number of the ED samples, which are transported at once, is usually 1-5. The whole process for the ED samples is shown in figure 35.

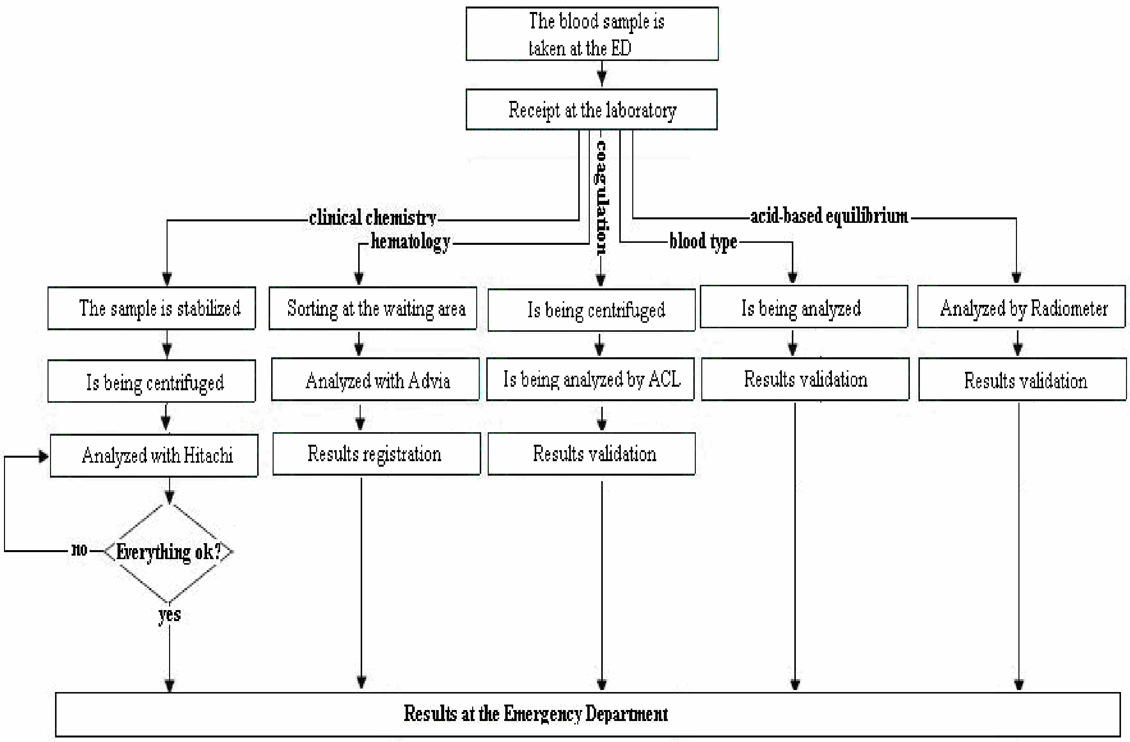


FIGURE 35 The emergency department sample flow in the laboratory

Processing of the other samples

The beginning of the process for the samples from other health care units is somewhat different from that for the ED samples. The ED samples are taken at the ED when needed, whenever there is a patient who needs to be tested, after which the sample is delivered to the laboratory right away. However, the samples from other units are delivered in larger batches and at certain times of the day by car. However, the processes between these two sample groups differ only at the beginning and after they have been handled by the same staff and same equipment (except for little variations on the operation). That is why only the beginning of the processing logic is described for the other samples.

The process starts at the arrival. The samples are delivered to the laboratory in larger batches, and the first phase is to receive and sort them. After that the process advancement depends on the sample type. If the sample belongs to clinical chemistry it has to be centrifuged. These samples are fed into the centrifuge. After the centrifuge has performed its action, they are put into the racks and delivered to the clinical chemistry area. They don't have to be stabilized like the ED samples. Nevertheless, corks are removed with a special machine. After that they follow the same processing logic as the ED samples. Other samples can be delivered forward after the sorting right away. After that they proceed to their own processing areas and follow the same process phases as the ED samples.

The samples from other units are transported in racks, in larger batches than the ED samples. Usually the batch size is between 50-200 samples. Also their priority is lower than that for the ED samples. This means that they are processed and analyzed after the ED samples. The process flow of the other samples is shown in Figure 36.

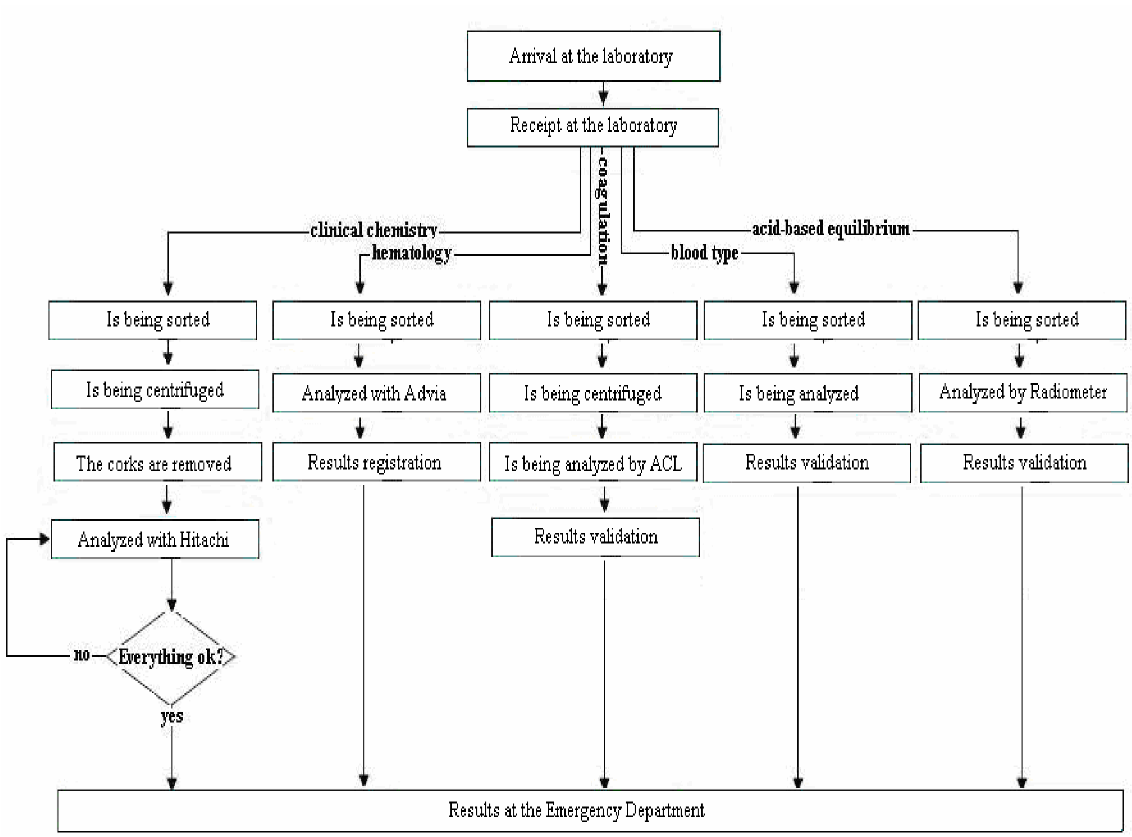


FIGURE 36 Process flow for the samples from other health care units

The samples arrive at the laboratory in two different ways. They are fetched from the emergency department by a laboratory technician; alternatively some other Central Finland health care unit can send them to the laboratory by car. If the sample is from the ED, it possesses a higher priority rating than the samples from other health care units. This feature divides the samples into two different groups (priority groups) depending on the location from where they were delivered to the laboratory. Because there are different flows for each priority group, the arrival distributions are defined for both groups individually. Also the first few phases of the process differ between these two groups, so the operation logic and route definitions are described for both priority groups separately.

6.1.5 Data collection and statistical analysis

Data was collected by tracking the tubes through the process. It was carried out by an external consultation company. They labeled the tubes, and the lab personnel at different workplaces wrote down the sample number and the time when they saw a tube with a certain label. The gathered data were then used in the model. Operation times for each phase of the process were defined using the Stat:Fit statistical software. The collected data in an existing text file were loaded into a data table, and the distributions were fitted to the input data by using the Auto:Fit property. The distributions were ranked according to their relative goodness of fit. An indication of the distribution being accepted as a good representation of the input data was also given. The highest ranked distributions were selected for the model. The process times for each phase are summarized in Table 35.

TABLE 35 Processing times for each specimen group (T=Triangular, E=Exponential, U=Uniform, P5=Pearson 5)

Clinical chemistry (ED)	**Time(min)**		**Clinical chemistry (other samples)**	**Time(min)**
Walking time + blood test	T(4,8.15,26.5)		Receipt	5 sec/tube
Receipt	10 sec/tube		Centrifuge	U(10,1)
Stabilization	15 min		Sorting	E(6.4)
Centrifuge	U(10,2)		Corks off and shifting	U(3,1)
Hitachi analyzer	P5(2.58,18.5)		Waiting time before Hitachi	U(5.5,0.5)
			Hitachi analyzer	P5(2.58,18.5)
Hematology (ED)	**Time(min)**		**Hematology (other samples)**	**Time(min)**
Walking time + blood test	T(4,8.15,26.5)		Receipt	5 sec/tube
Receipt	10 sec/tube		Sorting	U(3,1)
Advia analyzer	ER(2,5.99)		Waiting time before Advia	U(4,1)
Results checking	U(3,1)		Advia	0.25 min/tube
			Results checking	U(3,1)
Coagulation (ED)	**Time(min)**		**Coagulation (other samples)**	**Time(min)**
Walking time + blood test	T(4,8.15,26.5)		Receipt	5 sec/tube
Receipt	10 sec/tube		Sorting	U(3,1)
Centrifuge	U(11,1)		Centrifuge	U(10,1)
ACL analyzer	P5(1.26,7.18)		ACL analyzer	P5(1.26,7.18)
Acid-base equilibrium (ED)	**Time(min)**		**Acid-base equilibrium (othet samles)**	**Time(min)**
Walking time + blood test	T(4,8.15,26.5)		Receipt	5 sec/tube
Receipt	10 sec/tube		Radiometer analyzer	U(4,2)
Radiometer analyzer	U(4,2)			
Blood type (ED)	**Time(min)**		**Blood type (other samples)**	**Time(min)**
Walking time + blood test	T(4,8.15,26.5)		Receipt	5 sec/tube
Receipt	10 sec/tube		Sorting	U(3,1)
Analyzer	U(660,60)		Analyzer	U(660,60)

6.1.6 Model validation

In both the model verification and validation, numerical and visual information was used. In the case of the ED samples numerical information (time stamps) was available, and it was used to verify and validate the ED sample flow. The main target variable was the average throughput time of different sample types. The validation was done by carrying out the confidence interval examination. First the real average throughput times were defined statistically from the real collected data. These times were:

- Coagulation: 98 minutes
- Hematology: 66 minutes
- Clinical chemistry: 94 minutes

The defined values were then compared with the values of the model shown in Figure 37.

REPLICATION ANALYSIS (Sample size 35)

Statistic	Avg	Median	Min	Max	Std Dev	Std Err
Coagulation sample - Average Value	97.18	93.65	86.80	113.86	10.18	4.55
Hematology sample - Average Value	64.23	64.53	53.39	72.10	4.14	0.82
Clinical chemistry sample - Average Value	96.02	95.52	85.39	103.79	4.24	0.84

FIGURE 37 The results of simulation in a numerical form

The results of the comparison are shown graphically in Figure 38.

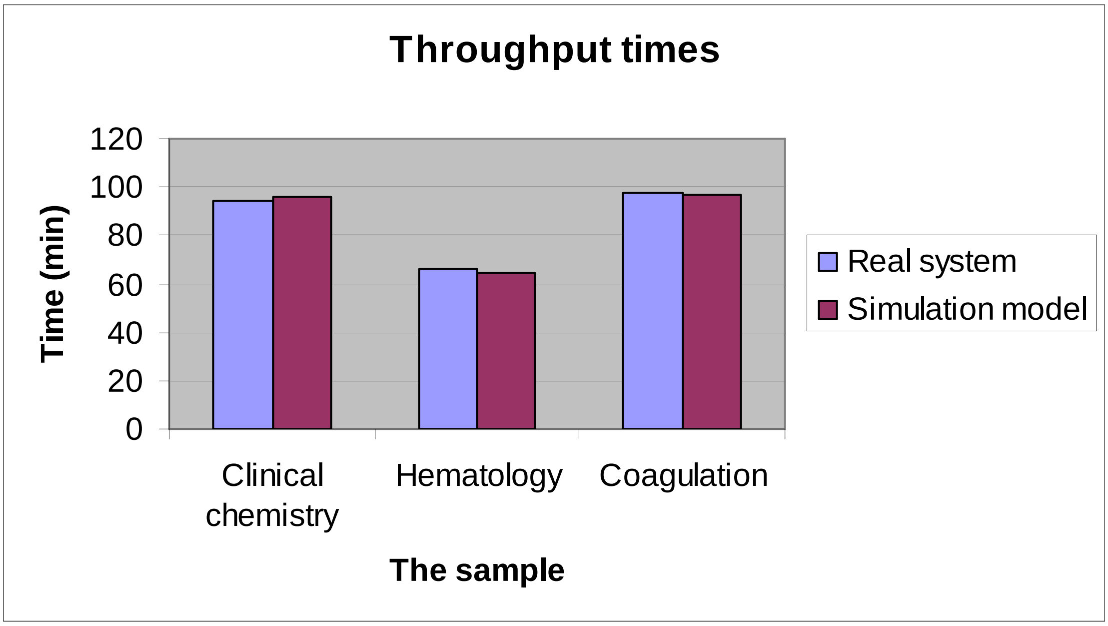


FIGURE 38 A comparison of the throughput time between the real system and the simulation model

The results showed that the error of the model was 2,1% in the case of clinical chemistry, 2,7 % in the case of hematology and 0,01% in the case of coagulation. However, in order to take the random features into account as well, the confidence interval examination had to be made (just as we did in ED simulation). We wanted to be 95 % confident about where the true mean falls so we defined the lower and upper limits by using the same equation that we used in model validation. This equation was:

95 % CI = p ± 1,96 * S,

where p is the average value of the patient's length of stay and S is the standard error of the mean and the value 1,96 was obtained from normal distribution.

95 % CI (coagulation) = 97,18 ± 1,96 * 4,55 = 97,18 ± 8,9 = 88,28 – 106,08.
95 % CI (hematology) = 64,23 ± 1,96 * 0,82 = 64,23 ± 1,6 = 62,63 – 65,83.
95 % CI (clinical chemistry) = 96,02 ± 1,96 * 0,84 = 96,02 ± 1,65 = 94,37 – 97,67.

As can be seen by examining the margin of error and performing the confidence interval examination, there are no significant difference between the model and real data. The model is therefore valid and can be used as decision support tool. The verification and validation of samples from other units was a little more difficult, because accurate time information wasn't available. In this case the model was verified by using its visual information. The model was examined thoroughly by the staff. The structure of the model was presented phase by phase and compared to the real world. After the staff had approved the operation of the model, it was ready to use.

6.1.7 Selecting a new preprocessor robot with the help of the simulation model

New equipment purchase and selection is a very challenging job, especially in a dynamic and complex environment, such as a laboratory. Usually the processes are studied manually and the main focus is on the qualities of the equipment (capacity, working methods, processing times, throughput times, etc.) and the selection is made based on that information. Of course it is important to know how efficient the robots are and how they will handle the samples. However, it is also important to find out how much handwork they will require around them. This aspect is quite often ignored, although it is a very important factor when improving the operation is attempted. Robots may still need various amount of handwork, and the impact on the staffing levels might not be felt as planned. It is important to find equipment which will automate the process the most and release the staff to perform some other activities in the process.

In the case of robot testing, the process was studied from the start only up to the tasks right after the robot phase, and the amount of handwork was selected as the main target variable. The handwork phases were defined in the model around the robot as follows: the tasks before the robot phase, the daughter-tube-making phase (done after the robot phase), and the other tasks after the robot phase.

In order to receive appropriate results, resources for every handwork phase were also defined. There was one laboratory technician for the preprocessing phase, one for the daughter tube process and one for the other after-treatment tasks. Using these same resources for each robot scenario and defining all the necessary tasks for every phase, it was possible to find out the amount of handwork. The results are presented using the utilization rate. The utilization rates of every resource in each scenario were compared to each other.

Because accurate information wasn't available, the data for every handwork phase and for every task around the robot were estimated by the staff. The simulation time was also selected to cover only the most crowded period which was 7 am -6 pm. Under the examination were only the samples from other health care units (not the ED samples). This was done because the ED samples were not going to use the robot during that period.

Altogether five different robot scenarios were defined and tested. Each scenario was created by replacing the centrifuges (three of them) in the original model with different robots. The robots were defined by using the information which the suppliers offered. There was information on the operation time, the capacity of the robot, and the capacity of the centrifuge. The qualities of the robots are presented in Table 36.

TABLE 36 The qualities of different robot candidates

Equipment	Capacity of centrifuge	Whole capacity (tubes/h)	Throughput time of centrifuged tube
Robot 1	72	500 tubes/h	15 min
Robot 2	96	400 tubes/h	21-37 min
Robot 3	96	400 tubes/h	21-37 min
Robot 4	40	160 tubes/h	15 min
Robot 5	40	160 tubes/h	15 min

6.1.8 Description of robot scenario 1

The specimens, in the case of robot 1, are delivered to the laboratory on their own rack. This means that the specimens are ready to be sent forward, without any operations, right after they have arrived at the laboratory. Because no preprocessing operations are needed, a laboratory technician delivers the sample rack to the robot. Before the samples are fed to the robot, they have to be separated. The robot does that. The specimens of clinical chemistry, special chemistry and coagulation go first through the receipt phase and immediately after that they are fed into the centrifuge and centrifuged for 10 min. Other specimens go through the receipt phase only. After the receival the specimens either go to the daughter tube processing phase or exit the robot. In the case of the daughter tube, a duplicate is made and, after that, the original and duplicate alike exit the robot. When the specimens exit the robot, all the others except coagulation specimens are sorted and placed into their own racks by the robot. The coagulation specimens have to be sorted manually. Also the specimens (daughter tubes) which are leaving the laboratory need to be corked. These two activities were the only handwork parts around the robot. The processing times were defined for both activities by the staff as follows: sorting of the coagulation specimen 5 sec/tube and corking 10 sec/tube. When all of these operations have been done, the samples advance in the process and the simulation ends. The process flow of robot scenario 1 is shown in Figure 39.

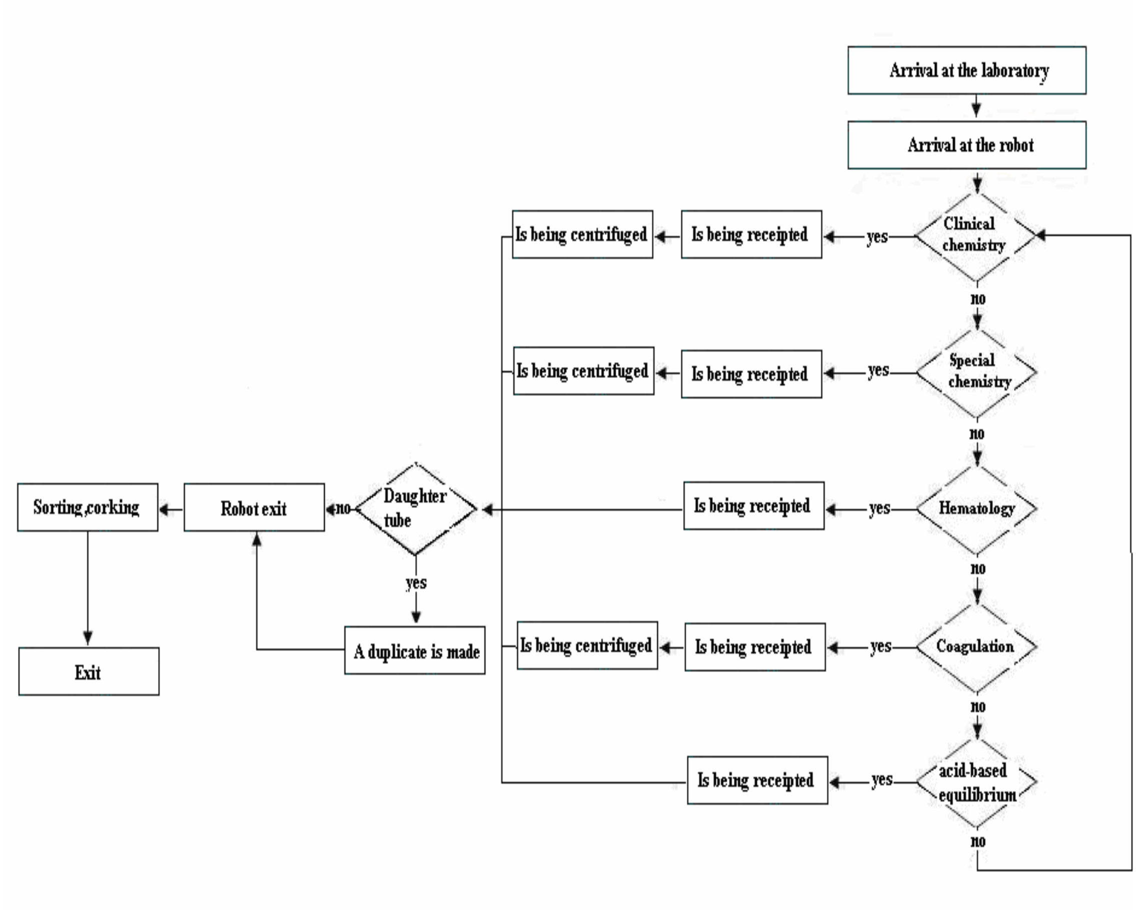


FIGURE 39 Process flow of robot scenario 1

6.1.9 Description of robot scenario 2

In robot scenario 2 the specimens are delivered to the laboratory on their own racks. It means that no preprocessing is required and the specimens can be delivered to the robot immediately. Before the specimens are fed to the robot, they have to be separated in order to get the different specimens into their correct places inside the robot. The robot does that. The specimens of clinical chemistry, special chemistry and coagulation first go through the receipt phase, and right after that they are fed into the centrifuge and centrifuged for 10 min. Other specimens go through the receipt phase only. The robot phase and all the phases after that follow the robot 1 process. The only difference between these two robots is in operation time and the capacity of centrifuge (see Table 1). The operation time and the capacity don't make any difference to the amount of the handwork, because all the samples are handled during the simulation run and all the handwork parts are exactly the same. Therefore the results are congruent with the results of robot 1.

6.1.10 Description of the scenario 3

The samples arrive at the laboratory on their own racks, so no preprocessing is required in this case either. The racks are delivered right away to the robot. First, all the samples go through the receipt phase and after that they are sorted by the robot in order to process them properly. The samples of clinical chemistry, special chemistry and coagulation are fed into the centrifuge and centrifuged for 10 min. Other samples go through the receipt phase only. This robot doesn't make the duplicates (daughter tubes); they are made manually after the robot phase. When the specimens exit the robot, they are either sorted and put on the racks, or delivered to the duplicating phase. In the duplicating phase a laboratorian makes a daughter tube manually and after that delivers the original tube and the duplicate on their racks. The duration of the duplication phase was estimated and tested by the staff, and their estimation was 30-60 sec/tube. Because any amount of time between 30 and 60 seconds was possible, uniform distribution was used to present the operation time. The operation time was therefore U(45,15). When the tubes are put on the racks, the racks are then sent forward and the simulation run ends. The process flow of robot scenario 3 is shown in Figure 40.

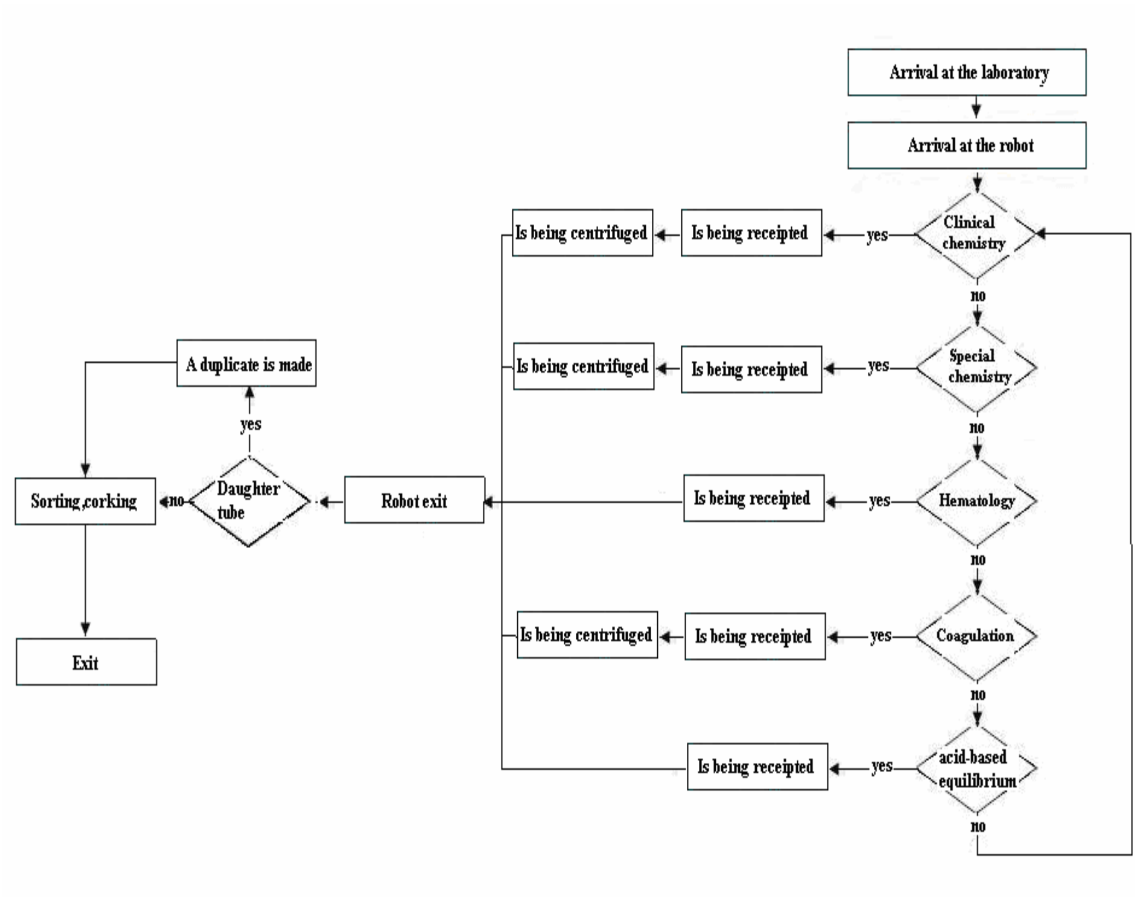


FIGURE 40 The process flow of robot scenario 3

6.1.11 Description of robot scenario 4

Unlike in the earlier robot scenarios, in this scenario the specimens are not delivered on their own racks to the laboratory. It means that they have to be shifted onto their own racks manually after their arrival. In order to get appropriate results, the time for that process was estimated by the staff. The estimation was 10 sec/tube. When the specimens have been put on their own racks, they are ready to be sent forward to the robot. Before they can be fed to the robot, however, some preparations need to be made. Every sample requires 1-2 buckets and one jet of pipette. These things have to be inserted before the specimen can be handled by the robot. To find out the amount of handwork, time estimation is needed here again. The staff measured and estimated the operation. Their estimation was 6 sec/tube for both operations.

Inside the robot the first phase for all the samples is the receipt phase. After that they are sorted by the robot in order to process them properly. The samples of clinical chemistry, special chemistry and coagulation are fed into the centrifuge and centrifuged for 10 min. Other samples go through the receipt phase only. This robot doesn’t make any duplicates (daughter tubes) either. The duplicates are made manually after the robot phase. When the specimens have exited the robot, they are either sorted and put into the racks or delivered to the duplicating phase. In the duplicating phase a laboratory technician makes a daughter tube manually, and after that delivers the original tube and the duplicate into their racks. The processing time definition for the duplicating process was the same as in the robot scenario 3. After the tubes have been put on the racks, they are then sent forward and the simulation run ends. The process flow of robot scenario 4 is shown in Figure 41.

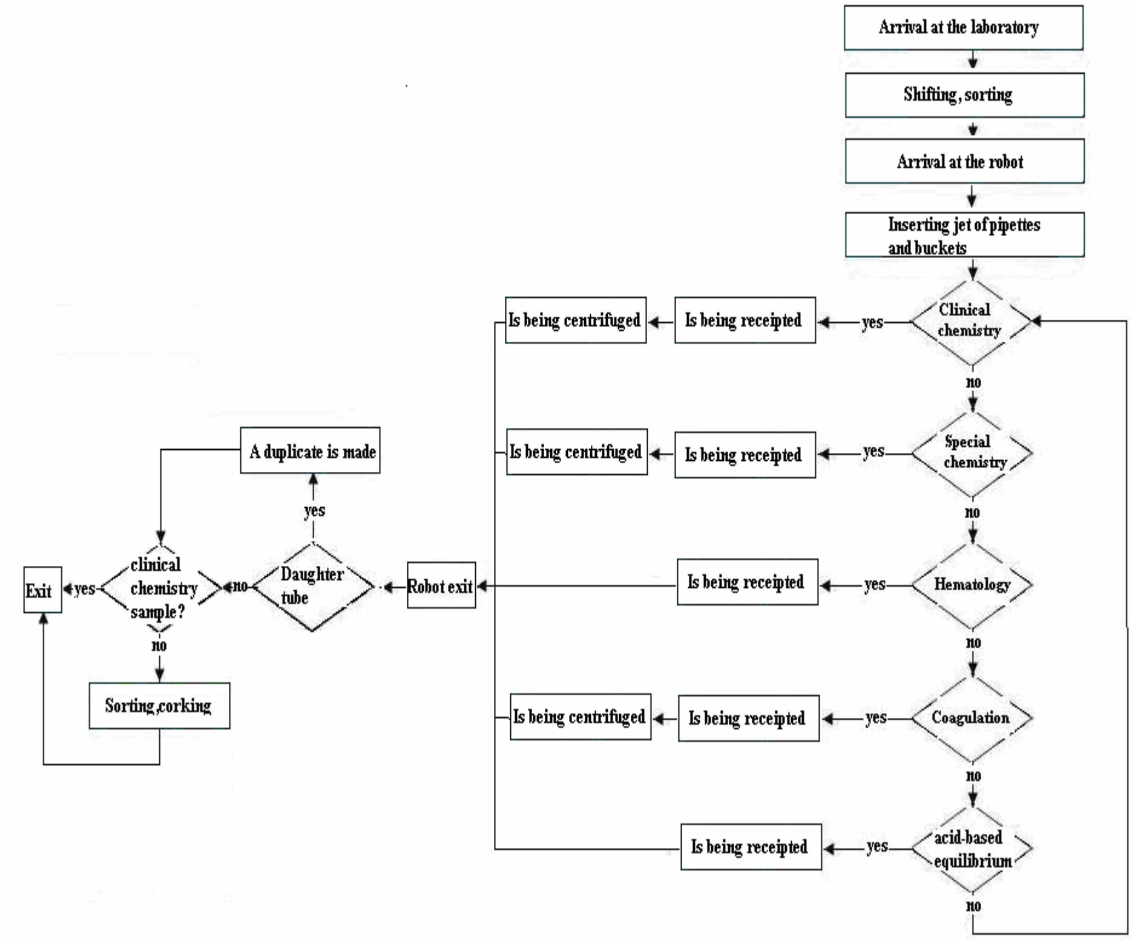


FIGURE 41 The description of robot scenario 4

6.1.12 Description of robot scenario 5

The process flow of robot 5 differs from the process flow of robot 4 only in the end part. The preprocessing tasks are the same and the robot phase also follows the same routines. The only difference is right after the robot phase, when the specimens exit the robot. In the case of robot 4, the specimens of clinical chemistry were automatically transferred forward to the analyzer and the other samples needed to be shifted and sorted into their own racks. But in this case also the specimens of hematology are partially processed by the robot. They are sorted automatically by the robot, and only the shifting part has to be done manually. Because the process flow is mainly the same as with robot 4, there is no need to describe the process flow on a more detailed level here. The simulation run settings were also the same as in the other robot scenarios so they do not need to be described either.

6.1.13 Results

After all the robot scenarios were tested, the results of each scenario were compared with each other. The utilization rates of all the defined handwork phases were examined. The results show that there were two robots, which required notably less handwork than the others. These were robot 1 and robot 2. Other robots occupied the staff significantly more. The results are shown in figure 42.

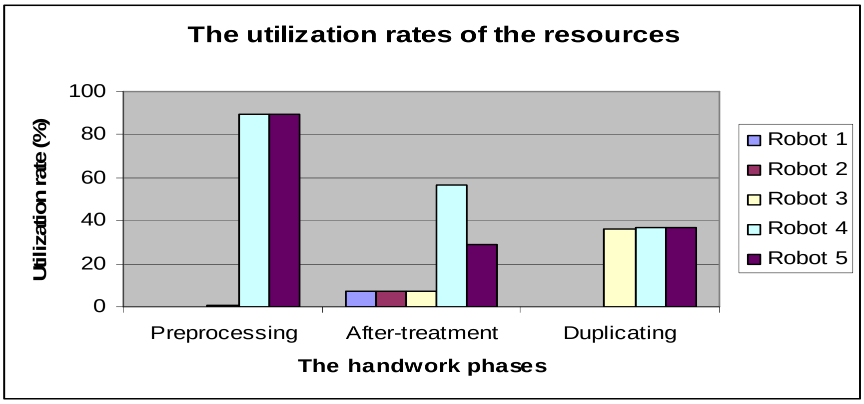


FIGURE 42 A comparison of the utilization rates between the different robot candidates

6.1.14 Conclusions

New equipment selections are normally made without using any tools. The decisions are usually based only on health care managers' and staff's own experience as well as on the technical information for the equipment. The throughput time is also usually used as the main target variable.

This kind of examination will not necessarily tell the whole truth about the suitability of the equipment for the laboratory. Because the effects on the whole operation are not known beforehand, this may lead to wrong decisions. The results in this study show that simulation is a very useful tool for new equipment selection. By using a simulation model the effects on the operation can be seen, and the robot candidates can be easily arranged in order of superiority.

The amount of handwork is also a very important variable to take into account when purchasing new equipment. If the main objective is to improve the whole operation, adequacy of the equipment efficiency is not going to assure that. As it was shown in this study, there is a lot of variation on the amount of the handwork around the different equipment candidates. The worst candidate may reserve more staff to handle the operation around it than the others, and this may lead to inefficiency in the operation of the clinical laboratory. All the problems mentioned can be avoided by using simulation and the right target variables.

7 DISCUSSION

The results obtained in this study showed that with the use of new technologies, alternative strategies, and resource reallocation it is possible to improve the operation of different heath care units and meet the challenges in the health care. This is the case especially in the emergency departments where the operation is too inefficient at this moment. Waiting times are too long and patients have to spend too much time in the process. The biggest problem is especially the passive waiting time which is the time when the patient just waits without getting any treatment or attention. By changing the process, using technological solutions, and allocating the resources differently it is possible to reduce the passive waiting time and still retain a good quality of care. This will improve the operation of the ED and increase patient satisfaction.

Usually the decisions about the best solutions are based on managers' and staffs' own experience and the results of traditional analytical tools. However, that kind of examination is not very reliable and efficient, because it does not show the effects of different solutions on the whole operation. It is impossible to predict the future effects just by examining the process without any numerical information. That is why a dynamic tool which is capable of showing the effects without implementation and in a numerical form is needed. What is needed is the ability to test different solutions without disturbing and risking the everyday activities.

Simulation is this kind of a tool. It is capable of taking into account environments which are complex, dynamic and contain random features. It gives information both in a numerical and visual form, which makes it very easy for different participants to see the effects of different solution proposals on the whole operation. It is a reliable method, because real data from the system being modeled is used in the development. Real data makes it possible to create an accurate abstraction of the system being modeled. Simulation has been used in manufacturing industry for decades, but, as shown in the literature and in this study, it has proven to be very efficient and appropriate tool for examining health care operations as well.

In this study the simulation model developed was used to create a universal mode of action for the ED. That was done by evaluating the effects of the triage-team method, the effects of a speech recognition system and the effects of a pneumatic tube delivery system on the patient process. These solutions were constructed together with the staff and were based on the problems found. All the solutions were tested with the simulation model by configuring them in the model and running them individually. The results of each scenario were then compared with the results of the original scenario. The target variables selected were the patient's length of stay (LOS) and the waiting times of different phases in the ED. Different solutions were used as decision variables.

All the alternative solution proposals were tested separately, but in order to see the effects if they are implemented together (partially or totally) they have to be tested together as well. Although all the alternative solutions improve the operation when they are implemented separately, it is difficult to validate the combined effects of two or more solutions without testing them together.

The results showed that the best single solution was the triage-team method which improved the operation substantially on its own. Although a pneumatic tube delivery system also improved significantly the present operation, it did not reach the same efficient level as the triage-team method. The triage-team method was significantly better than either of the other single solutions.

Although the triage-team method was the best single solution, it did not provide the best result when the combinations of different solutions proposals were taken under examination as well. The best improvement was achieved when all the solution proposals were implemented together. The results showed that implementing all the solutions proposals at the same time would decrease the patients' length of stay over 40 % (43,4 %).

However, it should be kept in mind that these results show the most optimal situation and in the real world the situation is slightly different. It is not always possible to work in the optimal way, and it may also be that the new working models will not be adapted in the most efficient way. This leads to a situation where the level of effectiveness and improvement depends on how well the new working models can be learned.

The aim of this study was to improve the operation of emergency departments especially from the efficiency point of view. The focus was on finding solutions and creating an operational model which would reduce passive waiting time as far as possible. However, the model can be used to examine the operation of the emergency department from other points of views as well. This means that the target variables can also be other than time-based variables.

Besides focusing on utilization and throughput analysis, the developed simulation model can be used to perform an activity-based-cost analysis as well.

In the ABC-analysis it is used to trace direct costs in an emergency department for all patients in the process. This kind of an approach is very useful, because it provides information on the cost effects of different changes. Costs are a very important factor in the present society, and they should be taken into account as well.

The simulation model provides an opportunity for that. However, it has to be remembered that with simulation it is possible to examine only direct and indirect overhead costs, and other costs, such as societal costs, are beyond its scope.

In order to perform an ABC-analysis with the simulation model, some definitions have to be made. ABC-analysis with simulation is based on time, and that is why information on resources (equipment costs, staff members' hourly wages) and other constant costs for each phase of the process need to be defined.

The possibilities of our simulation model do not end here; simulation can be used with optimization as well. These two methods can be used to define, for example, the optimal amount of resources for every shift. In this study optimization was not used because the amounts of different resources were quite small and it was possible to do the allocation effectively just by using the simulation model.

REFERENCES

Aharonson-Daniel, L., Paul, R.J. and Hedley, A.J. (1996), Management of Queues in Out-patient Departments: The Use of Computer Simulation. Journal of Management in Medicine, Vol.10, No 6, pp.50-58.

Allen, P. O., Ballash, D. W., and Kimball, G. (1997), Simulation Provides Surprising Staffing and Operation Improvements at Family Practice Clinics. In Proceedings of the 1997 Annual HIMSS Conference 4, pp.211-227.

Altinel, K. and E. Ulas, E. (1996), Simulation modeling for emergency bed requirement planning. Annals of Operations Research, Vol.67, pp.183–210.

Alvarez, A.M. and Centeno, M.A. (1999), Enhancing Simulation Models for Emergency Rooms Using VBA. In Proceedings of the 1999 Winter Simulation Conference, 1685–1693.

Amara, R. et al. (2003), Health and Health Care 2010 – Forecast and Challenge. The Institute for the Future. A Wiley Company: Princeton.

Anderson, J.G., and Anderson, M.M. (2005), Computer-Based Physician Entry in a Hospital: A Simulation Study, SCS, http://www.scs.org/scsarchive/getDoc.cfm?id=2033, May 13, 2005.

Arthur, J. L. and Ravindran, A. (1981), A Multiple Nurse Scheduling Model. AIIE Transactions, Vol.13, No 1, pp.55-60.

Asplin, B.R., Magid, D.J., Rhodes, K.V., Solberg, L.I., Lurie, N., and Camargo, C.A. Jr. (2003), A conceptual model of emergency department crowding, Ann Emerg Med, Vol.42, pp.173–180.

Baesler, F.F., and Sepúlveda, J.A. (2001), Multi-Objective Simulation Optimization for a Cancer Treatment Center. In Proceedings of the 2001 Winter Simulation Conference, Association for Computing Machinery, New York, pp.1405–1411.

Bagust, A., M. Place, and Posnett, J.W. (1999), Dynamics of Bed Use in Accommodating Emergency Admissions: Stochastic Simulation Model. BMJ, Vol.319, pp.155–158.

Benneyan, J. C., Horowitz, M. I., and Terceiro, M. B. (1994), Using Computer Simulation to Help Reduce Patient Waits. In Proceedings of the 1994 Annual HIMSS Conference, pp.323-342.

Benneyan, J.C. (1997), An Introduction to Using Computer Simulation in Healthcare: Patient Wait Case Study. Journal of the Society for Health Systems, Vol.5, No. 3, pp.1-15.

Blake, J. and Carter, M. W. (1996), An analysis of Emergency Room Wait Time Issues via Computer Simulation. INFOR, Vol. 34, No. 4, pp. 263-273.

Blasak R.E., Armel W.S., Starks D.W., and Hayduk M.C. (2003), The use of Simulation to Evaluate Hospital Operations between the Emergency Department and a Medical Telemetry Unit. In Proceedings of the 2003 Winter Simulation Conference, Association for Computing Machinery, New York.

Brailsford, S.C., L. Churilov, and Liew, S-K. (2005), Treating Ailing Emergency Departments With Simulation: An Integrated Perspective. http://www.scs.org/scsarchive/getDoc.cfm?id=2025, March 20, 2005.

Centeno, M.A., M. L Garcia, N. DeCario, and Rivera, C. (1995), Reducing Time in an Emergency Room via a Fast-Track. In Proceedings of the 1995 Winter Simulation Conference, pp.1048-1053.

Centeno, M.A., E. López, M.A. Lee, Carrillo, M., and Ogazon, T. (2001), Challenges of Simulating Hospital Facilities. In Proceedings of the Twelfth Annual Conference of the Production and Operations Management Society, Orlando, Fl.

Centeno, M., Giachetti, R. and Linn, R. (2003), A Simulation-ILP Based Tool for Scheduling ER Staff. In Proceedings of the 2003 Winter Simulation Conference, pp.1930–1938.

Chan, B. and Metzger, J. (1993), Process improvement in the emergency department: lessons learned from case studies in two urban teaching hospitals. Journal of the Society for Health Systems, Vol. 4, No. 2, pp. 15-24.

Chin, L., and Fleisher, G. (1998), Planning Model of Resource Utilization in an Academic Pediatric Emergency Department. Pediatr Emerg Care, Vol. 14, No. 1, pp. 4-9.

Connelly, L.G., and Bair, A.E. (2004), Discrete Event Simulation of Emergency Department Activity: A Platform for System-level Operations Research. Academic Emergency Medicine, Vol. 11, pp. 1177-1185.

Cooper, K., R. Davies, P. Roderick, D. Chase, and Raftery, J. (2002), The Development of a Simulation Model of the Treatment of Coronary Heart Disease. Health Care Manag Sci, Vol. 5, pp. 259-267.

Cote, M.J. (1999), Patient Flow and Resource Utilization in an Outpatient Clinic. Socio-Economic Planning Sciences, Vol. 33, pp. 231–245.

Dawson, K. A., et al. (1994), How to Conduct a Successful Emergency Center Staffing Simulation Study. In Proceedings of the 1994 Annual HIMSS Conference, Vol. 3, pp. 273–289.

DELFOI (2003), CASE: TAYS Finn Medi Delta automaatiolaboratorion simulointi.

Derlet, R.W., Richards, J.R. (2000), Overcrowding in the nation’s emergency departments: complex causes and disturbing effects. Ann Emerg Med, Vol. 35, pp. 63–68.

Derlet, R., Richards J, Kravitz R. (2001), Frequent overcrowding in U.S. emergency departments. Acad Emerg Med, Vol. 8, pp. 151–155.

Derlet, R.W. (2002), Overcrowding in emergency departments: increased demand and decreased capacity. Ann Emerg Med, Vol. 39, pp. 430–432.

Draeger, M. (1992), An Emergency Department Simulation Model Used to Evaluate Alternative Nurse Staffing and Patient Population Scenarios. In 1992 Winter Simulation Conference Proceedings. IEEE, Arlington, VA, pp. 1057-1064.

Dumas, M.B. (1984), Simulation modeling for hospital bed planning. *Simulation,* Vol. 8, pp. 69-78.

Dumas, M.B. (1985), Hospital bed utilization: an implemented simulation approach to adjusting and maintaining levels. Health Services Research, Vol. 20, pp. 43-61.

Edwards, R.H., J.E. Clague, J. Barlow, M. Clarke, P.G. Reed, and Rada, R. (1994), Operations research survey and computer simulation of waiting times in two medical outpatient clinic structures. Health Care Analysis: HCA. Journal of Health Philosophy and Policy, Vol. 2, No. 2, pp. 164-169.

Elbeyli, S., and Krishnan, P. (2000), In-Patient Flow Analysis Using ProModelTM Simulation Package. Food and Resource Economics Department.

El-Darzi, E., C. Vasilakis, T. Chaussalet, and Millard, P.H. (1998), A Simulation Modeling Approach to Evaluating Length of Stay Occupancy, Emptiness and Bed Blocking in a Hospital Geriatric Department. Health Care Manag Sci, Vol. 1, No. 2, pp. 143–149.

Erdem, H.I., T. Demirel, and Onut, S. (2005), An Efficient Appointment System Design for Outpatient Clinic Using Computer Simulation. SCS, http://www.scs.org/scsarchive/getDoc.cfm?id=1781 (refereed: May 4, 2005).

Evans, G.W., T.B. Evans, and Unger, E. (1996), A Simulation Model for Evaluating Personnel Schedules in a Hospital Emergency Department. In Proceedings of the 1996 Winter Simulation Conference.

Everett, J.E. (2002), A Decision Support Simulation Model for the Management of an Elective Surgery Waiting System. Health Care Manag Sci, Vol. 5, No. 2, pp. 89-95.

Farrington, P. A., Nembhard, H. B., Sturrock, D. T. and Evans, G. W. (1999), A Tutorial on Simulation in Health Care: Applications and Issues. In Proceedings of the 1999 Winter Simulation Conference. Informs Simulation Society, pp. 49–55.

Freedman, R. (1994), Reduction of Average Length of Stay in the Emergency Room Using Discrete Simulation. In Proceedings of the Simulation in Health Sciences Conference, pp. 6-8.

Glick, N.G., C.C. Blacmore, and Zelman, W.N. (2000), Extending Simulation Modeling to Active-Based Costing for Clinical Procedures. Journal of Medical Systems, Vol. 24, No. 2.

Gonzales, C., Gonzales, M., Rios, N. (1997), Improving the Quality of Service in an Emergency Room Using Simulation-animation and Total Quality Management. Computersind. Engng, Vol. 33, no. 1-2, pp. 97–100.

Groothuis, S., A. Hasman, P.E.J. van Pol, N.H.M.K. Lencer, J.J.J. Janssen, J.D.M. –J. Jans, J.L.M. Stappers, W.R.M. Dassen, P.A.F.M. Doevendans, and van Merode, G.G. (2004), Predicting Capacities Required in Cardiology Units for Heart Failure Patients via Simulation. Computer Methods and Programs in Biomedicine, Vol. 74, pp. 129-141.

Groothuis, S., G.G. van Merode, Y.J.M. Koppelman, and Hasman, A. (2005), Simulation at the Emergency Department.

http://www.scs.org/scsarchive/getDoc.cfm?id=2037 (refereed: February 2, 2005).

Hashimoto, F.S. Bell. (1996), Improving Outpatient Clinic Staffing and Scheduling with Computer Simulation. Gen. Intern. Med. 11(3), 182-184.

Healy, K., Withers, D. and Nelson, B. (1997), Success Stories in Simulation in Health Care. In Proceedings of the 1997 Winter Simulation Conference, Informs Simulation Society, pp. 1280-1285.

Hendershott, T. H. (1995), Resource Allocation/ Capacity Planning Using Simulation in the Laboratory. In Proceedings of the 1995 Annual HIMSS Conference, Vol. 2, pp. 363-370.

Huarng, F., and Lee, M.H. (1996), Using Simulation in Out-Patient Queues: A Case Study. International Journal of Health Care Quality Assurance, Vol. 9, No. 6, pp. 21-25.

Huddy, J. McKay, J. and Culp, K. (1999), Computer simulation: making better operational and architectural ED design decisions. J Emerg Nurs, Vol. 25, pp. 307–310.

Huebner, D. and Miller, L. (1996), Business Process Reengineering of an Outpatient Clinic Using Simulation. In Proceedings of the 1996 Annual HIMSS Conference, Vol. 1, pp. 87-100.

Iskander, W. H., and Carter, D. (1991), A Simulation Model for a Same Day Care Facility at a University Hospital. In Proceedings of the Winter Simulation Conference, pp. 846-853.

Kalton, A. G., Singh, M. R., August, D. A., Parin, C. M., and Othman, E. J. (1997), Using Simulation to Improve the Operational Efficiency of a Multi-Disciplinary Clinic. Journal of the Society for Health Systems, vol. 5, No. 3, pp. 43-62.

Kilmer, R.A., A.E. Smith, and Shuman, L.J. (1997), An Emergency Department Simulation and a Neural Network Metamodel. J Soc Health Syst., Vol. 5, No 3, pp. 63–79.

Kirtland, A., J. Lockwood, K. Poisker, L. Stamp, and Wolfe, P. (1995), Simulating an Emergency Department is as Much Fun as. In Proceedings of the 1995 Winter Simulation Conference, pp. 1039-1042.

Kraitsik, M., and Bossmeyer, A. (1992), Simulation Applied to Planning an Emergency Department Expansion. In Proceedings of the 1992 SCS Western Multiconference session on Simulation in Healthcare Services, pp. 19-27.

Kumar, A. and Kapur, R. (1989), Discrete Simulation Application - Scheduling Staff for the Emergency Room. In 1989 Winter Simulation Conference Proceedings. IEEE, Washington, DC, pp. 1112-1120.

Lane, D.C., C. Monefeldt, and Husemann, E. (2003), Client Involvement in Simulation Model Building: Hints and Insights from a Case Study in a London Hospital. Health Care Manag Sci, Vol. 6, No. 2, pp. 105–116.

Lange, V. (1997), Blueprints Designed to Improve Quality of Care Using simulation Tools, http://www.medmodel.com/stories.html (refereed: October 10, 2005.

Law, A.M. and Kelton, W.D. 2000. Simulation Modeling and Analysis. The McGraw-Hill Companies. Columbus.

Law, A. and McComas, M. (2001), How to build valid and credible simulation models, in Proceedings of the 2001 Winter Simulation Conference, IEEE Computer Society Press, pp. 22-29.

Levy, J. L., Watford, B. A., & Owen, V. T. (1989), Simulation Analysis of an Outpatient Services Facility. Journal of the Society for Health Systems, Vol. 1, No. 2, pp. 35-49.

Lopez-Valcarcel, B.G. and Perez, P.B. (1994), Evaluation of alternative functional designs in an emergency department by means of simulation. Simulation, Vol. 63, No. 1, pp. 20-29.

Lowery, J.C. (1991), Design and Validation of Methodologies for Determining Critical Care Bed Requirements, Health Services Organization and Policy, University of Michigan.

Lowery, J. (1996), Design of Hospital Admissions Scheduling System Using Simulation. In Proceedings of the 1996 Winter Simulation Conference, Coronado, California, United States, pp. 1199-1204.

Mahachek, A. R. (1992), An introduction to patient flow simulation for healthcare managers. Journal of the Society for Health Systems, Vol. 3, No. 3, pp. 73-81.

Martin E., Grønhaug, R., and Haugene, K. (2003), Proposals to Reduce Over-Crowding, Lengthy Stays and Improve Patient Care: Study of the Geriatric Department in Norway's Largest Hospital. In Proceedings of the 2003 Winter Simulation Conference, Association for Computing Machinery, New York, pp. 1876–1881.

Martinez-Garcia, A.I., and Mendez-Olague, R. (2005), Process Improvement with Simulation in the Health Sector, http://www.eu-lat.org/eHealth/Martinez-and-Mendez.pdf (refereed: April 20, 2005).

McCabe, J.B. (2001), Emergency department overcrowding: a national crisis. Acad Med, Vol. 76, pp. 672–674.

McGuire, F. (1994), An Emergency Department Simulation Model Used to Evaluate Alternative Nurse Staffing and Patient Population Scenarios. In 1994 Winter Simulation Conference Proceedings, IEEE, Orlando, FL.

McGuire, F. (1997), Using Simulation to Reduce Length of Stay in Emergency Departments. J Soc Health Syst, Vol. 5, pp. 81–90.

Merkle, J.F. (2005), Computer Simulation: A Methodology to Improve the Efficiency in the Brooke Army Medical Center Family Clinic, http://www.ache.org/mbership/AdvtoFellow/CASERPTS/merkle00.cfm (refereed: January 24, 2005).

Moreno, L., R.M. Agilar, C.A. Martin, J.D. Pinero, J.I. Estevez, J.F. Sigut, J.L. Sanchez, and Jimenez, V.I. (1999), Patient-Centered Simulation Tool for Aiding in Hospital Management. Simulation Practice and Theory, Vol. 7, pp. 373-393.

Morrison, B.P., and Bird, B.C. (2003), A Methology for Front Office and Patient Care Processes in Ambulatory Health Care. In Proceedings of the 2003Winter Simulating Conference.

Paksuniemi, M. et al. (2004), Wireless sensor and data transmission needs and available technologies for patient monitoring in the operation room and intensive care unit. IEEE Instrumentation and Measurement Technology Conference.

Pitt, M. (1997), A generalized simulation system to support strategic resource planning in healthcare. In Proceedings of the 1997 Winter Simulation Conference, Association for Computing Machinery, New York, pp. 1155-1162.

Pritsker, B. 1986. Introduction to Simulation and SLAM II. Systems Publishing Corporations. Indiana.

Puurtinen, M., Hyttinen, J., Malmivuo, J. (2003), Effect of Interelectrode Distance on ECG Potentials – Modeling Approach vs. Clinical Data. International Journal of Bioelectromagnetism, Vol. 5, No. 1.

Ramis, F.J., J.L. Palma, and Baesler, F.F. (2001), In Proceedings of the 2001 Winter Simulation Conference. ed. B.A. Peters, J.S. Smith, D.J. Medeiros, and M.W. Rohrer, eds.

Ratcliffe, J., T. Young, M. Buxton, T. Eldabi, R. Paul, A. Burroughs, G. Papatheodoridis, and Rolles, K. (2001), A Simulation Modeling Approach to Evaluating Alternative Policies for the Management of the Waiting List for Liver Transplantation. Health Care Manag Sci, Vol. 4, pp. 117-124.

Richard, J.M. (1997), Animated Simulation: Determining Cost Effective Nurse Staffing for an Acute Care Unit. Storming Media.

Richardson, L.D., Asplin, B.R., and Lowe, R.A. (2002), Emergency department crowding as a health policy issue: past development, future directions. Ann Emerg Med, Vol. 40, pp. 388–393.

Riley, L.A. (1999), Applied Simulation as a Decision Support System Tool: The Design of a New Internal Medicine Facility. In Proceedings of the 32nd Hawaii International Conference on System Sciences, pp. 1-6.

Ritondo, M., and Freedman, R. (1993), The Effects of Procedure Scheduling On Emergency Room Throughput: A Simulation Study. In Proceedings of the 1993 SCS Western Simulation Multiconference on Simulation in the Health Sciences and Services, pp. 8-11.

Rossetti, M.D., G.F. Trzcinski, and Syverud, S.A. (1999), Emergency Department Simulation and Determination of Optimal Attending Physician Staffing Schedules. In Proceedings of the 1999 Winter Simulation Conference, pp. 1532–1540.

Ruohonen, T. (2004), Poliklinikan toiminnan simulointi. Jyväskylän yliopisto. Tietotekniikan laitoksen pro gradu-työ.

Saunders, C.E., P.K. Makens, and Leblanc, L.J. (1989), Mod0eling Emergency Department Operations Using Advanced Computer Simulation Systems. Ann Emerg Med, Vol. 18, No. 2, pp. 134–140.

Sinreich, D. and Marmor, Y.N. (2004), A Simple and Intuitive Tool for Analyzing Emergency Department Operations, Haifa, Israel.

Su, S., and Shih, C-L. (2003), Modeling an Emergency Medical Services System Using Computer Simulation. International Journal of Medical Informatics Vol. 72, pp. 57-72.

Tanaka, K., J. Sato, J. Guo, A. Takada, and Yoshihara, H. (2004), A Simulation Model of Hospital Management Based on Cost Accounting Analysis According to Dicease. Journal of Medical Systems, Vol. 28, pp. 689- 710.

Taylor, S., and Kuljis, J. (2001), Simulation in Health Care Management: Modeling an Outpatient Clinic. Operational Research Society.

Triola, M.M., and Holzman, R.S. (2004), Computer Simulation of Pathogen Transmission in the Medical Intensive Care Unit: A Comparison of Two Probabilistic Methods. MEDINFO, pp. 1277-1281.

Trzeciak, S., and Rivers, E.P. (2003), Emergency department overcrowding in the United States: an emerging threat to patient safety and public health. Emerg Med J, Vol. 20, pp. 402–405.

Van Merode, G.G., Groothuis, S., Schoenmakers, M. and Boersna, H.H. (2002), Simulation Studies and the Alignment of Interests. Health Care Manag Sci, Vol. 5, No. 2, pp. 97–102.

Velianoff, G.D. (2002), Overcrowding and diversion in the emergency department: the health care safety net unravels. Nurs Clin North Am, Vol. 37, pp. 59–66.

Vemuri, S. (1984), Simulated Analysis of Patient Waiting Time in an Outpatient Pharmacy. American Journal of Hospital Pharmacy, Vol. 41, No. 6, pp. 1127-1130.

Vissers, J.M. (1995), Patient Flow Based Allocation of Hospital Resources. IMA J Math Appl Med Biol, Vol. 12, no. 3-4, pp. 259–274.

Vissilacopoulos, G. A. (1985), Simulation model for bed allocation to hospital inpatient departments. Simulation, Vol. 45, pp. 233-241.

Weng, M. L. and Houshmand, A.A. (1999), Healthcare simulation: a case study at a local clinic. In Proceedings of the 1999 Winter Simulation Conference, Cincinnati, USA, pp. 1577-1584.

Wilt, A. and Goddin, D. (1989), Health Care Case Study: Simulating Staffing Needs and Work Flow in an Outpatient Diagnostic Center. Industrial Engineering, pp. 22-26.

Wright, M.B. (1987), The application of a surgical bed simulation model. European Journal of Operational Research, vol. 32, pp. 32-36.

APPENDIX 1

HOITOJAKSO	Hoitojakson numero:	

Hoitojaksoa koskevat tiedot

Tuloaika pp: kk: vuosi: kellonaika:

Sukupuoli 1) mies 2) nainen **Ikä** ______	**Millä tullut** A) Ambulanssilla B) Taksilla C) Omalla autolla D) Linja-autolla E) Kävellen F) Muulla, millä ______
Edellisestä käynnistä alle 48t? 1) Kyllä 2) Ei	**Suoritus-kyky** 1) Omatoiminen 2) Tarvitsee jonkin verran apua 3) Tarvitsee paljon apua 4) Muiden avusta täysin riippuvainen 5) Lapsi (< 7 vuotias)
Mistä tullut 1) Tk:n ppkl, mikä tk ______ 2) Tk:n v-os, mistä ______ 3) Toinen sairaala/laitos, mistä ______ 4) Onnettomuuspaikalta 5) Kotoa 6) Muualta	**Triage** A) Hoito aloitettava välittömästi B) Hoito aloitettava kiireellisesti, < 10 min C) Hoito aloitettava kiireellisesti, < 1 tunti D) Hoito aloitettava < 2 tuntia saapumisesta

Tulosyy/oire (merkitään VAIN YKSI, tärkein)

Sisätaudit	**Neurologia**	**Kirurgia/traumat**
1) Hengenahdistus	8) Kouristelu	14) Nilkan alueen vamma
2) Rintakipu	9) Halvausoireet	15) Lonkan alueen vamma
3) Rytmihäiriö	10) Tajuttomuus	16) Yläraajan alueen vamma
4) Myrkytys	11) Päänsärky	17) Monivamma tai pään vamma
5) Raajan turvotus/kipu	12) Huimaus	18) Haava ja/tai jännevamma
6) Kuume, tulehdusoireet	13) Muut	19) Palovamma
7) Muut		20) Muut
Kirurgia/GE-potilaat	**Lastentaudit**	
21) Vatsakipu	25) Tulehdusoireet	
22) Verioksennus/-uloste	26) Hengenahdistus	
23) Virtsaumpi	27) Oksennus, ripuli	
24) Muut	28) Muut	

Potilas ohjataan

1) Erikoissairaanhoidon päivystykseen 2) Terveyskeskuksen yöpäivystykseen

Ajat	pp	kk	vvvv	tunti	minuutti
Hoitajakontakti					
Lääkärikontakti					
Tutkimusten tilaus: Rtg					
Tutkimukset valmiit: Rtg					
Tutkimusten tilaus: Lab					
Tutkimukset valmiit: Lab					
Hoitopäätöskontakti					
Sair. kert. kirjoitukseen					
Sair. kert. valmis					
Poistumisaika päiv.pkl					

ICD 10 diagnoosi (päiv. polilta poistuttaessa) ______

Toimenpidekoodi					

Minne siirretty

1) Tk:n v-os, mihin ______
2) Kotiin
3) Toinen sairaala/laitos, mihin ______
4) Päivystysosastolle
5) Erikoissairaanhoidon v-osastolle, numero: ______
6) CCU:hun
7) Teho-osastolle
8) Muualle, mihin ______

Poistumistila

1) Elossa
2) Kuollut

Konsultaatiot

Valitse konsultoidut erikoisalat ja merkitse konsultaatioiden kokonaislukumäärä

O Sisätaudit	kpl	
O Kirurgia	kpl	
O Neurologia	kpl	
O Anestesiologia	kpl	
O Muu	kpl	
Yhteensä	kpl	

Millä lähtenyt

Ulos sairaalasta
A) Ambulanssilla B) Taksilla
C) Omalla autolla D) Linja-autolla
E) Kävellen
F) Muulla, millä ______

Sisälle sairaalaan
A) Kävellen B) Pyörätuolilla
C) Rullasängyllä

Sairaalasta poistumistiedot

Sairaalasta poistumispäivä ____/____/____ (pp/kk/vvvv)

ICD 10 diagnoosi (sairaalasta lähdettäessä) ______

Sairaalasta poistumistila 1) Elossa, kotiin 2) Elossa, toinen sairaala tai laitos, mikä ______ 3) Kuollut

APPENDIX 2

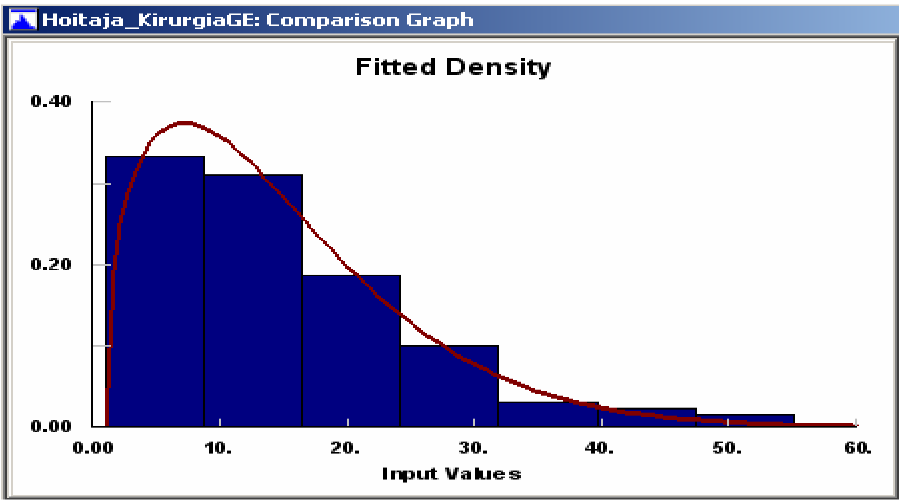
SurgeryGE

The distributions for SurgeryGE defined from the collected data by using the statistical software Stat::Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Weibull(1., 1.4, 15.2)	100
Gamma(1., 1.92, 7.12)	21.3
Inverse Gaussian(1., 16., 13.6)	16.9
Pearson 6(1., 27.8, 2.58, 6.17)	12.7
Inverse Weibull(1., 1.21, 0.146)	12.5
Lognormal(1., 2.33, 0.797)	9.74
Pearson 5(1., 1.65, 12.2)	8.15
LogLogistic(1., 2.12, 10.5)	6.34
Beta(1., 1.43e+006, 1.87, 1.95e+005)	4.52
Erlang(1., 2., 7.12)	4.2
Exponential(1., 13.6)	5.54e-003
Rayleigh(1., 12.2)	6.57e-007
Pareto(1., 0.411)	0.
Johnson SB(1., 35.5, 0.565, 0.767)	0.
Triangular(0., 55.7, 5.18)	0.
Uniform(1., 55.)	0.
Chi Squared(1., 11.3)	0.
Power Function(1., 55.6, 0.599)	0.

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Weibull).

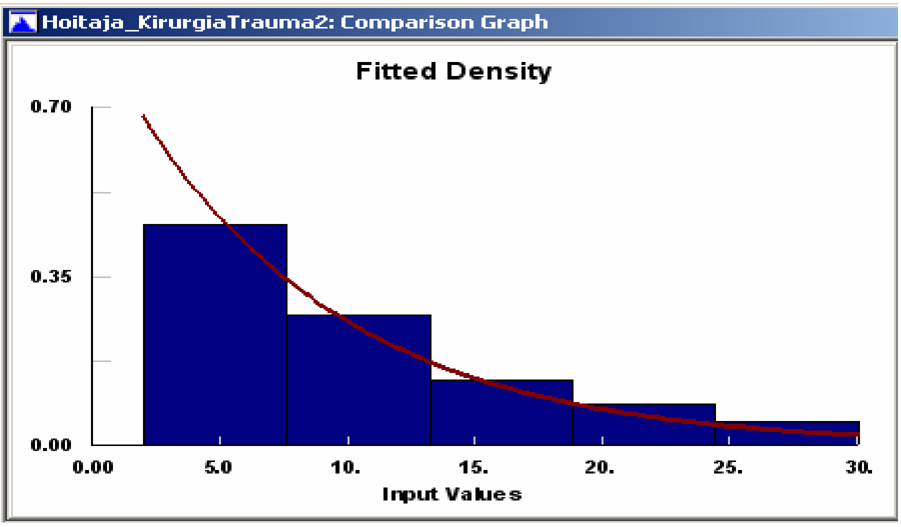
SurgeryTrauma

The distributions for SurgeryTrauma defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Exponential(2., 8.24)	100
Inverse Weibull(2., 1.28, 0.243)	25.6
Pearson 5(2., 1.67, 7.47)	11.3
Weibull(2., 1.33, 9.33)	9.22
Inverse Gaussian(2., 9.78, 8.24)	6.79
LogLogistic(2., 2.01, 6.21)	3.42
Lognormal(2., 1.83, 0.822)	2.63
Pearson 6(2., 20.6, 2.28, 6.5)	2.57
Gamma(2., 1.92, 4.3)	0.845
Beta(2., 6.37e+003, 1.73, 1.29e+003)	0.554
Power Function(2., 30.2, 0.661)	0.271
Pareto(2., 0.703)	2.21e-002
Triangular(1., 31.8, 4.65)	0.
Erlang(2., 2., 4.3)	0.
Rayleigh(2., 7.68)	0.
Uniform(2., 30.)	0.
Chi Squared(2., 7.18)	0.
Johnson SB(2., 19.2, 0.362, 0.686)	0.

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Exponential).

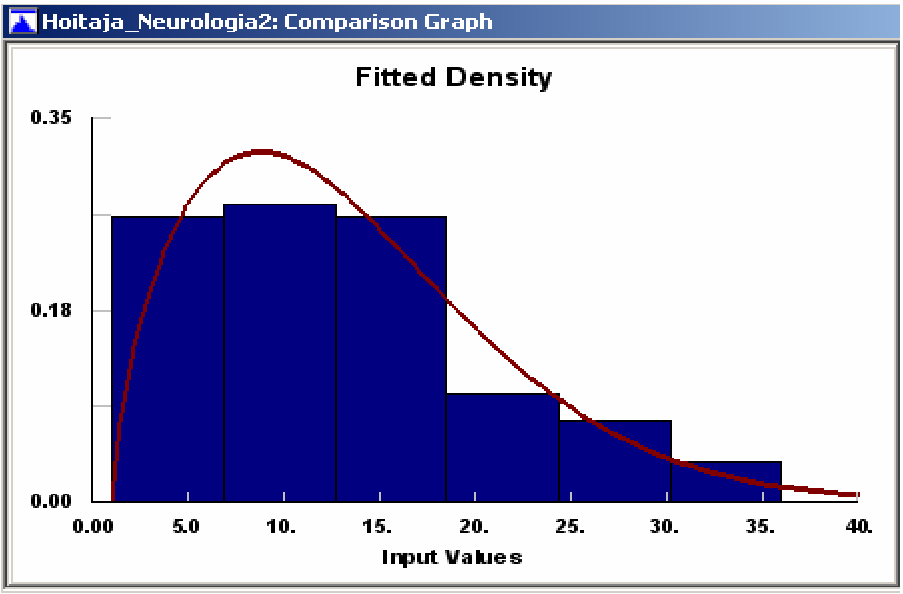
Neurology

The distributions for Neurology defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Weibull(1., 1.63, 14.)	99.6
Pearson 6(1., 36.3, 2.91, 9.38)	46.4
Lognormal(1., 2.29, 0.734)	38.3
Gamma(1., 2.59, 4.71)	28.1
Beta(1., 134, 2.13, 20.6)	25.2
LogLogistic(1., 2.41, 10.4)	15.4
Inverse Gaussian(1., 17.6, 12.2)	3.36
Triangular(0., 38.4, 4.74)	1.6
Inverse Weibull(1., 1.17, 0.149)	0.95
Pearson 5(1., 1.7, 12.3)	0.868
Rayleigh(1., 10.5)	0.463
Exponential(1., 12.2)	0.347
Erlang(1., 3., 4.71)	0.
Pareto(1., 0.424)	0.
Power Function(1., 36., 0.793)	0.
Uniform(1., 36.)	0.
Chi Squared(1., 10.9)	0.
Johnson SB	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Weibull).

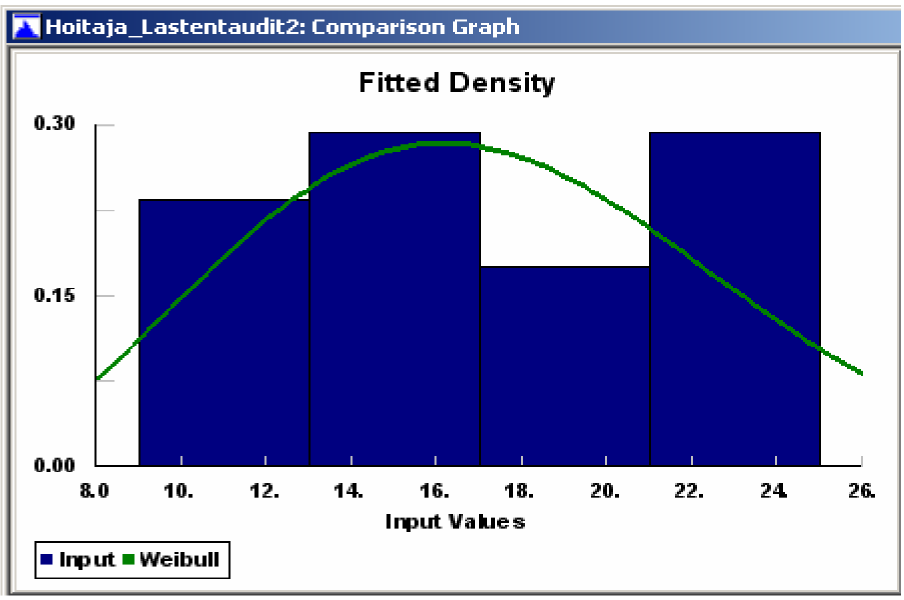
Pediatric

The distributions for Pediatric defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Weibull(5., 2.44, 13.9)	99.4
LogLogistic(5., 3.2, 11.4)	95.2
Gamma(5., 4.19, 2.93)	95.
Pearson 6(5., 345, 4.35, 123)	93.5
Erlang(5., 4., 3.07)	90.5
Rayleigh(5., 9.53)	78.7
Lognormal(5., 2.39, 0.528)	56.9
Chi Squared(5., 11.8)	46.3
Power Function(5., 25.1, 1.63)	46.
Pearson 5(5., 3.52, 33.)	25.5
Beta(5., 25., 2.02, 1.71)	18.9
Inverse Weibull(5., 1.86, 0.121)	15.5
Triangular(5., 26.8, 24.2)	6.41
Uniform(5., 25.)	4.38
Exponential(5., 12.3)	1.85
Pareto(5., 0.844)	7.5e-002
Inverse Gaussian	no fit
Johnson SB	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Weibull).

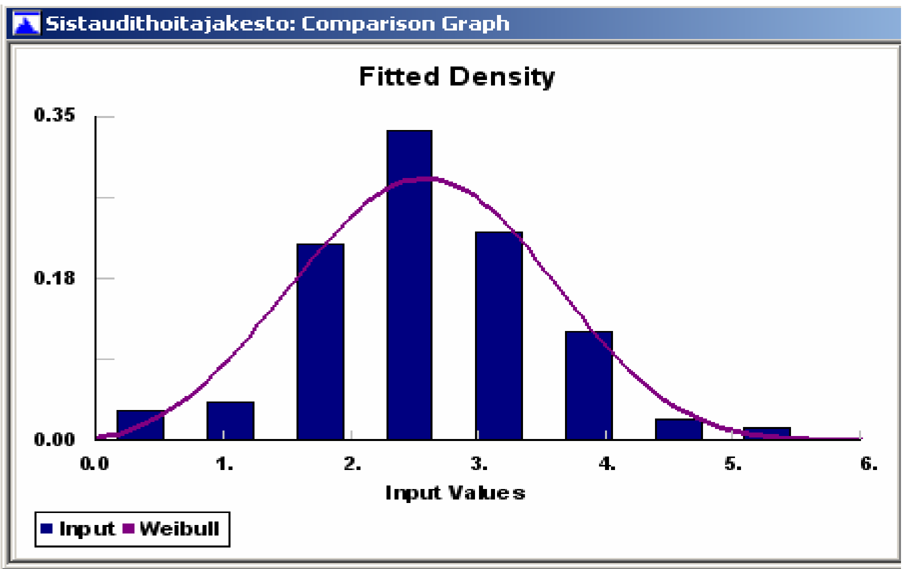
Internal medicine

The distributions for Internal medicine defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Weibull(-0.251, 3.3, 3.16)	56.8
Lognormal(-7.63, 2.32, 8.99e-002)	44.3
Pearson 5(-9.29, 168, 1.99e+003)	41.5
Gamma(-2.76, 33., 0.162)	33.8
Erlang(-2.76, 33., 0.162)	31.8
LogLogistic(-13.9, 31.8, 16.5)	19.9
Beta(0., 5.62, 3.84, 4.42)	18.6
Inverse Gaussian(-7.78, 1.32e+003, 10.4)	15.9
Normal(2.59, 0.922)	15.
Johnson SU(2.57, 2.9, -4.72e-003, 3.31)	11.3
Logistic(2.58, 0.519)	6.99
Pearson 6(0., 74., 7.89, 225)	2.92
Extreme Value IA(2.15, 0.871)	2.79e-002
Triangular(-4.6e-002, 5.68, 2.3)	1.37e-003
Extreme Value IB(3.07, 1.01)	8.48e-004
Exponential(0., 2.59)	0.
Uniform(0., 5.62)	0.
Chi Squared(0., 3.37)	0.
Power Function(0., 5.62, 1.2)	0.
Rayleigh(-9.02e+152, 6.38e+152)	0.
Inverse Weibull	no fit
Johnson SB	no fit
Pareto	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Weibull).

APPENDIX 3

SurgeryGE

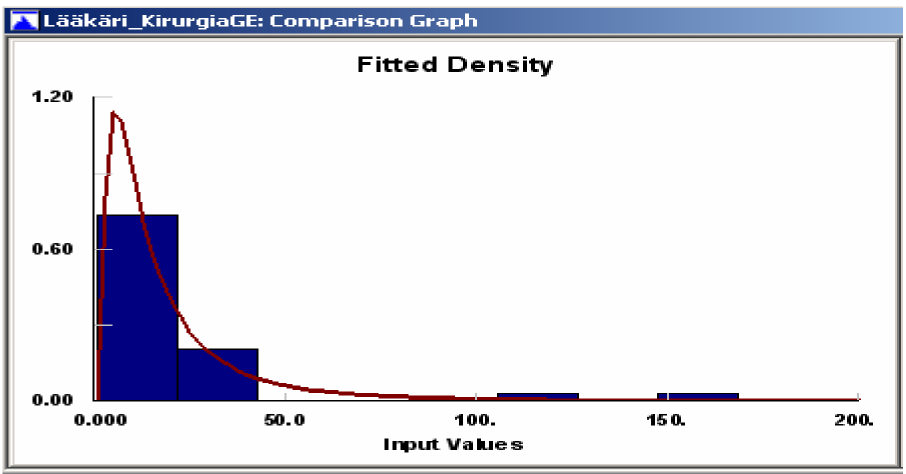
The distributions for SurgeryGE defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
LogLogistic(1., 1.79, 11.)	95.3
Lognormal(1., 2.48, 0.981)	52.9
Inverse Gaussian(1., 13.7, 21.)	45.6
Pearson 6(1., 5.95e-002, 210, 1.51)	40.5
Pearson 5(1., 1.5, 12.4)	38.9
Inverse Weibull(1., 1.33, 0.131)	31.5
Weibull(1., 0.898, 20.2)	26.7
Johnson SB(1., 202, 2.17, 0.81)	14.2
Erlang(1., 1., 20.5)	10.7
Exponential(1., 21.)	7.86
Gamma(1., 1.02, 20.5)	6.41
Beta(1., 5.01e+006, 0.999, 2.35e+005)	2.83
Power Function(1., 211, 0.349)	7.44e-006
Pareto(1., 0.397)	5.62e-006
Triangular(0., 174, 0.)	0.
Rayleigh(1., 27.8)	0.
Uniform(1., 168)	0.
Chi Squared(1., 12.9)	0.

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.

In the MedModel software the Loglogistic distribution was not included in the distribution definition, which is why the second best distribution was selected to represent the duration of the doctor contact. This distribution was the Lognormal distribution.



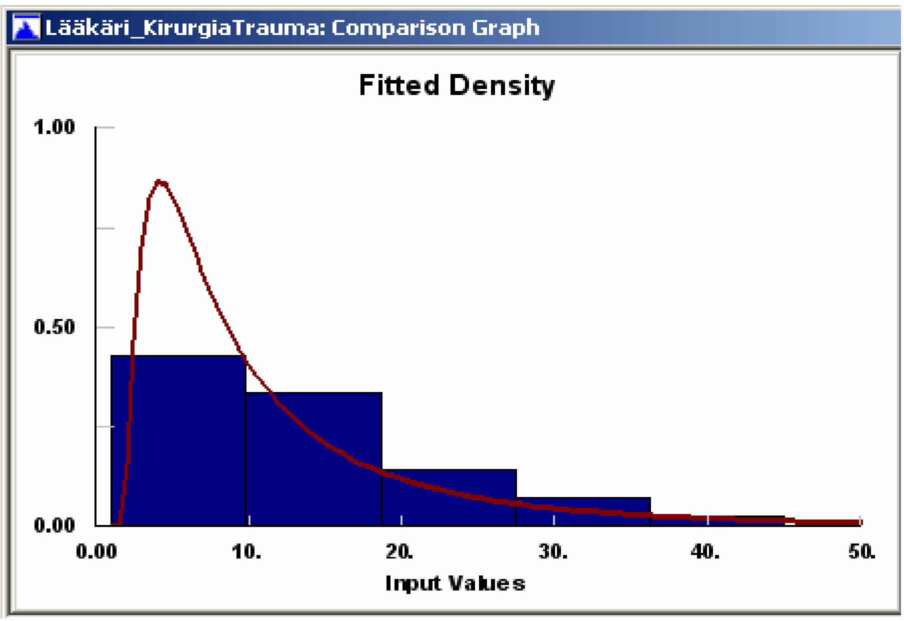
The graphical presentation of the most suitable distribution (Lognormal) for the doctor contact.

SurgeryTrauma

The distributions for SurgeryGE defined from the collected data by using the statistical software Stat:Fit were as follows:

distribution	rank
Inverse Gaussian(1., 10.2, 11.2)	75.3
Lognormal(1., 2.09, 0.883)	64.
Inverse Weibull(1., 1.09, 0.195)	61.8
Weibull(1., 1.28, 12.4)	56.6
Pearson 6(1., 27.9, 2.07, 5.98)	43.2
Exponential(1., 11.2)	40.9
Pearson 5(1., 1.34, 7.17)	39.7
LogLogistic(1., 1.95, 8.27)	35.7
Gamma(1., 1.69, 6.63)	30.6
Beta(1., 3.86e+003, 1.68, 580)	20.
Erlang(1., 2., 6.63)	0.58
Triangular(0., 46.8, 1.11)	5.55e-002
Rayleigh(1., 10.5)	5.81e-003
Power Function(1., 61.1, 0.499)	4.61e-004
Chi Squared(1., 9.07)	3.12e-004
Pareto(1., 0.455)	2.63e-006
Uniform(1., 45.)	0.
Johnson SB(1., 37.3, 0.967, 0.827)	0.

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



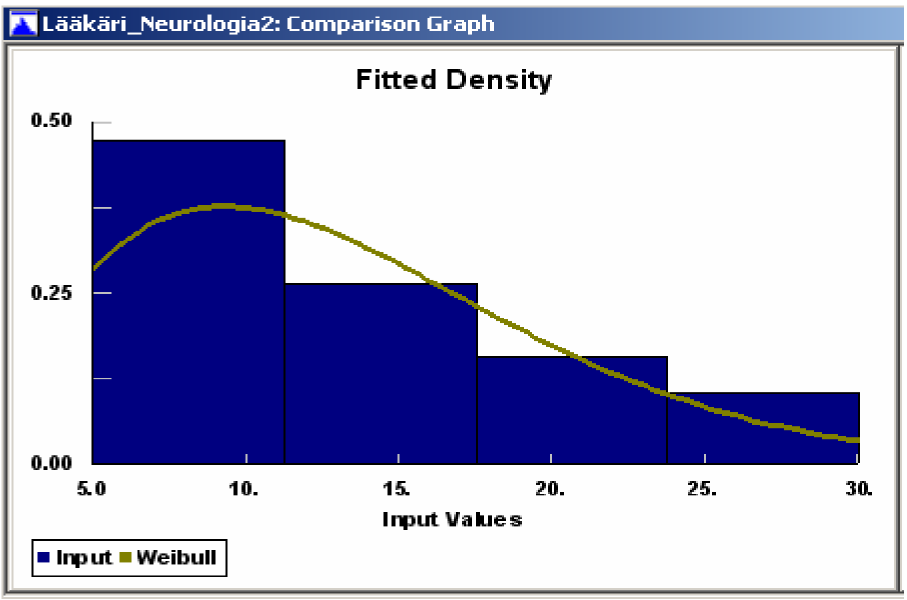
The graphical presentation of the most suitable distribution (Inverse Gaussian) for the doctor contact.

Neurology

The distributions for Neurology defined from the collected data by using the statistical software Stat:Fit were as follows:

distribution	rank
Weibull(2., 1.66, 12.8)	79.
Gamma(2., 2.26, 5.04)	64.
Erlang(2., 2., 5.71)	63.3
Triangular(2., 33.8, 3.67)	56.2
Pearson 6(2., 1.22e+003, 2.46, 267)	54.5
LogLogistic(2., 2.26, 9.55)	52.8
Beta(2., 30., 1.63, 2.71)	41.
Rayleigh(2., 9.5)	40.9
Lognormal(2., 2.2, 0.739)	34.8
Inverse Gaussian(2., 16.8, 11.4)	23.1
Pearson 5(2., 1.92, 13.)	16.5
Inverse Weibull(2., 1.38, 0.163)	16.1
Exponential(2., 11.4)	16.
Power Function(2., 31.7, 0.839)	5.33
Uniform(2., 30.)	2.23
Chi Squared(2., 9.99)	0.837
Pareto(2., 0.572)	2.14e-002
Johnson SB	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Inverse Gaussian) for the doctor contact.

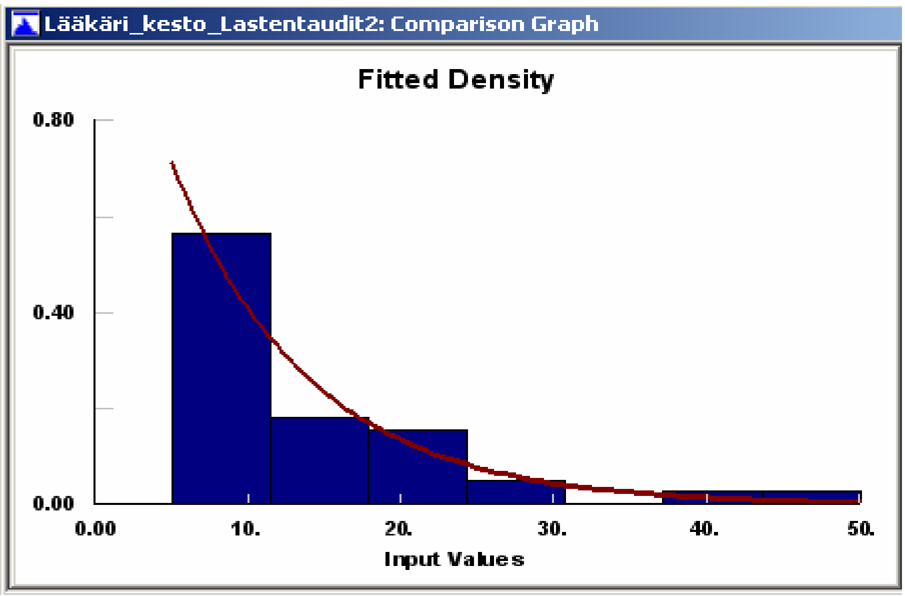
Pediatric

The distributions for Pediatric defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Exponential(5., 9.03)	100
Inverse Weibull(5., 1.69, 0.167)	0.419
Weibull(5., 1.38, 11.8)	0.369
Pearson 5(5., 2.6, 17.5)	0.141
LogLogistic(5., 2.54, 7.93)	0.128
Pearson 6(5., 0.951, 21.5, 2.9)	0.1
Pareto(5., 1.15)	8.15e-002
Lognormal(5., 2.11, 0.678)	6.47e-002
Inverse Gaussian(5., 26.8, 9.03)	1.32e-002
Beta(5., 8.63e+003, 2.13, 1.72e+003)	6.08e-003
Chi Squared(5., 9.27)	3.59e-005
Rayleigh(5., 9.85)	9.94e-007
Erlang(5., 6., 1.5)	9.66e-007
Gamma(5., 6.01, 1.5)	9.04e-007
Power Function(5., 54., 0.563)	0.
Triangular(4., 51.7, 4.)	0.
Uniform(5., 50.)	0.
Johnson SB	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Exponential) for the doctor contact.

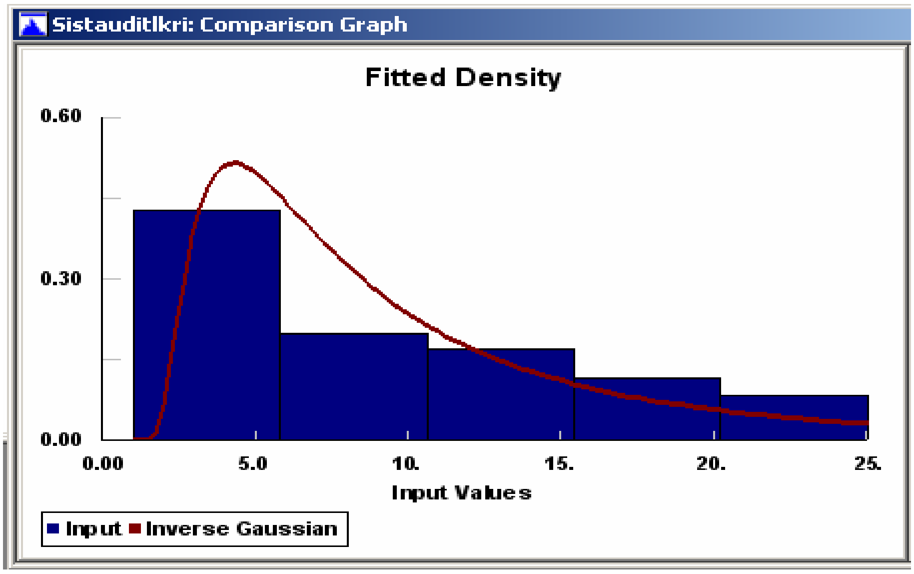
Internal medicine

The distributions for Pediatric defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Inverse Gaussian(1., 11.2, 9.57)	67.6
Triangular(0., 28., 3.2)	44.5
Pearson 5(1., 1.48, 7.62)	42.2
Lognormal(1., 2.02, 0.807)	33.
Inverse Weibull(1., 1.12, 0.204)	28.7
Erlang(1., 2., 4.33)	20.7
Weibull(1., 1.54, 11.)	15.5
LogLogistic(1., 2.13, 7.84)	13.6
Beta(1., 25., 1.26, 1.89)	12.8
Pearson 6(1., 1.17e+003, 2.15, 259)	11.9
Gamma(1., 2.21, 4.33)	10.
Power Function(1., 25.5, 0.845)	6.56
Exponential(1., 9.57)	5.38
Uniform(1., 25.)	0.36
Rayleigh(1., 8.34)	0.196
Chi Squared(1., 8.48)	1.18e-002
Pareto(1., 0.472)	3.65e-006
Johnson SB(1., 22., 0.222, 0.663)	0.

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Exponential) for the doctor contact.

APPENDIX 4

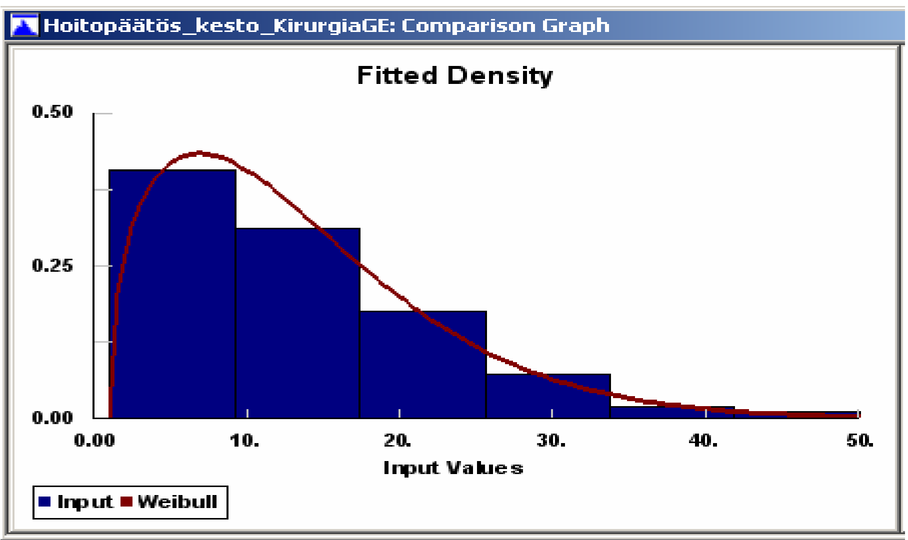
SurgeryGE

The distributions for Pediatric defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Weibull(1., 1.42, 13.8)	100
Inverse Weibull(1., 1.3, 0.156)	49.7
Erlang(1., 2., 5.87)	41.5
Inverse Gaussian(1., 16.5, 12.2)	28.6
Pearson 5(1., 1.83, 12.9)	22.8
Lognormal(1., 2.24, 0.77)	20.4
Pearson 6(1., 27.7, 2.64, 6.83)	20.
Gamma(1., 2.08, 5.87)	16.5
LogLogistic(1., 2.17, 9.46)	10.2
Beta(1., 1.17e+006, 1.94, 1.81e+005)	6.45
Exponential(1., 12.2)	0.
Triangular(0., 50.8, 4.23)	0.
Pareto(1., 0.43)	0.
Johnson SB(1., 27.4, 0.542, 0.852)	0.
Rayleigh(1., 11.)	0.
Uniform(1., 50.)	0.
Chi Squared(1., 10.4)	0.
Power Function(1., 59.3, 0.549)	0.

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



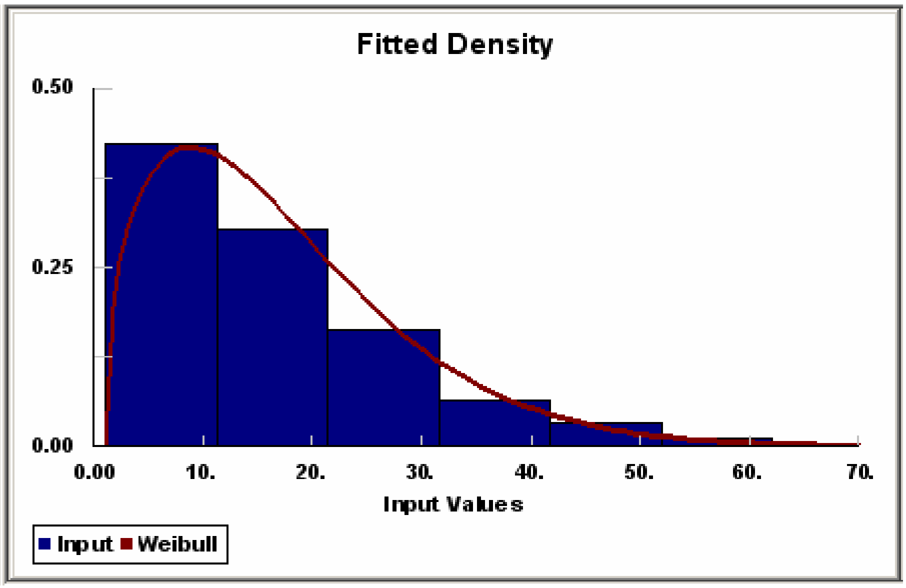
The graphical presentation of the most suitable distribution (Weibull) for the final doctor contact.

SurgeryTrauma

The distributions for SurgeryTrauma defined from the collected data by using the statistical software Stat:Fit were as follows:

distribution	rank
Weibull(1., 1.44, 17.9)	96.8
Pearson 6(1., 1.25e+004, 1.86, 1.42e+003)	81.6
Beta(1., 120, 1.63, 10.3)	51.5
Gamma(1., 1.99, 7.97)	51.1
Erlang(1., 2., 7.97)	49.4
Lognormal(1., 2.49, 0.836)	36.
Johnson SB(1., 101, 1.99, 1.03)	31.3
LogLogistic(1., 2.09, 12.8)	19.7
Inverse Gaussian(1., 16.3, 15.9)	2.56
Exponential(1., 15.9)	0.804
Inverse Weibull(1., 1.06, 0.128)	0.584
Pearson 5(1., 1.36, 10.9)	0.455
Triangular(0., 63.2, 2.75)	2.4e-002
Pareto(1., 0.392)	0.
Rayleigh(1., 14.1)	0.
Uniform(1., 62.)	0.
Chi Squared(1., 13.1)	0.
Power Function(1., 72.7, 0.562)	0.

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



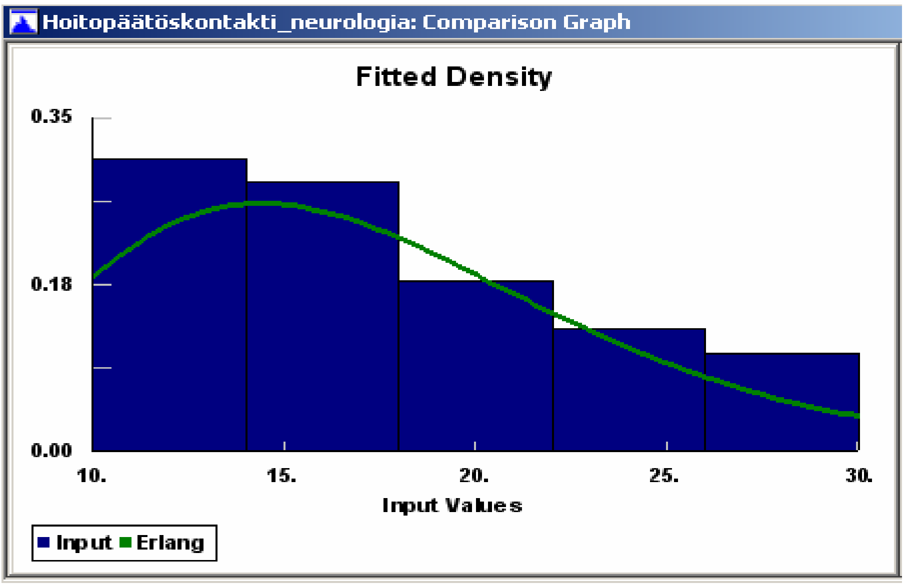
The graphical presentation of the most suitable distribution (Weibull) for the final doctor contact.

Neurology

The distributions for Neurology defined from the collected data by using the statistical software Stat:Fit were as follows:

distribution	rank
Erlang(1., 6., 2.69)	100
LogLogistic(1., 4.07, 14.8)	80.5
Gamma(1., 6.28, 2.57)	76.5
Pearson 6(1., 23.6, 10.3, 16.1)	61.5
Weibull(1., 2.66, 18.2)	59.8
Lognormal(1., 2.7, 0.404)	57.9
Inverse Gaussian(1., 92.5, 16.1)	57.1
Pearson 5(1., 6.48, 89.1)	41.5
Triangular(1., 34.6, 13.9)	28.8
Inverse Weibull(1., 2.85, 8.21e-002)	25.9
Johnson SB(1., 138, 4.59, 2.18)	23.5
Chi Squared(1., 15.9)	17.9
Rayleigh(1., 12.3)	17.
Beta(1., 30., 3.61, 3.46)	6.66
Power Function(1., 32.5, 1.33)	0.146
Uniform(1., 30.)	2.29e-002
Exponential(1., 16.1)	9.63e-006
Pareto(1., 0.361)	0.

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



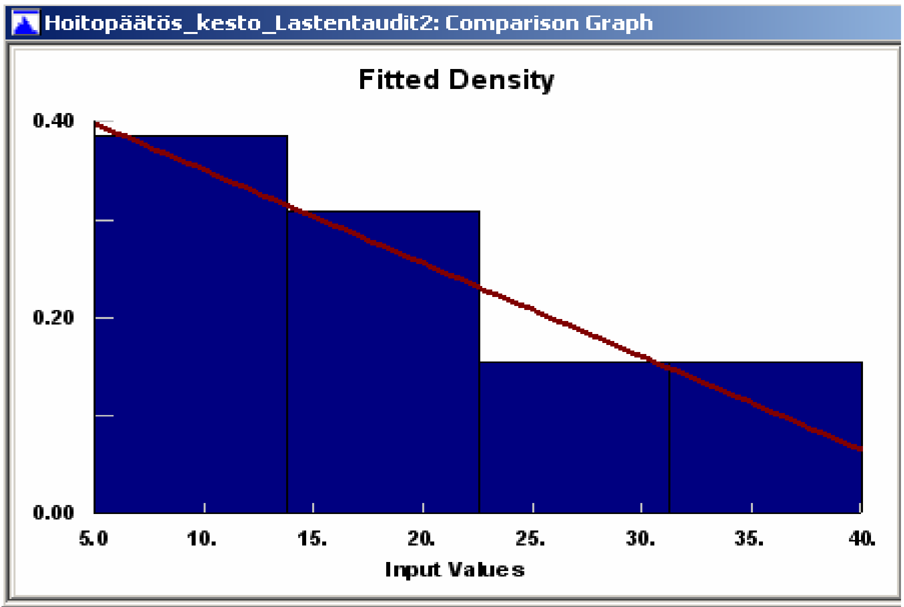
The graphical presentation of the most suitable distribution (Erlang) for the final doctor contact.

Pediatric

The distributions for Pediatric defined from the collected data by using the statistical software Stat:Fit were as follows:

distribution	rank
Triangular(4., 46.9, 4.)	100
Erlang(5., 1., 13.6)	42.
Gamma(5., 1., 13.6)	42.
Exponential(5., 13.6)	42.
Weibull(5., 1.77, 19.)	1.19
Pareto(5., 0.908)	1.17
Pearson 6(5., 40.6, 3.35, 9.)	0.828
Beta(5., 40., 1.6, 2.1)	0.711
LogLogistic(5., 2.44, 14.1)	0.694
Lognormal(5., 2.62, 0.677)	0.675
Uniform(5., 40.)	0.621
Inverse Weibull(5., 1.55, 0.103)	0.513
Pearson 5(5., 2.31, 25.)	0.498
Rayleigh(5., 13.8)	0.275
Johnson SB(5., 51., 0.873, 1.01)	0.196
Power Function(5., 41., 1.03)	0.161
Inverse Gaussian(5., 53.8, 13.6)	3.08e-002
Chi Squared(5., 14.7)	2.52e-003

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Triangular) for the final doctor contact.

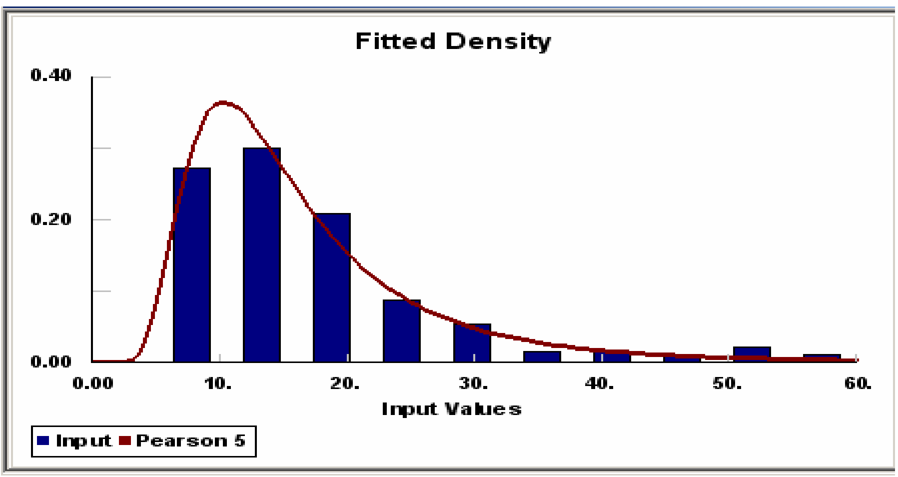
Internal medicine

The distributions for Pediatric defined from the collected data by using the statistical software Stat:Fit were as follows:

distribution	rank
Inverse Weibull(-9.18, 3.71, 4.75e-002)	100.
Pearson 5(-0.515, 4.15, 55.7)	90.9
Johnson SU(3.81, 2.56, -2.92, 1.39)	76.9
Lognormal(2.67, 2.44, 0.675)	75.3
Inverse Gaussian(1.96, 31.3, 15.1)	65.5
Pearson 6(5., 31.5, 2.25, 6.72)	55.2
LogLogistic(5., 2.11, 9.2)	47.2
Gamma(4.73, 1.49, 8.29)	30.7
Weibull(4.9, 1.2, 12.9)	14.4
Beta(5., 1.46e+005, 1.65, 1.95e+004)	8.12
Erlang(4.73, 2., 6.15)	5.09
Extreme Value IA(12.8, 6.65)	0.854
Exponential(5., 12.)	2.92e-002
Chi Squared(-18.7, 35.5)	7.38e-003
Logistic(15.3, 5.17)	3.52e-003
Rayleigh(1.04, 13.5)	5.12e-005
Normal(17., 10.5)	0.
Pareto(5., 0.931)	0.
Triangular(5., 60.6, 5.)	0.
Uniform(5., 60.)	0.
Extreme Value IB(23.1, 14.4)	0.
Power Function(4.98, 60.6, 0.502)	0.
Johnson SB	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.

The most suitable distribution for Pediatric would have been the Inverse Weibull-distribution, but because it was not included in the MedModel software distribution definitions, the second best distribution was selected instead. The second best distribution according to Stat:Fit was Pearson 5.



The graphical presentation of the most suitable distribution (Triangular) for the final doctor contact.

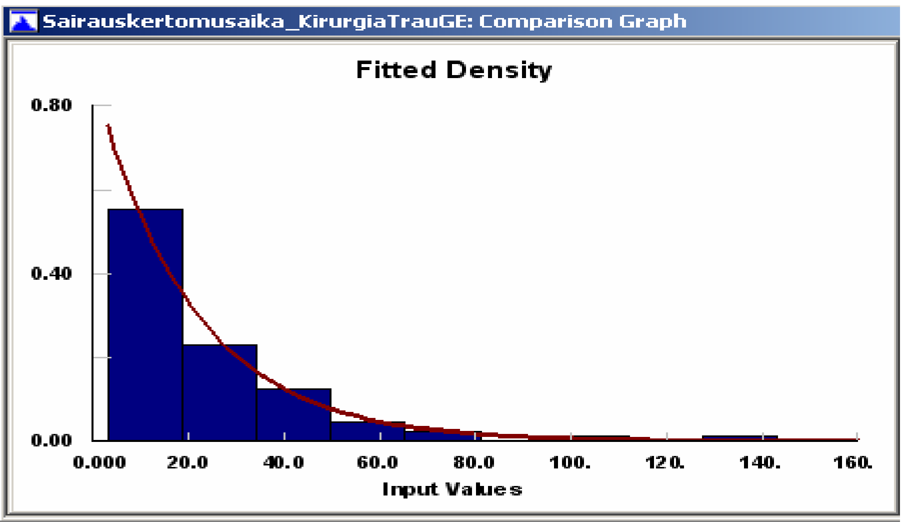
APPENDIX 5

SurgeryGE

The distributions for SurgeryGE defined from the collected data by using the statistical software Stat:Fit were as follows:

distribution	rank
Exponential(3., 20.7)	100
Lognormal(3., 2.57, 1.02)	56.1
Weibull(3., 1.05, 21.7)	39.1
Inverse Gaussian(3., 12.6, 20.7)	34.8
LogLogistic(3., 1.69, 13.4)	25.4
Pearson 6(3., 210, 1.3, 14.)	20.4
Gamma(3., 1.24, 16.7)	14.9
Inverse Weibull(3., 1., 0.128)	9.3
Beta(3., 455, 1.12, 22.6)	8.87
Pearson 5(3., 1.11, 8.66)	8.12
Erlang(3., 1., 16.7)	3.7
Triangular(2., 145, 3.64)	0.
Pareto(3., 0.581)	0.
Johnson SB(3., 91.2, 1.42, 0.822)	0.
Rayleigh(3., 21.9)	0.
Uniform(3., 143)	0.
Chi Squared(3., 14.1)	0.
Power Function(3., 158, 0.405)	0.

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



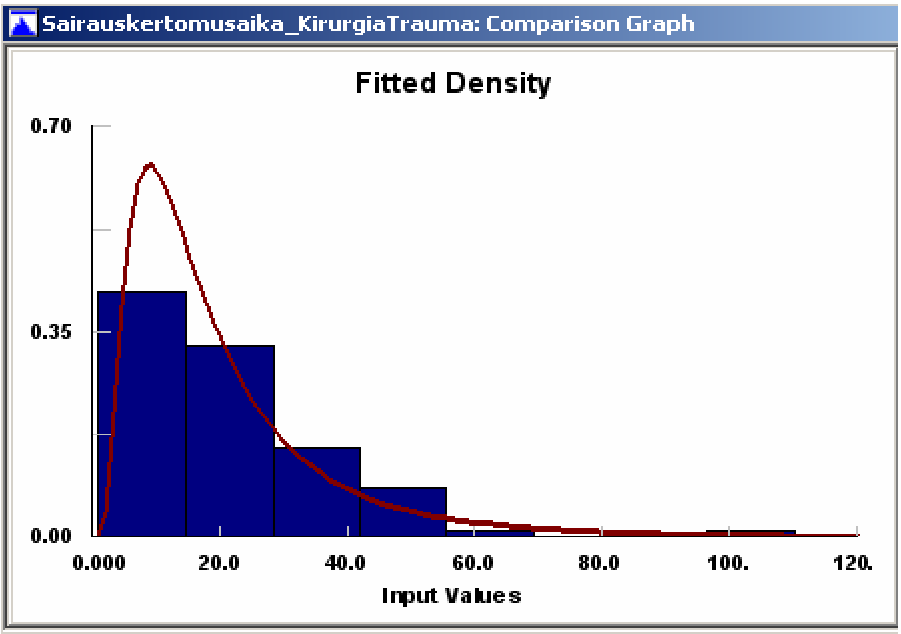
The graphical presentation of the most suitable distribution (Exponential) for the final doctor contact.

SurgeryTrauma

The distributions for SurgeryTrauma defined from the collected data by using the statistical software Stat:Fit were as follows:

distribution	rank
Lognormal(1., 2.69, 0.795)	100
Pearson 6(1., 67., 2.31, 8.84)	53.2
LogLogistic(1., 2.18, 15.)	47.3
Weibull(1., 1.35, 21.8)	45.9
Gamma(1., 1.96, 9.91)	28.4
Inverse Gaussian(1., 23.5, 19.4)	27.9
Beta(1., 110, 1.67, 7.88)	16.1
Erlang(1., 2., 9.91)	14.8
Pearson 5(1., 1.68, 17.9)	4.8
Inverse Weibull(1., 1.24, 0.102)	1.42
Exponential(1., 19.4)	0.
Triangular(0., 111, 1.14)	0.
Pareto(1., 0.367)	0.
Johnson SB(1., 55., 0.632, 0.771)	0.
Rayleigh(1., 18.1)	0.
Uniform(1., 110)	0.
Chi Squared(1., 15.7)	0.
Power Function(1., 388, 0.306)	0.

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



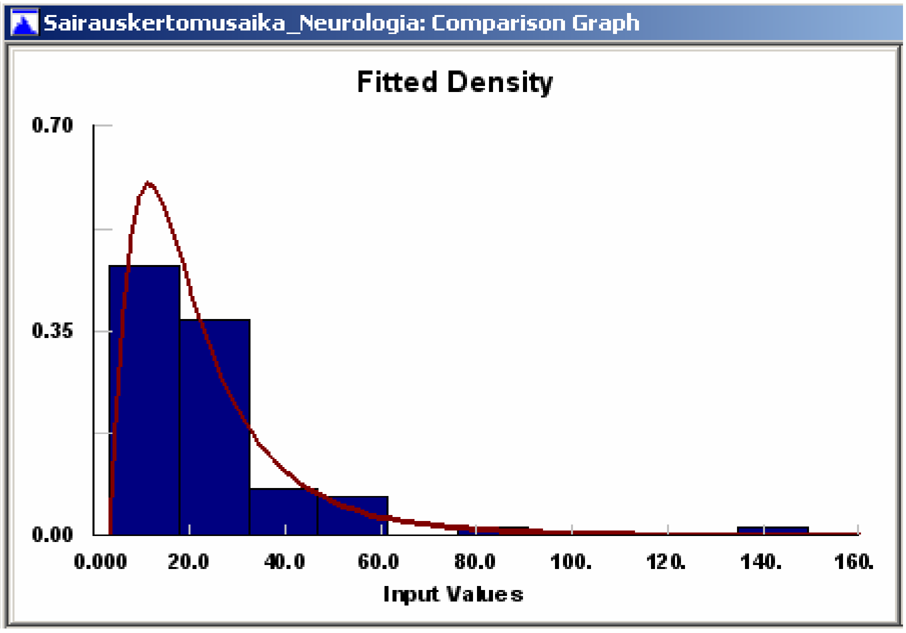
The graphical presentation of the most suitable distribution (Exponential) for the final doctor contact.

Neurology

The distributions for Neurology defined from the collected data by using the statistical software Stat:Fit were as follows:

distribution	rank
Pearson 6(3., 32.3, 2.5, 4.88)	86.6
Lognormal(3., 2.7, 0.846)	63.5
LogLogistic(3., 2.12, 15.2)	57.6
Gamma(3., 1.65, 12.6)	34.6
Weibull(3., 1.2, 22.6)	19.6
Inverse Gaussian(3., 19.9, 20.8)	14.
Beta(3., 716, 1.52, 49.7)	11.9
Pearson 5(3., 1.46, 14.8)	1.9
Inverse Weibull(3., 1.13, 0.104)	1.7
Exponential(3., 20.8)	1.37
Erlang(3., 2., 12.6)	6.59e-003
Triangular(2., 151, 3.96)	0.
Pareto(3., 0.551)	0.
Power Function(3., 377, 0.31)	0.
Rayleigh(3., 21.)	0.
Uniform(3., 149)	0.
Chi Squared(3., 15.9)	0.
Johnson SB	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



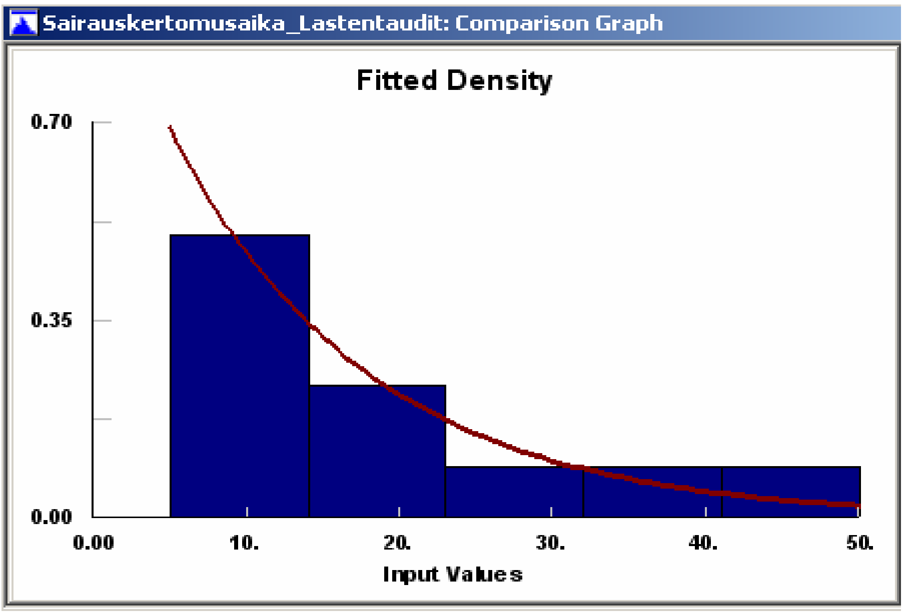
The graphical presentation of the most suitable distribution (Exponential) for the final doctor contact.

Pediatric

The distributions for Pediatric defined from the collected data by using the statistical software Stat:Fit were as follows:

distribution	rank
Exponential(5., 13.1)	100
Pearson 5(5., 1.2, 7.08)	73.1
Inverse Weibull(5., 1.04, 0.172)	65.8
Inverse Gaussian(5., 10.8, 13.1)	44.6
Lognormal(5., 2.25, 0.963)	15.
LogLogistic(5., 1.76, 9.56)	9.75
Pearson 6(5., 34.9, 1.74, 5.2)	7.38
Weibull(5., 1.17, 15.2)	7.37
Beta(5., 50., 0.914, 1.99)	3.45
Gamma(5., 1.7, 7.67)	1.46
Triangular(4., 53.9, 4.)	0.903
Pareto(5., 0.944)	0.747
Power Function(5., 50.7, 0.635)	0.466
Erlang(5., 2., 7.67)	2.86e-002
Rayleigh(5., 13.4)	4.6e-005
Uniform(5., 50.)	0.
Chi Squared(5., 10.4)	0.
Johnson SB	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Exponential) for the final doctor contact.

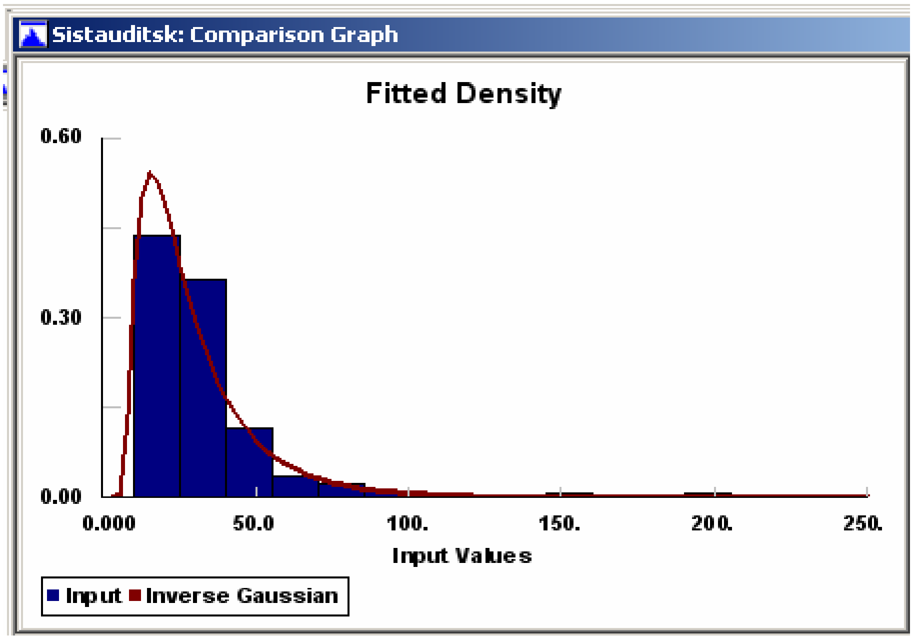
Internal medicine

The distributions for Pediatric defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Inverse Gaussian(3., 49.9, 26.8)	85.4
Lognormal(3., 3.06, 0.653)	72.6
Pearson 6(3., 10.5, 7.6, 3.99)	55.2
LogLogistic(3., 2.68, 21.)	36.2
Erlang(3., 2., 13.4)	26.6
Gamma(3., 2.31, 11.6)	16.7
Pearson 5(3., 2.68, 46.8)	8.71
Weibull(3., 1.39, 29.7)	2.12
Inverse Weibull(3., 1.7, 6.46e-002)	1.05
Exponential(3., 26.8)	2.25e-007
Triangular(3., 206, 9.16)	0.
Pareto(3., 0.473)	0.
Beta(3., 4.44e+003, 0.85, 96.)	0.
Power Function(3., 241, 0.414)	0.
Rayleigh(3., 25.1)	0.
Uniform(3., 205)	0.
Chi Squared(3., 22.2)	0.
Johnson SB	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Inverse Gaussian) for the final doctor contact.

APPENDIX 6

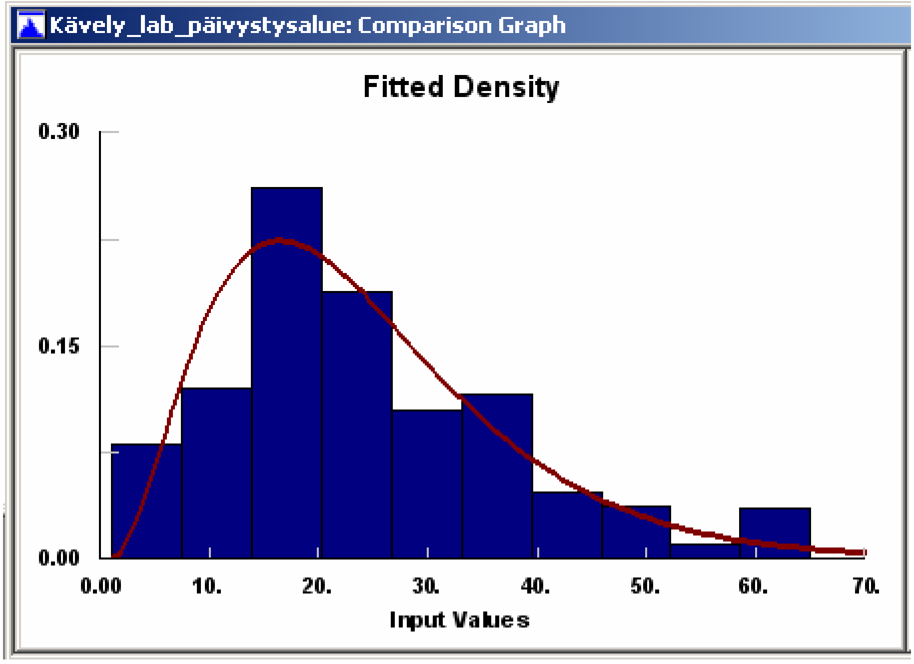
Walking to the emergency department

The distributions for the walking phase defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Erlang(1., 3., 7.74)	99.5
Gamma(1., 3., 7.74)	98.5
LogLogistic(1., 2.72, 20.7)	27.
Pearson 6(1., 223, 2.64, 25.7)	6.92
Weibull(1., 1.82, 26.6)	5.45
Beta(1., 116, 2.19, 8.42)	1.44
Rayleigh(1., 19.3)	4.69e-002
Lognormal(1., 2.97, 0.726)	1.26e-002
Pareto(1., 0.337)	0.
Inverse Gaussian(1., 28.3, 23.2)	0.
Exponential(1., 23.2)	0.
Uniform(1., 65.)	0.
Pearson 5(1., 1.33, 16.9)	0.
Power Function(1., 65.1, 0.838)	0.
Triangular(0., 66.7, 14.9)	0.
Inverse Weibull(1., 0.981, 7.75e-002)	0.
Chi Squared(1., 20.4)	0.
Johnson SB	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Erlang) for the walking phase.

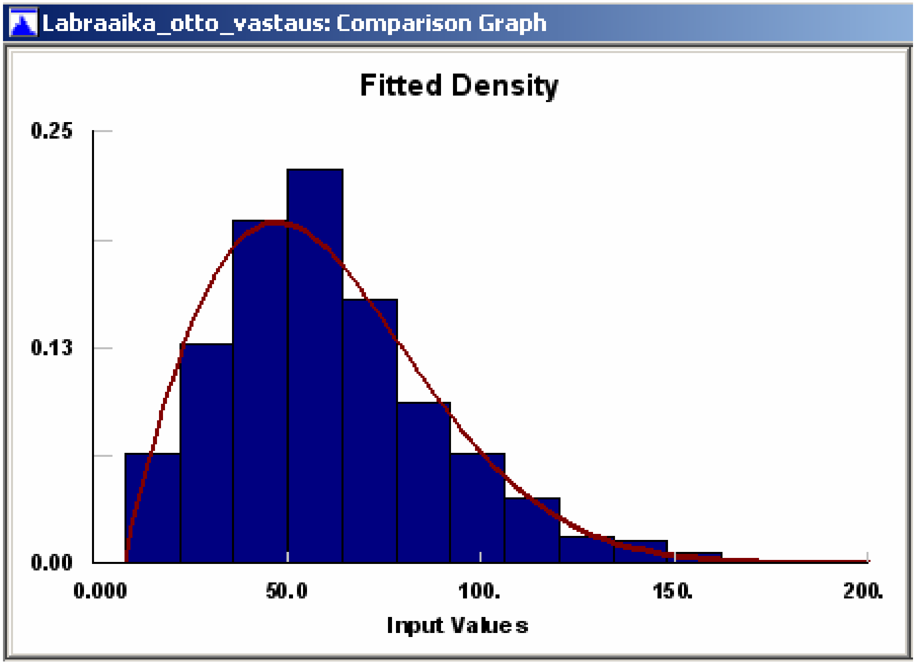
Walking to the laboratory and analysis

The distributions for walking and analysis phases defined from the collected data by using the statistical software Stat:Fit were as follows:

Auto::Fit of Distributions

distribution	rank
Weibull(8., 1.89, 58.5)	99.5
Rayleigh(8., 41.9)	54.2
LogLogistic(8., 2.72, 46.6)	1.99
Gamma(8., 2.72, 19.2)	1.21
Beta(8., 414, 2.43, 16.6)	0.957
Pearson 6(8., 709, 2.59, 36.)	1.27e-002
Erlang(8., 3., 19.2)	6.24e-003
Exponential(8., 52.1)	0.
Pareto(8., 0.529)	0.
Inverse Gaussian(8., 49.8, 52.1)	0.
Lognormal(8., 3.76, 0.746)	0.
Uniform(8., 162)	0.
Pearson 5(8., 1.1, 27.9)	0.
Power Function(8., 162, 0.779)	0.
Triangular(7., 163, 41.9)	0.
Inverse Weibull(8., 0.89, 3.59e-002)	0.
Chi Squared(8., 43.8)	0.
Johnson SB	no fit

Distributions given by the statistical software Stat:Fit. The results are in descending order of goodness of fit.



The graphical presentation of the most suitable distribution (Weibull)