

UNIVERSITY OF LOUISVILLE

MASTERS INTERNSHIP

University of Louisville Hospital Emergency Department Simulation

How to improve patient satisfaction and increase ED's revenue

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Contents

Μ	lanagement Summary	2
1	Introduction of the problem	3
2	Literature Review	4
3	System Description	7
4	Data Analysis	9
5	Experimental Design	21
6	Analysis of Results	25
\mathbf{C}	onclusions	33
Fι	ıture Work	34
R	eferences	35
Α	Model Description	37
в	Flowcharts	53

Management Summary

The University of Louisville Hospital Emergency Department (UofL Hospital ED) is experiencing problems with the large (and increasing) number of patients coming in. Due to hospital space limit, it is almost impossible to expand the number of ED beds. So other solutions need to be found to cope with these extra patients. In order to find solutions without actually affecting the daily operations of the Emergency Department, a simulation model is developed and different ED options are investigated.

The following options are investigated:

- 1. a physician and a nurse see the patient together when both a nurse and a physician are available
- 2. hire a nurse that is dedicated to discharging and admitting patients
- 3. make extra beds available in the hospital where patients can be held to wait when the decision is made that they are going to be admitted to the hospital
- 4. hire some nurses until 8pm instead of 7pm
- 5. the following combinations of the above stated options; 1 + 2, 1 + 3, 2 + 3 and 1 + 2 + 3.

All options shown above are also investigated with one more nurse than what is the case at the moment. In order to find out what the impact of all options can be, all options are simulated with arrival rates varying from the current arrival rate to a 20% higher arrival rate than the current one, in steps of 2.5%.

The results, shown in tables 6.1 and 6.2, indicate that the best option to implement is the combination of 1 + 2 + 3 and the extra nurse. This will make it possible to have more revenue without having to invest significant amounts of money. This combination also is the safest choice to implement, because when one of the options turns out not to work as expected, the other changes will probably make sure that extra revenue can made after.

A problem that is not investigated using the simulation model but that may have its influence on the process and throughput times at the ED is the fact that around the nurse shift changes in the hospital, the number of people that are put in their assigned bed (when they are going to be admitted to the hospital) drastically decreases. This cannot be explained by anything other than human behaviour not wanting to have extra work at the end of a shift. This causes patients to stay longer at ED than necessary and makes it impossible for new patients to enter the ED faster. A solution for this problem may be to spread the moments that nurses start working at the hospital.

Chapter 1 Introduction of the problem

The University of Louisville Hospital (UofL Hospital) is having problems with the increasing number of people coming to their Emergency Department (ED). Until 2008, about 37,000 patients visited the ED every year. Since 2008 the number of patients increased rapidly, 40,000 patients are expected in 2010. It is to be expected that this number will increase even more in the future. The main problem is that the capacity of the ED cannot be increased because of the lack of space in the building, so other solutions have to be found in order to provide the patients with the care they need. The focus of the research is on the number of beds available during the day and the patient satisfaction.

According to the staff, the main problem is the time the patient has to wait at ED after treatment is finished to the moment that the patient is admitted or sent home. Another problem seems to be the fact that when a patient needs to be admitted and has to get a bed assigned, no inpatient beds are available. The next problem is that even when an inpatient bed is available, it is not clean in a significant number of times.

It is impossible to eliminate all of the problems stated above, but it might be possible to improve the total process by making some minor adjustments to the system. The best way to find how a system responds to changes without affecting the real system is a simulation model. That is what will be done for this case as well.

In order to find the best solution to this problem, a literature review is conducted in order find possible solutions. Real time data is analysed in order to be able to make a realistic simulation model and several solutions in different compositions are analysed in order to determine the best option.

Chapter 2

Literature Review

A lot of papers have been written on the increasing number of people visiting ED's around the world. Some focus on how to prevent people from coming to ED, while other focus on how to get patients through ED as fast as possible. In order to identify solutions that may be applicable to the UofL Hospital ED, the main cause has to be identified first; why do that many people go to an ED? After that the problems at the ED have to be identified and then possible solutions can be identified.

Why do people go to an Emergency Department?

The main reasons for people to go to an Emergency Department seem to be the difficulty of getting an appointment at a general practitioner, the feeling of pain or the availability of resources such as X-ray or the possibility of getting prescription drugs (Gentile et al., 2010). For the UofL Hosptial the difficulty of getting an appointment at a general practitioner can be considered to be the major reason for people to attend the ED, because a large portion of patients is uninsured. This can not be changed as the United States ED's act as a safety net for all uninsured Americans (Schull et al., 2007), (Paul et al., 2010). A lot of these patients actually don't necessarily need emergency care (Weinick et al., 2010), (Vartak et al., 2009), (McGuigan and Watson, 2010), but as the Emergency Medical Treatment and Labor Act states that ED patients can not be turned away, they will have to be taken care of and will use resources at the ED. Another reason for the increasing number of patients is the fact that older patients need more emergency care. And so, because the population is growing older more people will attend an ED (McCaig and Nawar, 2006).

Why does an Emergency Department get overcrowded and what does it cause?

Overcrowding of the ED can be defined as a situation in which more patients are at the ED than beds are available. In the case of the UofL Hospital, this happens quite frequently, especially at the end of the afternoon. The patients that usually cause overcrowding are (Kolb et al., 2008):

- patients that are waiting to be admitted at ED
- patients that are monitored in non-treatment areas
- patients waiting for transfer to an inpatient unit in the hospital

The main reasons for overcrowding are (Derlet and Richards, 2000):

- increased complexity and acuity of patients presenting to the ED
- overall increase in patient volume
- lack of beds for patients admitted to the hospital
- delays in service provided by radiology, laboratory, and ancillary services

An overcrowded ED does not only increase waiting times for patients, prolonged pain and suffering and patient dissatisfaction. It also leads to ambulances being diverted to hospitals further away, decreased productivity, frustration among staff and patients and even violence (Derlet and Richards, 2000).

What are possible solutions?

What catches the eye is that especially the last two types of patients stated above causing overcrowding do not really need the care provided at an ED, they can be taken care of in for instance a dedicated holding room (van der Vaart et al., 2010). This not only makes extra beds available at the ED, it also prevents the nurses at the ED from doing work that's not strictly necessary.

Another solution may be to use a team approach when a patient arrives (Medeiros et al., 2008). At this time a patients first goes through triage, where he has to tell what happened. After he is admitted at the ED a nurse comes to see the patient, and he has to tell his story again. After a while, the physician will see him and he will have to tell the story again. When using a team approach, the goal is to eliminate the extra time that is needed because a story has to be told to several persons over and over again.

A solution in order to prevent patients from waiting before they can be transported to their inpatient bed, can be to hire an extra nurse or technician that's dedicated to taking care of these people (or dedicate an already hired nurse or technician) (Han et al., 2009). This will help the other nurses and technicians to speed up their actual job; to take care of patients that really need care and not worry about people that have to moved somewhere in between jobs.

Other ways the speed up the process a bit, may be to place resources at other places, so that nurse and technicians do not have to walk or search too much. Or relocating for instance the X-ray machines so that they can be accessed more easily.

In order to reduce the amount of people not needing urgent care going to ED, a Fast Track (van der Vaart et al., 2010) can be used. This track must take care of the people having just a cold, or the flu.

Different ways of staffing may also be a solution, for instance when you know that most Mondays are significantly busier than the other weekdays, it may be useful to hire extra people on Monday only. At the moment, most hospitals have the same staffing every day of the week.

Which solutions are applicable to the UofL Hospital ED?

The problems of why people go to an ED are kind of "system problems" that can not be solved easily, so the focus of the research will not be on this. The UofL Hospital tries to cope with most people not needing emergency care by letting them go through the FirstCare Track, this is a Fast Track taking care of the less urgent people. No research is needed for that. Relocations of resources such as X-ray or bandages is also not a good, first because it's not easy to model and secondly because the space at the ED is limited, so changes would be minor.

What might be possible in the UofL Hospital, is to make a holding room for patients not needing immediate care any more, or waiting to be moved to an inpatient bed or to go home. Another possibility is to hire a nurse dedicated to taking care of these patients, so without having a holding area. Another option to consider is the team approach, although physicians are usually busy, it can be worth the try to save much needed time.

Different staffing options can also be considered. When a good analysis is made of the busy and quiet hours at the ED, the staffing can be adjusted to these findings.

Chapter 3

System Description

The UofL Hospital ED is an emergency department like many others in the US. In order to show what the process that will be simulated looks like, a description of the entire process will be presented in this chapter. A flowchart of the process van be found in appendix B. Because data like the arrival rate of patients are of high importance for the model, their analysis will be discussed along the way.

Description of the system

A patient can come to the emergency department in three ways:

- walks in himself
- transferred from another hospital
- brought in by Emergency Medical Services (EMS)

Because no data is available on what part of the patients comes in via the various ways and because the way of arrival does not really matter for the actual ED process, the assumption is made that all patients just "come in". After analysis of the hourly arrivals in the year 2010, the arrival rates shown in figure 4.1 showed up. We can clearly see a pattern in the arrivals. The inflow is mainly high on working days between 9 and 15, but especially high on Monday mornings. During the night, only a few people come in. The arrivals are assumed to be exponentially distributed (this is verified trying several simulation configurations).

After the patient came in, he goes through triage. Where he gets a first consultation and an armband with some data like his number. After this is done, the vital signs are checked and he is given a priority, which he does not know. The triage nurse then decides where the patient has to go to, either the First Care Track (the UofL Hospital Fast Track) or the actual Emergency department. In most cases the patient will now be sent back to the waiting room where he stays until a place at either First Care or ED is available. When being in the waiting room, the patient may decide to leave, he then is recorded as "left without being seen" (LWBS).

Data is available on what part of the patients coming in go to which department or leave without being seen. A graphical representation of these data can be found in figure 4.2. One can clearly see that during the night, most people go to ED, while during daytime many of the patients coming in are sent to the First Care Track. We also notice that about 2% of the patients leave without being seen. When the patient is taken out of the waiting room he either goes to ED or First Care. When the patient goes to First Care he actually leaves the Emergency Department process, that's why, for modelling purposes, this patient is removed from the system. When the patient goes to ED, he is placed in an ED bed and waits to be seen by an ED nurse for the first time. After the nurse has finished her job the patient waits to be seen by a physician. After being seen by the physician he waits for treatments, tests are conducted, waits for test results and he may have to be helped by a nurse a few times. This goes on until the decision is made whether he will be admitted or discharged. From triage to this decision usually takes about four to five hours.

After that decision is made, the patients either waits to go home (wait for a nurse to be available to discharge him, this can take up to 1.5 hours), or waits for an inpatient bed to be assigned. Data is available on the time it takes for a bed to be assigned; in 2010 it took on average one hour and 53 minutes for a bed to be assigned (see figure 4.4).

After the inpatient bed is assigned two things can happen; the bed is either clean or not. The chances of having no clean inpatient bed at the time the bed is assigned can be found in figure 4.6. As we can see, the chance of having no clean inpatient bed varies heavily over the day and throughout the week. When the bed is not clean, it needs to be cleaned, which takes about eighteen minutes according to the available data (see figure 4.4). When the bed is clean though, a nurse has to be available to move the patient to his bed, as with the discharged patients, this can take up to 1.5 hours (see figure 4.4). The same goes for patients that can be put into their bed after it is cleaned.

When the patient is in his bed, a new patient can enter the Emergency Department. And the entire process starts over again.

Resources

The resources in the model are as follows:

- three physicians at all time
- at least eleven nurses at all time
 - two more nurses starting at 11am
 - two more nurses starting at 1pm
 - back to eleven nurses at 7pm
- 29 ED beds

In chapter 5 explanation is giving on resources that will be varied in the simulation model.

Chapter 4

Data Analysis

In order to make a good simulation model, a lot of data is needed. Preferably real time data. The UofL Hospital provided us with about one and a half year of data on the amount of arrivals every hour and about 8 months of data on the process times for admitted patients. Furthermore they provide us with a lot of summarized data in order to be able to validate the model.

Analysis of the available data

Data are available on two parts of the process;

- the number of arrivals and to which department (ED or First Care) the patient is sent
- the times in between the steps that are made when a patient is admitted

Number of arrivals and department to go to Data is available on the number of arrivals at the ED from January 2009 to September 2010. Since we know that the number of arrivals increases every year, only the data of 2010 are used for this analysis. The number of arrivals is shown in figure 4.1. When we take close look at this figure, we see that starting at 7am, the number of people attending the ED steadily rises until noon, when the number starts dropping steadily. Not all of these people got to ED, part of them goes to First Care and about 2% leaves without being been. The fractions of the amount of arrivals that go to each department are shown in 4.2. We can see that during the day a larger part of patients is sent to First Care and that especially during the evening and night, people leave without being seen. When figure 4.1 and 4.2 are combined, figure 4.3 results.

In order to incorporate these data into the simulation model, some assumptions have to be made. For the arrival rates we assume exponential arrivals, e.g. a poisson proces. This assumption is right when the mean of the data points is close or equal to the standard deviation of the data points, for the arrivals this more or less is the case, so the assumption can be used. Some validation runs on the arrivals using these input data proved that this exponential distribution is applicable for all hours of the day and all days of the week.

In order to make use of the data shown in figure 4.2, all patients get assigned a chance (a five decimal number between zero and one). Using this chance they will be assigned to the right department. So:

• when $chance \leq ED fraction$: the patient goes to ED

				day d	of the w	eek		
		Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
	0	5.0	5.4	5.5	4.9	4.9	4.5	5.5
	1	4.5	4.2	4.4	3.4	4.0	4.3	5.6
	2	4.3	3.7	3.2	3.1	2.9	3.5	4.3
	3	4.8	2.7	3.3	2.7	3.1	3.2	4.4
h	4	3.8	2.7	2.3	2.3	3.1	2.4	3.7
 ^	5	3.3	2.6	2.0	2.3	2.8	2.2	3.5
	6	2.8	3.1	3.0	2.8	3.0	2.9	3.0
u r	7	3.6	4.9	3.9	4.3	4.7	4.5	3.5
1	8	5.3	7.8	6.6	7.1	6.9	7.1	5.4
^	9	5.9	11.1	9.8	9.4	9.7	9.3	6.1
f f	10	7.1	12.4	11.6	10.7	9.3	9.5	7.3
	11	7.0	12.2	10.5	10.8	10.4	11.1	8.3
•	12	7.1	12.3	11.7	10.8	9.3	10.8	7.8
ι h	13	7.7	11.1	11.2	10.8	11.4	10.6	7.8
	14	6.9	11.9	10.0	9.9	9.7	10.1	7.8
e	15	7.8	10.1	9.2	9.3	8.8	8.5	7.9
Ч	16	7.8	9.8	9.4	9.2	8.6	9.3	7.4
u o	17	7.9	9.2	7.9	8.3	8.5	8.1	8.0
a v	18	7.6	9.2	8.7	9.0	8.3	8.8	7.0
у	19	8.0	9.1	8.4	8.2	8.4	8.1	7.0
	20	6.3	8.3	7.5	7.8	6.6	8.4	7.0
	21	6.3	8.0	7.3	7.4	7.8	7.1	7.6
	22	6.3	6.3	5.8	6.2	6.3	7.2	6.3
	23	5.7	6.0	5.1	5.8	5.6	7.2	5.1

Figure 4.1: Average number of arrivals per hour (hour of the day/day of the week)

- when $EDfraction < chance \leq EDfraction + FTfraction$: the patient goes to the Fast Track
- when $chance \geq 1 LWBS fraction$: the patient leaves without being seen

When the patient leaves without being seen, no data will be recorded any more, the same goes for patients that go to First Care. When the patient goes to ED, he undergoes his treatment. For the treatment itself no actual data are available, so assumptions are made on the processing times in this part of the simulation. These assumptions are approved by the Hospital staff and are thought to be realistic.

Admission times After the decision is made that a patient is going to be admitted, a bed slip is passed. This will make that sure a bed will be assigned to the patient. In figure 4.4, the most left column, we can see the time it takes on average for a bed to be assigned. Unfortunately, not enough data was available to make different probability distributions for each hour of the day, especially not for the hours during the night. The number of data

			,	Ë						Ë,	rst Cai	e					_ 、	WBS			
	Sunday	Monday	Tuesday	Nednesday	Thursday	Friday	Saturday	Sunday	Monday	Tuesday	Nednesday	Thursday	Friday	Saturday	Sunday	Monday	Tuesday	Nednesday	Thursday	Friday	Saturday
	0.98	0.97	0.93	0.96	0.96	0.98	0.87	0.01	0.01	0.01	0.01	0.02	0.01	0.04	0.02	0.02	0.07	0.03	0.02	0.01	0.09
	0.99	0.98	0.94	0.97	0.93	0.99	0.94	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.01	0.01	0.06	0.03	0.06	0.01	0.04
	0.98	0.98	0.99	0.98	0.98	0.99	0.92	0.01	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.02	0.01	0.02	0.02	0.01	0.05
	0.97	0.98	0.99	0.98	0.96	0.97	0.94	0.01	0.00	0.00	0.00	0.02	0.00	0.04	0.02	0.02	0.01	0.02	0.02	0.03	0.03
	0.97	0.96	0.97	1.00	0.96	0.95	0.94	0.01	0.00	0.00	0.00	0.01	0.01	0.02	0.03	0.04	0.03	0.00	0.03	0.04	0.04
	0.97	0.99	1.00	0.99	1.00	0.99	0.95	0.02	0.01	0.00	0.00	0.00	0.01	0.05	0.01	0.00	0.00	0.01	0.00	0.00	0.00
	0.94	0.87	0.93	0.95	0.87	0.91	0.93	0.04	0.12	0.07	0.05	0.13	0.09	0.07	0.01	0.01	0.00	0.00	0.00	0.00	0.00
	0.65	0.62	0.61	0.56	0.68	0.70	0.64	0.34	0.37	0.39	0.44	0.31	0.30	0.34	0.01	0.01	0.00	0.00	0.01	0.00	0.02
_	0.62	0.56	0.62	0.54	0.57	0.52	0.58	0.37	0.44	0.38	0.46	0.42	0.48	0.41	0.01	0.00	0.00	0.00	0.00	0.00	0.01
_	0.58	0.50	0.56	0.53	0.56	0.50	0.62	0.42	0.49	0.43	0.46	0.43	0.50	0.38	0.00	0.01	0.01	0.01	0.01	0.00	0.01
	0.56	0.48	0.55	0.55	0.53	0.51	0.59	0.43	0.51	0.44	0.45	0.46	0.47	0.41	0.00	0.02	0.01	0.01	0.01	0.02	0.00
	0.57	0.52	0.56	0.59	0.58	0.55	0.55	0.42	0.47	0.42	0.40	0.41	0.45	0.45	0.01	0.01	0.01	0.01	0.00	0.00	0.00
	0.64	0.55	0.56	0.56	0.61	0.60	0.62	0.36	0.44	0.42	0.43	0.38	0.40	0.37	0.00	0.01	0.02	0.01	0.01	0.00	0.00
	0.62	0.54	0.53	0.55	0.54	0.56	0.62	0.38	0.43	0.46	0.44	0.45	0.42	0.38	0.00	0.02	0.01	0.01	0.01	0.02	0.00
	0.56	0.53	0.59	0.57	0.55	0.57	0.61	0.44	0.46	0.41	0.42	0.45	0.41	0.38	0.00	0.01	0.01	0.01	0.00	0.02	0.01
	0.59	0.57	0.63	0.57	0.55	0.57	0.60	0.40	0.42	0.36	0.41	0.44	0.42	0.40	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	0.70	0.60	0.57	0.59	0.62	0.65	0.69	0.29	0.38	0.41	0.40	0.37	0.35	0.30	0.00	0.02	0.01	0.01	0.01	0.01	0.00
	0.65	0.54	0.65	0.60	0.65	0.67	0.65	0.35	0.44	0.33	0.40	0.33	0.32	0.35	0.01	0.02	0.02	0.00	0.01	0.00	0.00
	0.69	0.59	0.56	0.57	0.62	0.62	0.70	0.30	0.39	0.43	0.39	0.37	0.37	0.28	0.01	0.02	0.01	0.03	0.01	0.01	0.02
	0.68	0.60	0.63	0.65	0.59	0.67	0.69	0.30	0.39	0.35	0.32	0.40	0.31	0.29	0.02	0.02	0.02	0.03	0.01	0.01	0.01
	0.66	0.69	0.66	0.60	0.64	0.73	0.78	0.33	0.28	0.30	0.35	0.34	0.25	0.21	0.01	0.04	0.03	0.04	0.02	0.02	0.00
	0.69	0.61	0.68	0.73	0.72	0.74	0.74	0.28	0.35	0.29	0.25	0.25	0.23	0.25	0.03	0.04	0.03	0.02	0.04	0.03	0.01
	0.79	0.78	0.70	0.73	0.73	0.79	0.80	0.18	0.18	0.29	0.26	0.26	0.17	0.18	0.03	0.04	0.01	0.02	0.01	0.04	0.01
	0.93	0.83	0.82	0.84	0.87	0.86	0.87	0.06	0.14	0.14	0.12	0.11	0.11	0.13	0.01	0.03	0.04	0.03	0.02	0.03	0.00

Figure 4.2: Fraction of patients going to department shown (hour of the day/day of the week)

Figure 4.3: Number of patients going to department shown (hour of the day/day of the week)

points was enough though to determine a fitting distribution for the entire day. Analysis with SPSS 17.0 showed that a beta distribution represents that data points sufficiently when using $\alpha 1 = 0.164$ and $\alpha 2 = 1.906$. A QQ-plot of the distribution with these parameters is shown in figure 4.5. We can see that the fit is good (except for the extremely high values), so this distribution can be used.

After a bed is assigned, it may happen that the assigned bed is not clean yet. The chances of a bed not being clean after assignment are shown in figure 4.6. We can clearly see that this varies highly over time. These numbers are based on the 2010 data. The data is used in the model by comparing a chance (a five decimal number between zero and one) that is given to the patient (another one than the one stated before in order to prevent correlation effects) to the chances shown in figure 4.6. So:

- when *chance* < *CleanBedChance*, the bed is not clean
- when $chance \geq CleanBedChance$, the bed is clean

The time it takes for a bed to be cleaned is shown in figure 4.4, in the middle column. We see that the variation over the day is pretty low compared to the total time patients are on the ED, so we assumed a single distribution would represent the data well enough (also having in mind that not enough data points are available for single hour of the day distributions). An appropriate distribution is chosen using SPSS 17.0, a gamma distribution with $\kappa = 1.318$ and $\theta = 31.134$ showed up to be the best fit. A QQ-plot is shown in figure 4.7. We can see that this is an appropriate representation of the data points, so it can be used in the model.

When the bed is clean and the patient is ready to be discharged from the ED, a nurse will need to make sure that the patient actually is discharged. In figure 4.4, the rightmost column, we can see that it takes one hour and 26 minutes on average for a patient to be in the bed and discharged. These times are based on 2010 data. It would be nice to have this hold up as an output of the model, but since it is not totally reliant on the availability of nurses and possible paperwork or eventualities it has to modelled as an input in order to get a valid model. Analysing the data with SPSS 17.0 resulted in a lognormal distribution with $\mu = 0.05$ and $\sigma^2 = 0.644$. A QQ-plot of the data points and this distribution can be found in figure 4.8. As can be seen, this distribution represents the data sufficiently.

Staffing influences on the process

While talking to the hospital staff, we noticed that a positive or negative spike might occur in the amount of bed assignments around the time the nurses come to work or go home, because they want to avoid having new inpatients just before leaving and thus moving these bed assignments forward in time. This spike should be occurring around 7am and/or 7pm, the times most nurses come to work and go home. Fortunately, data was available (January 2010 to August 2010) on the times that the bed assignments occurred. A histogram with a polynomial trend-line is shown in figure 4.9. A close look at the histogram shows that almost all values are on, or pretty close to, the trend-line, except for the values around 7am and 7pm. Between 7 and 8am, significantly more bed are assigned than expected. In order to check if these spikes occur because of the amount of bed slips passed just before, another histogram is made of the amount of bed slips that are passed per hour of the day. This histogram is shown in figure 4.10. We can see that nothing can explain the differences from the trend we just noticed, also having in mind that no inpatients will be discharged during the night, it is

		Time in when the being clean, when the being clean, when the being clean to be assignment bed as	Time the time to the bed from bed assignment to the bed is not clean	the bed being ready to
	0	02:04	00:10	01:25
	1	02:39	00:12	01:21
	2	02:09	00:11	01:27
	3	02:34	00:11	01:26
	4	02:42	00:13	01:18
h	5	02:59	00:18	01:20
0	6	03:02	00:20	01:33
u	/	02:48	00:21	01:34
r	8	03:07	00:20	01:30
0	9 10	02:16	00:24	01:24
f	10	02:23	00:29	01.38
	11	01.23	00:15	01.21
t	12	01.30	00.27	01.25
n o	13 1/	01.34	00.30	01.20
C	15	01.14	00.27	01.20
d	16	01.21	00.30	01.32
а	17	01.00	00.20	01.32
у	18	01:17	00:21	01:31
	19	00:59	00:17	01:25
	20	01:34	00:14	01:28
	21	01:44	00:13	01:22
	22	01:49	00:12	01:17
	23	01:44	00:08	01:24
	avg	01:53	00:18	01:26

Figure 4.4: Times for different processes in the Emergency Department, per hour of the day

Estimated Distribution Parameters

	-	VAR00011
Beta Distribution	Shape1	0.164
	Shape2	1.906





Figure 4.5: QQ-plot for beta distribution, fitted on the data points for the time between admit decision and bed assignment

				day	of the w	veek		
		Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
	0	0.20	0.21	0.19	0.24	0.20	0.13	0.14
	1	0.23	0.25	0.23	0.24	0.32	0.10	0.20
	2	0.16	0.24	0.34	0.17	0.15	0.12	0.22
	3	0.08	0.25	0.26	0.15	0.20	0.15	0.12
	4	0.26	0.33	0.22	0.23	0.25	0.13	0.08
h o	5	0.22	0.35	0.41	0.39	0.14	0.21	0.27
	6	0.40	0.26	0.33	0.35	0.42	0.32	0.21
u	7	0.33	0.52	0.42	0.64	0.40	0.29	0.17
r	8	0.36	0.48	0.42	0.29	0.40	0.54	0.24
	9	0.30	0.50	0.25	0.41	0.39	0.32	0.21
0	10	0.44	0.21	0.42	0.71	0.50	0.47	0.29
I	11	0.31	0.25	0.55	0.47	0.46	0.35	0.15
t	12	0.52	0.53	0.58	0.42	0.46	0.47	0.39
h	13	0.43	0.40	0.63	0.55	0.53	0.48	0.36
е	14	0.52	0.44	0.52	0.58	0.39	0.39	0.38
	15	0.38	0.34	0.55	0.69	0.61	0.39	0.29
d	16	0.18	0.40	0.60	0.59	0.62	0.45	0.27
a	17	0.19	0.37	0.70	0.41	0.48	0.22	0.13
у	18	0.26	0.47	0.54	0.32	0.38	0.14	0.19
	19	0.23	0.41	0.36	0.27	0.26	0.20	0.15
	20	0.10	0.31	0.32	0.36	0.31	0.09	0.20
	21	0.22	0.22	0.31	0.30	0.29	0.13	0.04
	22	0.23	0.24	0.25	0.25	0.20	0.17	0.18
	23	0.19	0.12	0.33	0.14	0.17	0.04	0.10

Figure 4.6: Chance of having no clean bed after a bed is assigned (hour of the day/day of the week) $\,$

Estimated Distribution Parameters

		VAR00010
Gamma Distribution	Shape	1.318
	Scale	31.134





Figure 4.7: QQ-plot for gamma distribution, fitted on the data points for the time it takes to clean a bed

Estimated Distribution Parameters

	_	VAR00007
Lognormal Distribution	Scale	0.050
	Shape	0.644

Lognormal P-P Plot of VAR00006



Figure 4.8: QQ-plot for lognormal distribution, fitted on the data points for the time it takes for a patient to be discharged after a bed is ready and clean



Figure 4.9: Number of bed assignments per hour of the day

impossible that extra beds are suddenly available at 7am. This must have something to do with the attitude of the nurses receiving the new inpatients. The same thing occurs at 7pm, but because of the larger numbers it is easier to see. Between 6 and 7pm, a lot less beds are assigned than what has to expected and between 7 and 8pm, quite a bit more beds are assigned than what has to expected. After looking at figure 4.10, we again conclude that the low number of beds assignments between 6 and 7pm has nothing to do with the number of bed slips passed. Actually more beds should be assigned, because a lot of bed slips are passed between 5 and 6pm.

As indicated before, there is some time between the assignment of a bed and the time the patient is in it. To check whether this phenomenon cancels out the findings stated above, a histogram is made of the times the new inpatients are put into their assigned bed. This histogram is shown in figure 4.11. This figure not only confirms the findings stated above, it also shows that the problem is even worse than what was to be expected after looking at figure 4.9 and figure 4.10. We see that between 7 and 8am and 7 and 8pm significantly less patients are put in their assigned bed than what has to be expected. This is the first hour of the "new shift" of nurses, indicating that this shift change causes quite some delays in the process.

It is difficult to incorporate these findings in the model. But it confirms that a part of process is disrupted by human behaviour not wanting to have new inpatients just before going home, possibly causing unwanted overtime or causing to "bother" the new shift with extra work. To tackle this problem, the hospital can try to hire nurses at different times, for instance a few from 6am, a few from 7am and a few from 8am and then sending them home again at 6pm, 7pm and 8pm. Doing this might eliminate the feeling that new inpatients can cause extra work just before going home, because other nurses, working different times, can take over these patients; preventing overtime.



Figure 4.10: Number of bed slips per hour of the day



Figure 4.11: Number of patients in bed per hour of the day

Chapter 5

Experimental Design

As mentioned in chapter 2, three main changes are applicable to the UofL Hospital ED and so will be investigated using the simulation model. The three changes are:

- 1. Let the physician and nurse see the patient together when the patient enters the ED, do this only when both a nurse and a physician are available. This will save time because the patient will not have to tell his story several times and test can be conducted faster after the arrival of the patient. This solution will save approximately twenty minutes per patient treated like this
- 2. Hire a nurse that is dedicated to discharging patients. At the moment a nurse will discharge patients only when she has nothing else to do. Because of this it takes on average one and a half hours for patients to be discharged. With a nurse dedicated to doing this, this can be reduced to about twenty to thirty minutes
- 3. Make space available in the hospital where patients can be put to wait when the decision is made that they are going to be admitted. By doing this, patients no longer will have to wait and use resources at the ED while they do not necessarily have to be there. ED Beds will be available earlier than they currently are, and patients can leave the ED up to two and a half hours faster than they do now. This will be done by a newly hired nurse
- 4. All combinations of the above stated options, so 1 + 2, 1 + 3, 2 + 3 and 1 + 2 + 3. In case of combination 2 + 3 and combination 1 + 2 + 3, only one extra nurse will perform all new tasks

In order to check if the problem is not just a staffing problem, also the following changes are investigated:

- hire the nurses that are added to the default number of nurses during the day until 8pm instead of 7pm
- all scenarios with a base number of nurses of eleven (current number) and twelve, so all combinations shown above are also simulated with a base number of twelve instead eleven nurses

Trying to change the staffing for particular days or hours of the day is not performed, this would make the analysis too complicated and too extensive. After a solution is found, a new study could investigate the best way of staffing for various days or parts of the year. To monitor the effect of these changes, several performance measures need to monitored. In this case the following performance measures are monitored:

- the time from entering the hospital to the moment the discharge/admission decision is made, time from entering to leaving is not comparable for all options because the changes may affect the process times after the discharge/admission decision
- the average number of beds available
- the fraction of the time zero beds are available
- the average number of nurses available

To check what amount of extra patients can be handled after each alteration of the process, all options are also investigated with eleven different arrival rates; ranging from the current number of arrivals to 25% more arrivals than at the moment in steps of 2.5%.

Run length, number of replications and warm up time

The length of each run is set to eighty days, which means about eleven consecutive weeks. This length is chosen because it is thought to be short enough to allow fast computation yet long enough to account for the variations in number of arrivals.

To be sure the calculated values don't differ because of the variation caused by the nature of simulation, the number of necessary replications has to determined. The number of replications needed is based on a 95% confidence interval and a relative allowed error of 5%. Calculations showed that at least four replications per attempt are needed to stay within the allowed 5% relative error. In order to be sure the relative error stays below 5% for all options, a number of ten replications is chosen to perform all experiments with (the running time of the model is sufficiently low to allow this).

A warm up time also has to be determined. Because this process is continuous and the model starts being empty, the point at which the model can be considered "working normally" has be determined. In figure 5.1 we can see the moving average of the throughput times for all patients from the the beginning of the simulation to about the 1000th patient leaving the system (averages of twenty replications). In order to determine when the process begins showing steady state results, the moving averages need to be more or less steady. We can see that especially the moving average with w=50 starts being reasonably steady after about 130 patients. A good guess for the warm up period would be 130 patients, but to be sure that no warm up effects are included in the data (and because the run length is long enough) a warm up period of 200 patients is chosen, which means about two days.

Number of upstairs beds

To reduce computation time (eliminating the need to compute all scenarios with all possible numbers of upstairs beds) and to maximize the possibility to implement the scenario, an appropriate yet low number of upstairs has to be determined to make sure the analysis that is done is realistic. We briefly investigated the influence of having one to six upstairs beds on the throughput time. All other parameters for this case are as they currently are. In table 5.1 we can see that the influence of having more beds gradually decreases. When having more than four upstairs beds, the marginal influence of an extra bed is close to zero. Because



Figure 5.1: Chart to determine appropriate warm up time for the simulation

we want the number of upstairs beds to be as low as possible in order to be able to easily implement it, yet as high as possible to maximize impact, four upstairs beds seems to be the best choice.

rumber of upstans beds	Change in throughput time
1	-2.3%
2	-3.3%
3	-3.9%
4	-4.1%
5	-4.2%
6	-4.2%

Table 5.1: Influence of having different numbers of upstairs beds on the throughput time Number of upstairs beds | Change in throughput time |

Chapter 6

Analysis of Results

After performing a full factorial simulation run, the results of the simulation can be analysed. In order to calculate the extra costs and revenue coming with each of the solutions, some assumptions have to be made. The following assumptions are made:

- a nurses' salary is \$60,000 a year (payscale.com)
- a nurse gets \$30,- per hour, works 40 hours a week (payscale.com)
- to add one nurse to the base amount of nurses, 4 extra nurses need to be hired (168 hours per week need to be hired extra)
- an outpatient brings in \$174,- in revenue for the hospital (Mahajan et al., 2005)
- an inpatient brings in \$1,480,- in revenue for the hospital (Bayley et al., 2005)
- all extra capacity will be used, so when more patients can be treated, more will come to the ED
- 38,000 patients are expected for 2010
- 24% of the patients coming to ED will be admitted

Before looking at the financial results, we first look at the performance measures mentioned in chapter 5. All measures are taken with an arrival rate as it is in 2010.

In figure 6.1 the throughput times (in seconds) for the patients are shown. We can see that the best scenario's save up to 1000 seconds per patient, meaning that on average about 15 minutes are saved. This seems to be not impressive, but since we know through Little's Law that we can handle more patients when the throughput time is lower, every improvement in throughput time must be valued. Knowing that most improvement come from patients having to wait less or not needing to tell their story several time, most improvements (except for hiring the nurses one hour extra) can be considered significant. We see that the having an extra nurse does not cause a lot of difference in throughput time.

In figure 6.2 the average number of beds available per scenario is shown. We can see that especially the upstairs beds and the admit nurse solution cause huge improvements. Hiring extra nurses, hiring them longer or letting the nurse and physician see the patient together do not really improve the performance measure. Having more beds available means less pressure for the staff and faster service for patients.



Figure 6.1: Throughput times per scenario, for both a base number of 11 and 12 nurses



Figure 6.2: Average number of ED beds available per scenario, for both a base number of 11 and 12 nurses

Figure 6.3 shows the chance per scenario of having zero ED beds available. These measures are inversely related to the measures shown in figure 6.2. The main difference is that we now see that having an extra nurse improves the process a bit.

In figure 6.4 we find the average number of nurses available. We can see that some of the scenarios do not let the number improve, but let it deteriorate. The cause probably is that because patients waiting for discharge or admission need less care than patients that are undergoing treatment at the ED. So more people will be undergoing treatment since less people will be waiting for admission or discharge. Meaning that less nurses will be available because they have more to do.

After looking at figures 6.1, 6.2, 6.3 and 6.4 we may conclude that the options and combinations all have advantages and disadvantages. Letting the nurse and physician see a patient at the same for instance leads to lower throughput times, but does not really improve the number of beds that are available. When looking at the upstairs bed alternative, we see that is improves the throughput time less than the previous option, but improves the amount of beds available during the day drastically.

In the previously shown figures, we could not see to what extent extra patients can be dealt with. To determine what extra amount of patients can be handled, we assume that the most important measure is the throughput time. Comparing the initial throughput time with the throughput times of all options with varying arrival rates (from 1.0 tot 1.25 times the current arrival rate) resulted in the maximum extra amount of patients. These extra amounts are shown in table 6.1, the second column, for having 11 nurses and in table 6.2, the second column, for having 12 nurses.

The tables show that the scenarios where patients are being moved out the ED faster, are the scenarios where most extra patients can be taken care of. When the scenarios are combined, even more extra patients will be able to come to ED. When comparing the 11 nurse table and the 12 nurse table, we can see that having an extra nurse makes it possible to handle an extra 2.5% of patients.

When we now look at the other columns in table 6.1 and 6.2, we see the costs and benefits of the options we've investigated. The costs are based on the extra resources that need to be hired, so for instance an extra nurse for the admit nurse option (meaning that in total four extra nurses to be hired, all getting \$60,000), or four nurses one hour extra each day for the 8pm in stead of 7pm option (so four times one hour per day, 365 days per year). The benefits are based on the extra amount of patients that can be taken care of with each of the options. So for example, for the upstairs beds scenario, 5% extra patients can come to the ED. So 0.05*38,000 = 1,900 extra patients, of which approximately 24% will be admitted, bringing in \$1,480,- in revenue per patient and the other 76% will be bringing in \$174,- per patient.

We can see that all options can be profitable, except for hiring the nurses until 8pm instead of 7pm. Combining the options seems to be the best alternative. When looking at the 12 nurse table, we see that having an extra nurse will be profitable as well. For the admit nurse and the upstairs bed scenario, we see that the profit will be less with eleven nurses, the cause of this may be that the extra amount of patients that can be handled is just within the margins of the investigated extra amounts of patients and so don't show up in the calculations. In order to be sure, some extra simulation run should be done with different arrival rates.

A graphical representation of the profits per scenario from table 6.1 and 6.2 is shown in figure 6.5. One can see that it is best to implement all options. When one of the option turns out no to work as well as expected, the other options though will probably take care of the extra patients that need to be taken care of.



Figure 6.3: Chance of having zero beds available per scenario, for both a base number of 11 and 12 nurses



Figure 6.4: Average number of nurses available per scenario, for both a base number of 11 and 12 nurses

Scenario	Max. extra patients	Costs	Revenue	Total
Base scenario	0.0%	\$-	\$-	\$-
Hire nurses untill 8pm instead of 7pm	0.0%	\$43	\$-	\$(43)
Upstairs beds	5.0%	\$240	\$926	\$686
Nurse and physician together	2.5%	\$-	\$463	\$463
Admit nurse	5.0%	\$240	\$926	\$686
Nurse/physician + upstairs beds	7.5%	\$240	\$1,389	\$1,149
Admit nurse $+$ nurse/physician	10.0%	\$240	\$1,852	\$1,612
Admit nurse + upstairs beds	7.5%	\$240	\$1,389	\$1,149
Admit nurse + upstairs beds + nurse/phys.	10.0%	\$240	\$1,852	\$1,612

Table 6.1: Results having a base number of 11 nurses. Dollar amounts are in 1000's

Table 6.2: Results having a base number of 12 nurses. Dollar amounts are in 1000's

Table 0.2. Results having a base number	of 12 nurses. Donar an	iounts a	re in 1000 s	`
Scenario	Max. extra patients	Costs	Revenue	Total
Base scenario	0.0%	\$240	\$-	\$(240)
Hire nurses untill 8pm instead of 7pm	0.0%	\$283	\$-	\$(283)
Upstairs beds	5.0%	\$480	\$926	\$446
Nurse and physician together	5.0%	\$240	\$926	\$686
Admit nurse	5.0%	\$480	\$926	\$446
Nurse/physician + upstairs beds	10.0%	\$480	\$1,852	\$1,372
Admit nurse + nurse/physician	12.5%	\$480	\$2,315	\$1,835
Admit nurse + upstairs beds	10.0%	\$480	\$1,852	\$1,372
Admit nurse + upstairs beds + nurse/phys	12.5%	\$480	\$2,315	\$1,835



Figure 6.5: Extra profit per scenario, for both a base number of 11 and 12 nurses

Conclusions

In order to take care of the problem of high numbers of patients coming to the ED and long waiting times at the UofL Hospital ED waiting room, it is best to try to implement the admit nurse option, the upstairs beds option and to let the nurse and physician see the patient at the same time. As we can see in table 6.1 and 6.2, it will not work to hire the nurses one hour extra per day, so this option has to dropped. When changing the process like this, the ED should be able to cope with an extra 10% of patients coming in while having only a minor increase in costs.

When implementing the upstairs bed option and the admit nurse option, attention needs to paid to the fact that the extra nurse, hired to care of patients that are ready to admitted or discharged, is doing only what her tasks are. So this new nurse should not be doing anything else than making sure that the patients are moved out of the ED as fast as possible. When other tasks are performed, the impact of the new way of working may decrease to impact of just having an extra nurse to the eleven base nurses, which impact is fairly small as can be seen in table 6.2.

Regarding the scenario where the nurse and physician consult the patient at the same time we should emphasize that this can only happen when both a nurse and a physician are available. When one of the two "resources" is not available the patient will have to follow the standard procedure in order to keep the total process going, it may take a little longer, but when people are waiting for another, the whole process may come to a standstill.

As can be seen in chapter 4, a part of the problem may also be caused by the nurses in the hospital itself not wanting to receive new inpatients around the times of shift changes. No solution can be found for this problem using the simulation model, but this problem may be solved by spreading the times the nurses are scheduled. This eliminates sudden changes to the staffing and should make the shift change more fluently, possibly preventing the nurses from trying to keep out the new inpatients until the next shift or until the new shift is totally up and running.

After implementation of all shown above, the throughput time of patients will drastically decrease when having the number of patients coming in at the moment, but even when up to 10% more patients come to the ED, the throughput time and thus the patient satisfaction will improve. Shorter throughput time also means less work in progress (in case the same number of people come in), so more beds available during the day, another objective of this research.

Future Work

In order to get an even better representation of reality it is recommended to extend the model with the following things:

- resources such X-ray, CT-scans or MRI's
- different priorities for patients, based on their acuities
- medical technicians tasks
- more detailed work schedules

In order to be able to introduce these things, the most important thing is to have more data available on all steps in the process, for instance on the following processing steps:

- how long it takes to perform specific tests
- how long it takes for test results to be available
- what is patient acuity level distribution
- which treatment(s)/test(s) patients having a certain acuity undergo
- how long a nurse is working with a patient
- how long a physician is working with a patient
- which tasks nurses, physicians and technicians perform and how long the tasks take

It may be good to monitor everything that happens at the ED for a week by just being there. After doing this, all data can be summarized, analysed and used in the model. It would be even better to let the hospital keep track of everything happening. This is mainly important because patients with differing acuities may follow different routes at the ED, meaning that the processing times may differ more than they currently do.

Besides data on the times of the steps in the process it is just as important to have more data on which treatments patients undergo. When this is available, the routing in de model can be improved and the model will represent reality even more.

Another option that may be good to investigate is different staffing schedules. Using another schedules than the current might improve and optimize the number of nurses available during the day. Because a huge number of options will be possible, this will take quite some time to simulate, but the advantages can be huge financially as well as in system performance.

As mentioned before, some of the problems are caused by the people that need to take care of the new inpatients. An inventory should be made on what the possibilities are to change this. It may be possible to hire people on differing times or let the work be done by other people than it is been done by at the moment.

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Appendix A

Model Description

In this appendix, a detailed description will be given about how the simulation model works. Most of it can also be found in the comments of the model code. An overview of the model can be found on page 38

As we can see on page 38, the model consists of three main blocks:

- the Entry
- the Emergency Department
- the Fast Track

In the Emergency Department block, two sub-blocks can be found

- the No Admission Block
- the Admission Block

Next to the Emergency Department Block we see the Upstairs bed block. This block is only used when the Upstairs Bed option is switched on.

Below the Emergency Department Block, a block with all controls is situated. In this description, all controls will be discussed. Especially important is the Data icon, in this frame (see page 39), all data is collected, all variables are stored and all parameters can be changed.

In order to understand what is stored, tracked and calculated we first look at the Data frame, where all of this happens. Then we go through the model like a patient would do (also see Appendix B), explaining every Method as we encounter him.



Model Variables	Model Param.	Output Data			
HourOfDay=-1	Bed=1				
DayOfTheWeek=1	Clean=1				
Run=10	HoldUp=1				
Experiment=12	ArrivalRate=1	AvgPhyAva	AvgBedAva	AvgNurseAva	AvgUpBedAva
SimDay=1	Both=false				
ERBedsAvailable=29	Upstairs=false				
	AdmitNurse=1000	· · · 🔳 · ·	. 🔚	· 🔳 · · ·	
NursesAmount=11	WarmupPatients=200	ZeroPhyAva	ZeroAvailable	ZeroNurseAva	ZeroUpbedAva
NursesAvailable=11	ERBedsAmount=29				
	InitNurse=11				
PhysicianAmouint=0	UpStairsBedsAmount=4	· · ·	· 🔢 · ·	· 🔳 · ·	· 🔢 · ·
PhysicianAvailable=3		. PhyStats	Stats	NurseStats	UpBedStats
UpStairsBedsAvailable=4					
		· · · 📑	· 🔢 · ·	· 📳 · ·	
PatientCount=0		Discharged	BSSToBed	Waiting	
Input Data					
		· · ·	· 💷 · · ·	· 🔳 · · ·	
		Admitted	Total	WaitingEmpty	
· · III · · · · ·					
ChanceOfNoCleanBed	NursesSchedule				
		· · ·	· 📳 · ·		
		Warmup	TPTTimes		
· · · 🔠 · · · · ·	· 🔢 · · · ·				
. PatientStatusChance .	NurseQueue				
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· · · 🔠 · · · ·		DataGenerator	DataWriter		
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Data Frame

The data frame is shown on page 39. We explain what every variable, parameter, table and generator do in the model.

Model Variables

HourOfDay keeps track of the hour of the day it is. It is changed every hour by the ArrivalRateGenerator

DayOfTheWeek keeps track of the day the week it is. The days are represented by numbers, 1 to 7, 1 meaning Sunday and 7 meaning Saturday with the rest in between.

Run tracks the replication number, the simulation number it is in for every experiment

Experiment is the number of the experiment the model is running at that moment

SimDay tracks the day of the replication/experiment it is. All replications are 80 days, so Simday can be a number from 1 to 80

NursesAmount is the number of nurses working at that moment

NursesAvailable is the number of nurses that is doing nothing at that moment

PhysicianAmount is the number of physicians working at that moment, this will always be 3, but can be changed if desired

PhysicianAvailable is the number of physicians doing nothing at that moment

UpStairsBedsAvailable is the number of Upstairs Beds that are available at that moment

PatientCount counts the number of patients that have entered the system from the beginning of each replication

Model Parameters

Bed , with this parameter the time it takes for a bed to be assigned can be manipulated. When this parameter is 1.0, the time it takes for a bed to be assigned is like it is at the moment, but when changed to for instance 1.1, it takes 10% longer for a bed to be assigned and when it is 0.9, it takes 10% less time for a bed to be assigned

Clean, with this parameter the time it takes for a bed to be cleaned can be manipulated. When this parameter is 1.0, the time it takes for a to be cleaned is like it is at the moment, but when changed to for instance 1.1, it takes 10% longer for a bed to be cleaned and when it is 0.9, it takes 10% less time for a bed to be cleaned

HoldUp , with this parameter the time it takes for a patient to be admitted after the bed is ready can be manipulated. When this parameter is 1.0, the time it takes for a patient to be admitted after the bed is ready is like it is at the moment, but when changed to for instance 1.1, it takes 10% longer for a patient to be admitted after the bed is ready and when it is 0.9, it takes 10% less time for a patient to be admitted after the bed is ready

ArrivalRate , with this parameter the arrival rate of patients can be modified. When this parameter is 1.0, the arrival rate is default, when changed to for instance 1.05, 5% more patients will come in

 ${\bf Both}$, the parameter can be true of false. When it is true, the nurse and physician will see the patient together when both are available. when it is false the patient always see a nurse first and then go to a physician

UpStairs , with this parameter the upstairs beds option can be switched on or off. When it is true, the option is on. When it is false, the option is turned off

AdmitNurse , using this parameter, the admit nurse option can be triggered. By default this parameter is 1000, but when changed to 333 the admit nurse option is turned on

WarmupPatients , the parameter determines the number of patients that are considered "warm up patients", so no data about these patients is stored in the output tables

ERBedsAmount is the number of beds available on the ED, by default this is 29, but it can be changed to other values in order to figure what the impact is of having more or less beds

InitNurse is base number of nurses, by default eleven nurses are available at all times, supplemented with extra nurses during the day. By changing this parameter, the number of eleven can be changed

UpStairsBedsAmount is the number of upstairs beds that are available when the upstairs beds option is switched on, by default this number is four, but when desired, it can be changed

Input Data

ChanceOfNoCleanBed, shows per hour of the day, per day of the week, the chance of having no clean bed when an inpatient bed is assigned to a patient. Is used in the Admission method to check whether a patient will have a clean bed or not.

PatientStatusChance, contains the chances per hour of the day, per day of the week that a patient will go to one of the blocks (ED, FastTrack or LWBS). The first seven columns show the chances that a patient goes to ED, the second seven columns show the chances that patient goes to FastTrack and the last seven columns show the chance that a patient leaves without being seen. The chances of the three options added together are 1. Is used in the WalkInGen Method to determine where a patient will go.

NurseSchedule contains the schedule when extra nurses come in and leave (the row numbers are "hour of the day + 1"). Is used in the ArrivalRateControl method to determine the number of nurses at each moment of the day

NurseQueue contains the queue of patients waiting to be taken care of by a nurse. Is used in the PersonAvailable method to check where a nurse needs to go and is used by the InQueue method to write a patient into that needs care

ArrivalsPerHour contains the total average number of patients coming in every hour of the day and every day of the week. Is used in ArrivalRateControl to set the number of arrivals per hour

HomeQueue contains the queue of patients waiting to be admitted or discharged. Is used in MoveHomeNurse.

DoctorQueue contains the queue of patients waiting for a physcian. Is actually not used at the moment because the queue is FCFS and only at one buffer, but can be used when priorities for patients are introduced

OutputData

 ${\bf AvgPhyAva}~$, contains the average number of physicians available per simulation run. Is used by DataWriter.

AvgBedAva , contains the average number of beds available per simulation run. Is used by DataWriter.

AvgNurseAva , contains the average number of nurses available per simulation run. Is used by DataWriter.

AvgUpBedAva, contains the average number of upstairs beds available per simulation run, only when the upstairs beds option is switched on. Is used by DataWriter.

ZeroPhyAva , contains the part of the time zero physicians are available per simulation run. Is used by DataWriter.

ZeroBedAva , contains the part of the time zero beds are available per simulation run. Is used by DataWriter.

ZeroNurseAva , contains the part of the time zero nurses are available per simulation run. Is used by DataWriter.

ZeroUpBedAva, contains the part of the time zero upstairs beds are available per simulation run when the upstairs beds option is switched on. Is used by DataWriter.

PhyStats , at the end of each simulation run, statistics about the physicians are written to this file so that the DataWriter method can calculate the values that are put in the earlier mentioned tables

Stats , at the end of each simulation run, statistics about the ED beds are written to this file so that the DataWriter method can calculate the values that are put in the earlier mentioned tables

NurseStats , at the end of each simulation run, statistics about the nurses are written to this file so that the DataWriter method can calculate the values that are put in the earlier mentioned tables

UpBedStats , at the end of each simulation run, statistics about the upstairs beds are written to this file, when the upstairs beds option is switched on, so that the DataWriter method can calculate the values that are put in the earlier mentioned tables

ToDecision , this table contains the times it took for patients to get to the point that the discharge/admit decision was made. Used in the Admission method

BSSToBed , this table contains the time it took for patients that are going to be admitted from the moment the bed slip was passed to the moment they are put in to their bed. Used in the BedAvaible method

Waiting , this table contains average parts of time a patients is waiting for a nurse or physician. Is used by the BedAvaible method

Admitted, this table contains the time it took for patients that are going to be admitted to get to the moment they are put in to their bed. Used in the DataWriter method

Total, this table contains the times it took for patients to get through the entire system. Is used by the BedAvaible method.

WaitingEmpty , this table contains part of the time the waiting room was empty per simulation run. Is used by the DataWriter

TPTTimes , this table contains the average throughput times of all experiments and replications performed. Is used by Datawriter

 ${\bf DataGenerator}$, triggers the DataWriter method one second before the end of the simulation

DataWriter , this method writes data to the table files discussed before and does some other things:

- it write the portion of the time that no one is in the waitingroom to the WaitingEmpty table
- it computes the percentage of the time zero beds are available and writes it to the ZeroBedAva table
- it computes the average number of beds available and writes it to the AvgBedAva table
- it computes the percentage of the time zero nurses are available and writes it to the ZeroNurseAva table
- it computes the average number of nurses available and writes it to the AvgNurseAva table
- it computes the percentage of the time zero upstairs beds are available and writes it to the ZeroUpBedAva table
- it computes the average number of upstairs beds available and writes it to the AvgUpBedAva table
- it computes the percentage of the time zero physicians are available and writes it to the ZeroPhyAva table
- it computes the averags number of physicians available and writes it to the AvgPhyAva table
- it writes the average total throughput time in to the TPT times table
- it makes sure the simulation stops after the method is triggered

The Entry Block

Now we know where all data is stored and manipulated we can run through the main process. We start at the entry block, found most left on page. 38

Transfer, WalkIn and EMS A patient enter via either one of these sources (Transferred from another hospital, walk in himself, or brought by an ambulance (EMS)). The arrival rates are changed every hour of the day by the ArrivalRateGenerator. After the patient has arrived, a lot of attributes are assigned. This is done by the WalkInGen method

WalkInGen This method takes care of the following things:

- determines to which department the patient goes using a uniformly distributed number between 0 and 1 and comparing that number to the chances given in the PatientStatusChance table
- determines if a patient will be admitted or not (when going to ED), using a uniformly distributed number between 0 and 1 and comparing that number with 0.24 (the percentage of ED patients that will be admitted).
- give the patient a uniformly distributed number between 0 and 1 representing the chance of having no clean inpatient bed, this will be used later on in the process
- give the patient the time it will take him to get through the hold up part of the process, based on a lognormal distribution (HoldUp attribute)
- give the patient the time it will take him to get his inpatient bed cleaned (when not clean), based on a gamma distribution (BedCleanTime attribute)
- give the patient the time it will take him to get an inpatient assigned, based on a beta distribution (BedASSN attribute)
- give the patient his Patient ID
- adjusts the PatientCount variable

Register After the patient has entered and has gotten all his attributes, the patient moves to the Register object. Multiple patient can be registered at the same time, the processing time is exponentially distributed with $\mu = 15$ minutes

QuickRegister After the patient is registered, some data is collected. This can only be done one patient at a time. The processing time is exponentially distributed with $\mu = 3$ minutes

ArmBand Now the patient will get an armband with his data on it, like urgency and patient number. This will take 45 seconds per patient.

VitalSigns Now the vital signs of the patient will be checked, the processing time is exponentially distributed with $\mu = 10$ minutes. When the patient leaves this object, the VitalSignsToED method is triggered

VitalSignsToED This method does the following things:

- check where to patient needs to go to:
 - if LWBS, the patients will be deleted
 - if FastTrack, the patient moves to the FastTrack object
 - if ED, the number of available beds will be checked. If no available the patient is moved to the waiting room, else he will be moved to the WaitForNurse1 object

The FastTrack Block

When patient is sent to the FastTrack, it will be staying in the FastTrack object for one minute and will then leave the system via the drain object.

The Emergency Department Block

WaitForNurse1 When the patient enters the Emergency Department Block at the WaitForNurse1 object, the InQueue method is triggered. The patient stays here until he is next in line to be seen

InQueue The InQueue method is triggered at several objects in the model:

- when the patient arrives at WaitForNurse1:
 - when the nurse/physician option is switched on:
 - * check if a nurse and a physician are available:
 - $\cdot\,$ if yes, send the patient to the NurseAndPhysician object and make a nurse and a physician unavailable
 - $\cdot\,$ if no, check if a nurse is available
 - \cdot if only a nurse is available, send patient to the Nursing1 object and make a nurse unavailable
 - \cdot if no nurse is available, stay in the WaitForNurse1 object and write the patient data into the NurseQueue table
 - when nurse/physician is switched off:
 - * check if a nurse is available
 - $\cdot\,$ when available the patient can be sent to the Nursing1 object and a nurse is made unavailable
 - \cdot when no nurse is available, stay in the WaitForNursing1 object and write patient data into the NurseQueue table
- when the patient arrives at WaitForPhysician:
 - check if a physician is available:
 - * if yes, move to the PhysicianCheck object and make a physician unavailable
 - * if no, write patient data into the DoctorQueue table (this table is not actually used, but can be used with an extended version of the model)
- when the patient arrives at WaitForNurse2, WaitForNurse3 or WaitForNurse4:
 - check if a nurse is available:
 - * if yes, move to the corresponding successor (Nursing2, Nursing3 or Nursing4) and make one nurse unavailable
 - $\ast\,$ if no, stay at the entered object and write the patient data into the NurseQueue table
- when the patient arrives at WaitForHome or WaitForHome1:

- check if a nurse is available and if no one else is waiting for a nurse
 - * if yes, move the patient to the corresponding successor (NurseHome or Nurse-Home1) and make one nurse unavailable
 - $\ast\,$ if no, write patient data into the HomeQueue table and stay in the object that was just entered

Nursing1 In this object, the patient is treated by a nurse. The processing time is exponentially distributed with $\mu = 30$ minutes. When the patient is ready at this object, the PersonAvailable method is triggered

PersonAvailable When the patient leaves an object where a person is used, this method is triggered. It does different for the different objects that can be left

- when Nursing1, Nursing2, Nursing3, Nursing4, NurseHome or NurseHome1 are left then:
 - check if some one is waiting to be seen by a nurse
 - * if yes, get the patient data from the NurseQueue table and go see that patient
 - * if no, make an extra nurse available and trigger the MoveHomeNurse method
- when PhyscianCheck is left:
 - check is some one is waiting to be seen by a physician
 - * if yes, go see that patient
 - * if no, make an extra physician available
- when NurseAndPhysician is left:
 - first check if some one is waiting for a physician
 - * if yes, go see that person and check if the nurse can also see some one:
 - \cdot if yes, go see that patient
 - \cdot if no, make an extra nurse available and trigger the MoveHomeNurse method
 - * if no one is waiting to be seen by a physician, check if some one is waiting in the WaitForNurse1 object:
 - $\cdot\,$ if yes, move that person the NurseAndPhyscian object
 - $\cdot\,$ if no, make an extra physician available and check if the nurse can go see a patient in the yet known fashion

MoveHomeNurse The MoveHomeNurse method is triggered when an extra nurse becomes available, this means that that nurse has nothing else to do and can send some one home:

- check if a patient is waiting to be sent home or to be admitted
 - if yes, get the patient data from the HomeQueue table and take care of the first patient in line
 - if no, do nothing

NurseAndPhysician In this object, the patient is treated by a nurse and a physician. The processing time is exponentially distributed with $\mu = 35$ minutes. When the patient is ready at this object, the PersonAvailable method is triggered

WaitForPhyscian When the patient enters this object, the InQueue object is triggered. The patient waits here until a physician becomes available and he is next in line

Ready This is a dummy object, to make sure that right methods can be triggered after leaving the NurseAndPhysician object. No processing time is involved

PhysicianCheck In this object, the patient is treated by a physician. The processing time is exponentially distributed with $\mu = 25$ minutes. When the patient is ready at this object, the PersonAvailable method is triggered

WaitForTest This object is made to represent the time it takes to wait for tests. The processing time is exponentially distributed with $\mu = 10$ minutes

PerformTest This object is made to represent the time it takes to perform tests. The processing time is exponentially distributed with $\mu = 5$ minutes

WaitForTestResults This object is made to represent the time it takes to wait for test results. The processing time is exponentially distributed with $\mu = 10$ minutes

WaitForNurse2 When the patient enters this object, the InQueue object is triggered. The patient waits here until a nurse becomes available and he is next in line

Nursing2 In this object, the patient is treated by a nurse. The processing time is exponentially distributed with $\mu = 30$ minutes. When the patient is ready at this object, the PersonAvailable method is triggered

MoreTreatmentAndTests This object is made to represent the time it takes to perform more tests and treatment. The processing time is exponentially distributed with $\mu =$ 10 minutes

WaitForNurse2 When the patient enters this object, the InQueue object is triggered. The patient waits here until a nurse becomes available and he is next in line

Nursing2 In this object, the patient is treated by a nurse. The processing time is exponentially distributed with $\mu = 30$ minutes. When the patient is ready at this object, the PersonAvailable method is triggered

EvenMoreTreatmentAndTests This object is made to represent the time it takes to perform more tests and treatment. The processing time is exponentially distributed with $\mu = 30$ minutes. When the patient leaves this object the Admission method is triggered

Admission This method checks if a patient will be admitted or not and send him to right place in the system. This method also writes data about the patient to the data frame (ToDecision table)

- It first checks if the patient will be admitted or not:
 - if no, send him to HomeHoldUp in the No Admission Block
 - if yes first check if the upstairs beds option is switched on
 - * if no, send the patient to the BedGetAssgined object in the Admission block and check if the bed that will be assigned is clean or not by comparing the BedChance attribute of the patient with the ChanceOfNoCleanBed table
 - * if yes, checks if upstairs beds are available
 - if yes, send the patient to the ToUpstairs object next to the Upstairs Bed block and check if the bed that will be assigned is clean or not by comparing the BedChance attribute of the patient with the ChanceOfNoCleanBed table
 - if no, send the patient to the BedGetsAssigned object in the Admission block and check if the bed that will be assigned is clean or not by comparing the BedChance attribute of the patient with the ChanceOfNoCleanBed table

The No Admission Block

HomeHoldUp In this object the patient waits to be discharged. The time this takes is given to the patient by the HoldUpTime attribute by the WalkInGen method

WaitForNurseHome When the patient enters this object, the InQueue object is triggered. The patient waits here until a nurse becomes available and he is next in line to be sent home

NurseHome In this object, the patient is seen by a nurse. The processing time is exponentially distributed with $\mu = 5$ minutes. When the patient is ready at this object, the PersonAvailable method is triggered

SendHome When the patient leaves this object, the BedAvaible method is triggered. No processing time is involved

BedAvaible When a bed becomes available, this method is triggered. It first checks if some one waiting in the WaitingRoom object

- if yes, move the first patient in line to WaitForNurse1
- if no, make an extra bed available

This method also writes data to the Data frame (tables: Admitted (if admitted), BSSToBed (if admitted), Total and Waiting)

The Admission Block

BedGetsAssigned In this object the patient waits for a bed to be assigned. The time this takes is giving to the patient by the BedASSN attribute in the WalkInGen. When the patient leaves this object, the ToCleaning method is triggered

ToCleaning This method checks if the patient will have a clean bed or not by checking the CleanBed attribute of the patient:

- if yes, send the patient to the Cleaning object
- if no, send the patient to the NoCleaning object

Cleaning Here the patient waits for his bed to be cleaned. The time this takes is given to the in the BedCleanTime attribute in the WalkinGen method

NoCleaning This is a dummy object. No processing time is involved

WaitForNurse4 When the patient enters this object, the InQueue object is triggered. The patient waits here until a nurse becomes available and he is next in line

Nursing4 In this object, the patient is seen by a nurse. The processing time is exponentially distributed with $\mu = 15$ minutes. When the patient is ready at this object, the PersonAvailable method is triggered

AllKindsOfHoldUps In this object the patient wait to be admitted. The time this takes is given to the patient in the HoldUpTime attribute by the WalkInGen method

WaitForNurseHome1 When the patient enters this object, the InQueue object is triggered. The patient waits here until a nurse becomes available and he is next in line to be admitted

NurseHome In this object, the patient is seen by a nurse and be admitted. The processing time is exponentially distributed with $\mu = 5$ minutes. When the patient is ready at this object, the PersonAvailable method is triggered

LeaveER When the patient leaves this object, the BedAvaible method is triggered. No processing time is involved

The Upstairs Bed Block

ToUpstairs This object makes sure that it takes some time for a patient to be moved upstairs. The processing time is exponentially distributed with $\mu = 20$ minutes. When the patient leaves this object, the UpHoldUp method is triggerd

UpHoldUp This method moves the patient to the UpBedGetsAssigned object and checks if some one is waiting for an ED bed

- if yes, move the first person in the waiting room to the WaitForNurse1 object
- if no, make an extra ED bed available

UpBedGetsAssigned In this object the patient waits for a bed to be assigned. The time this takes is giving to the patient by the BedASSN attribute in the WalkInGen. When the patient leaves this object, the ToCleaningUp method is triggered

ToCleaningUp This method checks if the patient will have a clean bed or not by checking the CleanBed attribute of the patient:

- if yes, send the patient to the UpCleaning object
- if no, send the patient to the UpNoCleaning object

UpCleaning Here the patient waits for his bed to be cleaned. The time this takes is given to the in the BedCleanTime attribute in the WalkinGen method

UpNoCleaning This is a dummy object. No processing time is involved

UpHoldUps In this object the patient wait to be admitted. The time this takes is given to the patient in the HoldUpTime attribute by the WalkInGen method

UpBedAvailable When the patient leaves this object, the UpBedAva method is triggered. No processing time is involved

UpBedAva This method makes an extra upstairs bed available

Not yet mentioned objects

EventController This object takes care of starting and terminating the simulation runs. It is configured to start tracking statistics after two days and to end the simulation after eighty days

ExperimentManager Using the experiment manager all experiments are performed. It is now set to do ten replications per experiment with a confidence interval for the results of 95%

Init This method initializes all settings after each replication of an experiment

Reset This method resets the whole model after an experiment (not used at the moment) **ArrivalRateGenerator** This generator is triggered every hour of the day, it triggers the ArrivalRateControl method

ArrivalRateControl This method keeps track of several things:

- the hour of the day
- the day of the week
- the day of the simulation

It also sets some parameters for the model:

- the arrival rate of the patient in the WalkIn object
- the number of nurses working at that moment in the NurseAmount variable

Appendix B

Flowcharts

The flowchart can be found on the next three pages. It is divided in three, pieces:

- the overall view
- the Emergency Room
- the part where patients wait to be admitted



Page 2 of flowcharts



