MODELING THE EFFECT OF RESIDENT LEARNING CURVE IN THE EMERGENCY DEPARTMENT

by

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Abstract

The University of Kansas Medical Center's Emergency Department is adopting a new residency program. In the past, generalized Residents have supported attending physicians during a required three month rotation in the Emergency Department. As of July 2010, the University of Kansas Medical Center's Emergency Department has switched to a dedicated Emergency Medicine Residency program that allows recently graduated physicians the opportunity enter the field of Emergency Medicine. This thesis shows that although not initially a dedicated residency program provides an advantage to the Emergency Department.

Discrete Event Simulations have been used to predict changes in processes, policies, and practices in many different fields. The models run quickly, and can provide a basis for future actions without the cost of actually implementing changes in policies or procedures. This thesis applies a learning curve in a Simulation Model in order to provide data that the University of Kansas Medical Center's Emergency Department can utilize to make decisions about their new Residency Program. A generalized learning curve was used for the base model and compared to all alternatives. When it was compared with an alternative curve following a Sigmoid Function (Logistic Function), there were no significant differences. Ultimately, a Gompertz Curve is suggested for hospitals attempting to develop or improve their residency programs using learning curves because it is easily fitted to their desired shape.

This thesis shows the effect that Residents have on the performance of the Emergency Department as a whole. The two major components examined for the generalized learning curve were the initial position for first year residents determined by the variable α, and the shape of the curve determined by the variable β. Individual changes the value of α had little effect. Varying values of β have shown that smaller values elongate the shape of the curve, prolonging the amount of time it takes for a resident to perform at the level of the attending physician. Each resident's personal value of β can be used to evaluate the performance in the emergency department. Resident's who's β value are smaller the emergency department's expected value might have trouble performing.

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Chapter 1 - Introduction

1.1 Introduction

In all businesses, across all industries, there is uncertainty. The healthcare industry is no exception and must adapt to a highly volatile environment in order to survive. Services provided in the Emergency Department are through reimbursement by insurance companies or by the Centers of Medicare and Medicaid Services (CMS). Members in government would like to hinder the rapidly rising costs of modern medicine in order to ease the burden on taxpayers. (Bodenheimer 2005) Health insurance companies share that same desire, because rising costs can cut into their profits. Here in lies the problem. Hospitals are stuck in the middle of an industry that creates machines and medications that are expensive but necessary, and a population that will continue to have trouble paying for them. (Richard Hillestad 2005) (Elliott S. Fisher 2009)

In this climate, hospitals are left with a few choices, often looking to reducing costs in any way possible. Many hospitals are finding that approved overtime leads to nonstandard shift work, higher levels of stress and fatigue, which are cited as causes of high employee turnover. (Peter C. Winword 2006) (Linda D. Scott 2006) When it comes to physicians, hospitals realize hiring residents might be a cost effective option to reduce overall payroll expenses or as a supplementary workforce that covers excess demands with lower costs. According the University of Maryland Medical Center the average salary of a medical Resident is about $52,000 a year, as opposed to the average salary of an Emergency Department Physician which is about $249,000 a year. (CNN 2009) By no means should the Residents be considered any less qualified to work in the Emergency Department, as they have had the benefits of being taught the most recent methods and techniques shortly before being employed. Conversely Residents require significant amounts of time and training to become proficient in the emergency department. The ability to provide fast and reliable diagnoses is crucial to maintain an adequate level of care to patients' pressing medical conditions.

Most attending physicians in the emergency department have the benefit of experience, and have established a relatively stable process. Residents on the other hand, present a unique challenge in that they are new, and must learn how to perform in an environment that is new to them. Learning curves have been used to describe the incremental improvement of performance work environments ranging from manufacturing to health care. (J. Deane Waldman 2003) (Alexander J. McLeod Jr. 2008) This thesis presents the use of learning curves to predict the impact of a new Residency program in the Kansas University Medical Center's Emergency Department. A Discrete Event Simulation Model was constructed to predict the effects of potential changes to the process, priorities, and policies in the Emergency Department.

1.2 Research Motivations

One of my first jobs as an Industrial Engineer was to develop a simulation model for the Kansas University Medical Center's Emergency Department in the spring of 2009. It was supposed to be a three week position, but turned into a two year position incorporating many different hospitals. During the summer of 2010, I returned to Emergency Department to shadow the attending physicians, residents, nurses, nurse practitioners, health technicians, and administrators. During that summer, I was informed that the Emergency Department was going to develop a new residency program. Given my history with the staff, and my familiarity with their environment and Discrete Event Simulation software, I knew that I could help them continue to provide excellent care to their patients. This thesis provides beneficial analysis of their systems and potential alternatives now that there is a more specific need when evaluating their new Residency program.

The addition of a more focused Residency program adds another level of complexity to an already complicated system. Previous models have used fairly stable assumptions based on professionals that have already been established in the Emergency Department. Because this residency program is so new, the administrators in the Emergency Department don't have the convenience of using historical data as basis for policy decisions. Some of the data this is available to them is that of performance of the attending physicians. Although this data does not relate directly to the residents, it can be modified to fit our purposes using a few basic assumptions. The first assumption is that the residents start off less capable than the attending physicians. Second, the residents will become progressively better due to the experience they gain during each shift. Finally, the residency program trains residents for four years, after which they are considered to perform as well as the attending physicians. Since we have already collected data on the attending physicians and we know that the residents will eventually become physicians, we already have their final performance metrics for the residents. We don't know how much difference there is between the initial performances between the first year residents and the attending physicians, but we do know that they get better after each shift. In order to apply the true impact of the residents on the emergency department, we need an equation that can incrementally increase the level of performance of the residents.

Learning curves have been used in manufacturing setting to help predict the performance of newly hired workers. Simply put, a worker starts at a base line level of performance and over time their performance increases following a learning curve. After a certain amount of time the new worker reaches same level of proficiency of an experienced worker. Similarly the residents at the University of Kansas Medical Center's Emergency Department will start at a base level, and progress through four years in the residency program until they reach the performance level of an attending physician. Using this rationale, this thesis provides an accurate description of how residents impact the processes in the Emergency Department. It draws comparisons to data previously collected by myself and members of the Emergency Department.

To the best of our knowledge, there have been no published examples of Discrete Event Simulation Models describing the effects of Learning Curves in the Emergency Department. Although this model is specific to Kansas University Medical Center's Emergency Department, it serves an example for future studies on the resident workforce in any medical unit. It can be realized as a basic template for other hospitals and institutions as how to account for the effects of learning on a work environment. Further the data collected is unique in that no other report has collected this type of data with regards to physicians' tasks. Additionally, this thesis provides a starting point for data collection in future studies, and suggests areas in which others should investigate further.

1.3 Research Contributions & Objectives

In collaboration with the Kansas University Medical Center's Emergency Department, and Kansas State University's Health Care Operations Resource Center, this thesis presents an analysis of alternative models that simulate the effects of learning experienced by Emergency Department Residents as described by various learning curves. The Emergency Departments future needs are examined with the inclusion of the residents to provide insight for the Kansas University Medical Center.

The main contributions of this thesis are;

1. Determined the impact of different learning curves, and what significant parameters dominate the effects of learning
2. Suggested that residency programs develop a baseline level of performance by which to evaluate the progression of their residents
3. Studied the operational impact that residents and their learning have on the operations in the emergency department
    a. How long the impact lasted
    b. How the addition of the residents will perform with an increasing population
4. Established a foundation for future studies

1.4 Outline

The rest of the thesis is organized as follows. Chapter 2 is a comprehensive literature review of the existing works on Emergency Department operations, residents, work performance, and general learning curves. Chapter 3 overview of the Kansas University Medical Center's Emergency Department, followed by a literature review of generalized learning curves.

Chapter 3 begins with a detailed description the simulation model and all of its supporting components. After establishing how the model works, the outputs from the model are compared to the key metrics showing that the model accurately approximates the Kansas University Medical Center's Emergency Department.

Chapter 4 contains a several sets of different alternatives and their corresponding statistical analysis. These alternatives show the flexibility of the model and effects that a change has on the Kansas University Medical Center's Emergency Department.

Chapter 5 is a summary of this thesis with contributions, conclusions, and suggestions for future work. Suggestions are made about the use of learning curves as method to evaluate the progress of a resident's personal performance. They will focus primarily on future work, with suggestions that can make it easier for future research in the use of Discrete Event Simulation Models incorporating learning curves.

Chapter 2 - Background Information

2.1 Kansas University Medical Center

Kansas University Medical Center (KUMC) has the only nationally verified Level 1 Trauma Center in the Kansas City Metro Area. A Level 1 Trauma Center is the highest designation that can be achieved. The Emergency Department at KUMC sees about 46,000 patients each year. Their staff includes sixteen doctors and eighty-five supporting staff members. There are twenty-three patient rooms in the Emergency department with an additional seven hallway beds used as needed. The Trauma Room consists of two beds, and includes a trauma team comprised of a variety of specialists that are called upon when needed. A Fast Track area consists of five rooms, staffed with one physician assistant or a nurse practitioner to take care of patients with lower severity during the peak hours of the day.

There are always two doctors staffed meaning that they could be responsible for as many as twenty patients, depending on the situations within the emergency department. KUMC is a teaching hospital, so they have varying number of residents, medical students, nursing students and Emergency Medical Transport trainees who work with the Emergency Department staff. During the summer of 2010, the residency program changed to have only residents that were looking to move into an emergency medicine as a career. The residency program now has residents entering in periods of one year instead of just three months, with the potential to stay for four years. Meanwhile the patients are still coming in needing treatment, the inpatient area of the hospital is filling up, and everyone on staff is trying their hardest to make it all run smoothly. So how can a Discrete Event Simulation help them?

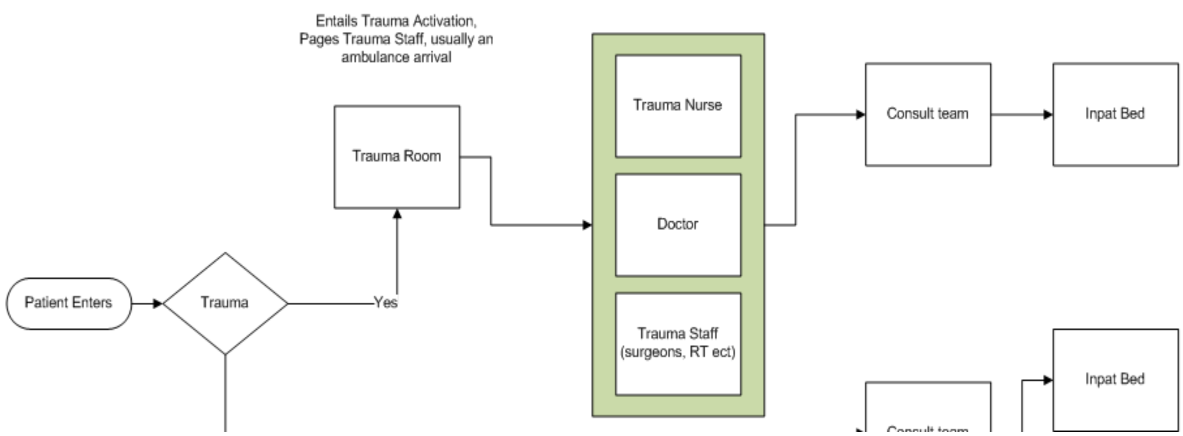
In all work environments there are bottlenecks; processes that determine the maximum rate that the system can perform. When examining a system, these bottlenecks stand out and are the usually the focus of improvement projects. Over time employees and administrators come up with innovative ideas and solutions that might solve their problems. But what else happens when a change is made? How much help do these solutions provide and are there any unintended consequences? This is where Discrete Event Simulation comes into play. Using a Discrete Event Simulation model we can evaluate the effects of a change. Whether it's a process changes, or a resource change, the simulation models can show the positive and negative effects before implementing the changes in real life.

2.1.1 Patient Acuity, Arrival Pattern and Flow

Emergency Departments across the country have been using the acuity levels to determine the severity of a patient for decades although most have differing qualifying criteria. (Mitchell 2008) Patients are assigned an acuity level by a triage nurse. Triage processes were originally developed by French doctors during World War I. Originally used at aid stations on the front lines, the practice has become much less morbid, but it is still very efficient. At the Emergency Department of Kansas University Medical Center patients are given an acuity level of 1 through 5, with 1 being the most critical conditions. All patients are processed by a triage nurse first, then the follow a process described below.

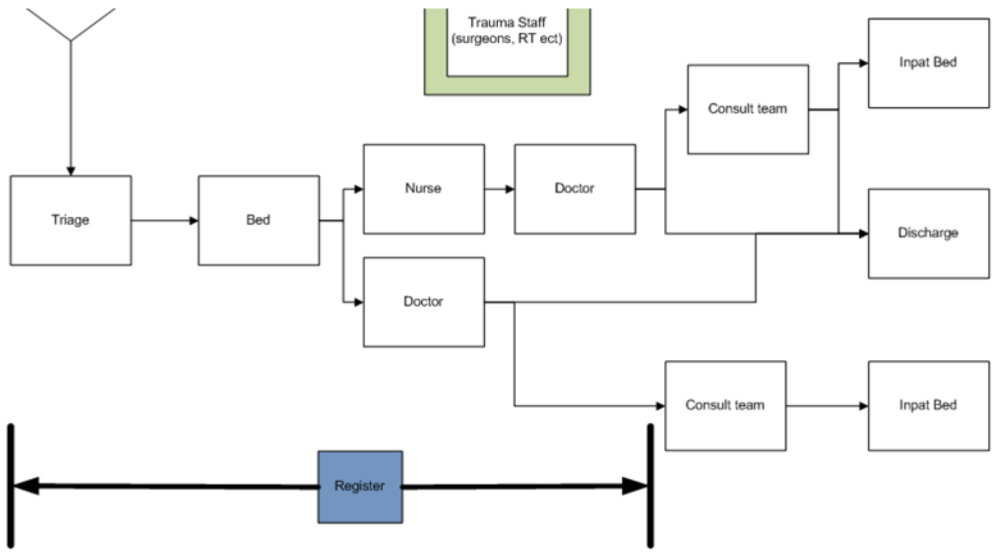
Figure 2:1 shows the path that an acuity level 2 patient takes through the Emergency Department. Patients of all acuity levels will follow the same path with the exception of the patients seen in the Fast Track which is discussed later in section 3.1.3. The only difference for fast track patients is that they will be seen in a fast track bed, and by a nurse practitioner instead of a doctor. Before a patient enters the Emergency Department at the Kansas University Medical Center, they are first evaluated to see if the patient's conditions warrant the trauma codes and procedures. If so then the patient is immediately sent to the trauma room. When a trauma code is activated, the Emergency Department pages a trauma team, consisting of several specialists in varying fields from other parts of the hospital. Usually a respiratory therapist, cardiologist, radiologists and one of the Emergency Department's attending physicians are constant members of the trauma staff. Additionally one of the Emergency Department's nurses is always on call to assist with trauma codes. This situation differs from the normal procedures, because the response of the trauma team has to happen within five minutes. After the immediate treatment is completed, the patient can be moved into either the intensive care unit or one of the inpatient areas in the hospital.

Figure 2:1 Trauma Patients Flow



Non-trauma patients will first be seen by a triage nurse, who will determine their acuity level. In Figure 2:2, the acuity level is 2, meaning there is a higher probability that they could be admitted. The path is the same for level all patients going through the emergency department, Once a bed becomes available a triage nurse takes the patient a room. Most often, a nurse will be the first person to contact the patient in the room, but on occasion the attending physicians are able to see the patient right away. First contact with the patient includes a detailed examination of the patient and the history of present illness. After which, the Emergency Department staff may draw labs, take x-rays, cat scans etc. The patient will remain in the Emergency Department during the tests and for any immediately required treatment. If the attending physicians determine that the patient is well enough to go home, the patient is then discharged; otherwise the attending physician pages a consulting physician.

Figure 2:2 Non Trauma Patients



When a consulting physician arrives in the Emergency Department, they reexamine the patient to determine whether or not to admit the patient to their specialty area of the inpatient. It's important to note that the registration in Emergency Department can happen at any point during the patient's stay up to the time that they are seen by the consulting physician. This process is typically doesn't get in the way of other processes and usually happens while the patient is waiting for results. If a patient is discharged, they are usually released immediately, but if the patient is admitted they often have to wait for an opening in the inpatient area the hospital.

2.1.2 Data Collection

There are three ways that data was collected for this new model. The first set of data comes from an information system created by EpicCare System. The Discrete Event Simulation model uses arrival data and patient demographics that are collected and reported by the EpicCare System. The adoption of the EpicCare System provided a major improvement to the amount of data that Kansas University Medical Center could collect. Additionally the EpicCare System provided a software interface for easier input of patient information.

The second method for collecting data was performed by a summer intern. During the summer of 2010, a recent Industrial Engineering graduate of Kansas State University who would return in the fall to start a master's degree, shadowed staff and observed the current process. The data collected by the summer intern can be broken into two parts, doctor activity shadowing, and room observations. Shadowing the doctors provided invaluable information about the how the doctors fit into the process as a whole. While shadowing, it became more obvious that the individual processing times for doctors are highly inconsistent, but they all followed a fairly standard process. The biggest observed variation was centered on the charting times, in which the doctor updated a chart containing information about the patient. It has been admitted by several of the attending physicians, but never directly observed, that it is very common for them to finish charting after their shift from home. A doctor estimated that on average, he spent two hours after each shift, entering information either at home or in the physician's area in the Emergency Department.

An example of the room observations is shown in the Figure 2:3 below. The summer intern recorded the activities in room 9 of the Emergency Department, along with several other rooms over the course of an eight hour shift on Thursday July 8th, 2010. Room observations were taken many times and of many different rooms between June and August of 2010. Most of the observed interactions were from nurses, but the data also provided information about the times regarding room cleaning, doctor interaction, health tech interaction, consult visits, x-ray (including portable machines), patient acuity and length of stay.

Figure 2:3 Room Observations

Date 7/8 Doctor Page Number
Room # 9 Acuity 2

OBS	HR	MIN	SEC	Who	HR	MIN	SEC	What	For Who/What
1	10	46	35	Pat	—	—	—		
2	10	47	03	RN	11	00	01		
3	10	47	03	[redacted]	10	47	55		
4	10	48	56	Tech	10	53	32	EKG	
5	10	49	11	Reg.	11	51	37		
6	10	50	18	Tech 2	10	54	07		
7	10	50	18	CN	10	59	20		
8	10	55	01	Tech	10	58	52		
9	11	06	55	[redacted]	11	15	02		
10	11	00	55	~~Res~~ MS	11	15	02		
11	11	02	07	RN	11	12	24		
12	11	02	07	RN'	11	02	20		
13	11	08	41	CN	11	08	55		
14	11	15	28	Res	11	27	56		
15	11	29	43	Port X-Ray	11	33	40		
16	11	35	02	Reg.	11	36	19		
17	11	38	37	Tech	11	43	12	escort Pat to	BR
18	11	51	35	RN	11	52	33		
19	12	16	09	[redacted]	12	15	56		
20	12	20	40	RN	12	21	41		
21	13	00	05	RN	13	04	26		
22	13	42	52	RN	13	43	13		

The third type of data collected for this study was by medical students. An example of the newest data collection sheet can be in seen Figure 2:4 below. A medical student shadowed a doctor for an eight hour shift and tallied what that doctor was doing in thirty second intervals. Meaning there were 120 tallies detailing what that doctor was doing during an hour. The first set of this data was collected over the summer of 2010, and it provided us summary of how much time a doctor spent on each of the listed tasks each day. Later in the fall of 2010, it was determined that the information was useful, but we wanted to know what order in which the events happened. The goal was to be able to say that if a doctor is doing a certain task, that the next task will be based on a percent. Data was collected again during the fall, which included the time for each tally.

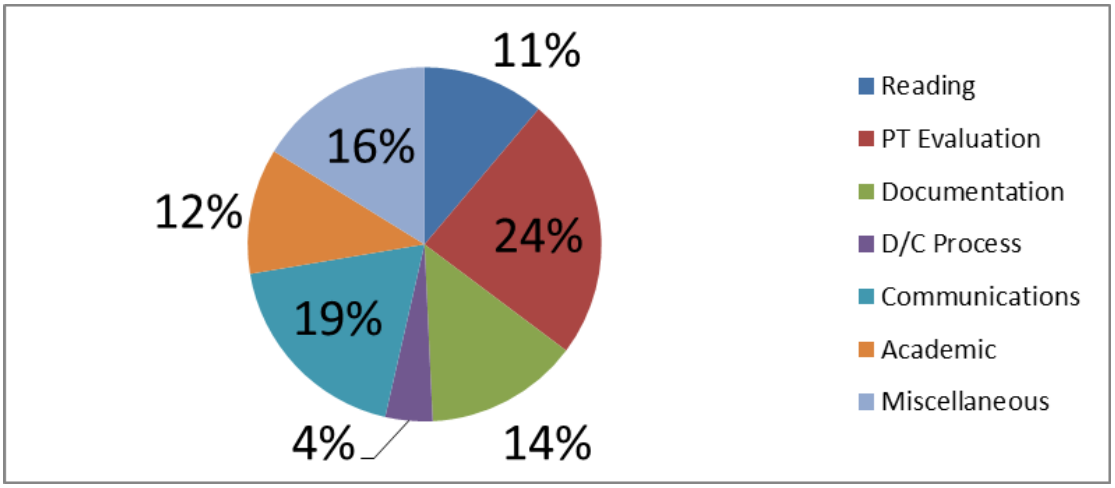
Figure 2:4 Doctor Tasks

Doctor: [redacted] Date 10/16/2010 Observer [redacted]

CATEGORY	1	2	3	4	5	6	7	8	9	10	11	12	13
Preview Chart & Pt Data													
Chart Review After Pt Seen													
Literature Search													
Reviewing Other Info													
READING													
HPI													
Background/ROS													
PE													
Procedure													
Educating Pt/Family													
PT EVALUATION													
Logging In													
Writing Orders													
Documenting - HPI													
Documenting - ROS													
Documenting - PE													
Results - Labs													
Results - Rad													
DOCUMENTATION													
Smartsets													
Dx													
f/u													
Pt Instructions													
Meds/Rx													
D/C PROCESS													
Consults Calling/Speaking													
Other ED Physicians													
Speaking W/Nurses													
Phone Calls Made													
COMMUNICATIONS													
Teaching													
Listening to MS 3-4													
Listening to Residents													
Listening to ARNP													
ACADEMIC													
Talking (Non-Pt Related)													
Travel													
Restroom/Breaks													
Eating													
Waiting On Other Teams													
Other (Specify Below)													
MISCELLANEOUS													
INTERRUPTIONS													

The Doctor Task tallying provided a very detailed overview of what the attending physicians do during the course of their work day. The tasks were broken down into seven categories; Reading, Evaluation, Documentation, Discharge Process, Communication, Academic and Miscellaneous. A summary of the tallies can be seen in the Figure 2:5 below.

Figure 2:5 Summary of Doctor Tasks



2.1.3 Previous Work with KUMC 2008

In the fall of 2008, an Industrial Engineering Senior Design team from Kansas State University was assigned to study the patient flow issues in the Kansas University Medical Center's Emergency Department. I was later hired on to the project as a consultant in January of 2009 to help the students develop simulation models that could accurately describe the flow of patients the KUMC Emergency Department. The project yielded a set of simulation models that could generate most numbers within 10% of the collected data from the previous year. The data considered for benchmarking includes times like, Door to Bed (DTB), Door to Doctor (DTD), Length of Stay (LOS), and Length of Stay to Admission (LOSA). Most of the benchmarking data was used to compare to the most recent literature describing hospitals of similar sizes because KUMC had not yet adopted a system that could track them. The most important benchmarking number that KUMC had was the number of patients who Leave Without Being Seen (LWBS) because they essentially represent a loss of revenue as cause longer periods of ambulance diversion time. While on diversion, the KUMC Emergency Department cannot accept ambulance arrivals causing ambulances to travel other hospitals and delaying patient treatment. Table 2:1 below shows some of numbers generated by the base model compared to the actual numbers from the hospital.

Table 2:1 Model Validation

General Metrics	Simulation	Hospital	% Difference
Total Arrivals	43295	43344	0%
Admissions	7549	8012	-6%
Discharges	35530	31365	13%
Diversions	803	730	10%
Trauma	382	274.49	39%
LWBS	4987	4686	6%
Roomed to Disposition	**Simulation**	**Hospital**	**% Difference**
AMA	201.9 Minutes	209.19 Minutes	-3%
LWBS	154.8 Minutes	163.18 Minutes	-5%
LBTC	171.8 Minutes	176.63 Minutes	-3%

The Table 2:2 shown below highlights the differences in expected revenue generated by the change in admission of patients from the Emergency Department from simulated changes to the base model. You can see that the in-patient buffer alternative shows the highest increase. Although the simulation generates correct numbers, the model itself would be difficult to adopt because it essentially adds more rooms and beds to the emergency department. Adding more rooms and beds to the Emergency Department would be very expensive and difficult. That specific alternative used ten extra beds as a buffer, for patients who had already been approved for admittance into the hospital area, but were waiting for an inpatient bed. The KUMC Emergency Department has a limited amount of space available for improvements and if they were to add that many additional beds, they would be full service rooms. After our final presentation, KUMC did add additional super fast-track rooms as well as several normal rooms to Emergency Department. These changes brought the KUMC Emergency Department to its current state of twenty-three patient rooms, seven hallway beds, five fast track rooms and 2 trauma beds.

Table 2:2 2009 Recommendations

2008-9 Possible Recommendations	% Difference
10 FT Rooms	17%
Double FT Beds	18%
Fill Empty FT Rooms	-7%
Super Fast Track	19%
Split Level 3	-14%
In-Patient Buffer	46%
Preempt Fast Track	5%

2.1.4 Previous Work with KUMC 2010

In the summer of 2010, another project with the Kansas University Medical Center's Emergency department began, with a yearlong duration. This new project was to provide another in-depth analysis of the Emergency Department with objective of developing and analyzing potential improvement alternatives to reduce the workload on attending physicians. It began with the collection of the previously mention data types; doctor shadowing, room observations, and task tallying. A summary of the suggested alternatives and their impact on the Emergency Department can be seen in the Table 2:3Table 2:3.

Table 2:3Table 2:3 shows several alternatives, and a few evaluations of a combination of those alternatives. The Average Dr. Utilization column refers to the average utilization of attending physicians. Unless noted otherwise, there are always two attending physicians on duty in the Emergency Department. It's important to note that simply decreasing the utilization isn't the only factor considered when evaluating each of the alternatives. The change in LWBS is a major factor, but what are not disclosed in this report are the costs and potential increases in revenue that could be generated by each of the alternatives.

Table 2:3 2010-11 Recommendations

#	Alternative	Avg Dr Utilization	Change in LWBS
1	24hr Fast Track	80.8%	2434
2	3 Doctors	75.4%	2216
3	4 Doctors	68.7%	2302
4	3 Doctors 12pm-8pm	83.8%	2102
5	3 Doctors 8am-12am	76.6%	2216
6	Scribes	81.7%	1635
7	Buffer Beds	99.5%	526
8	24Hr FT + 8am-12pm Dr 3	58.8%	2479
9	24Hr FT + Scribes	65.0%	2470
10	8am-12pm Dr 3 + Scribes	63.7%	2244
11	8am-12pm Dr 3 + Scribes +24 Hr FT	50.6%	2479

Just as in the 2008 project, adding Buffer Beds, provides a huge reduction in the number of LWBS, but the costs associated with expanding the Emergency Department ultimately prohibited this alternative. The Scribes alternative is based on the idea of having a health tech perform charting for the attending physicians as the attending physician performs all relevant tasks. Using the Scribes yielded a decrease in the number of LWBS but the coast of additional employees and their full time benefits ended up costing the hospital more than it a saved. Ultimately, the recommended solution presented by the 2010 project was extending the operating hours of the Fast Track. With the smallest cost, it presented the largest benefit to the Emergency Department.

2.2 Learning Curves

A review of learning curve literature provided several good sources of information about learning curves (Adam Janiak 2008) (Spence 1981) (Keir J. Warner 2010) (Yen 2009) (Biskup 2007). “A state-of-the-art review on scheduling with learning effects” (Biskup 2007), was one of the first pieces of literature that I came across that suggests variability in the learning curve due to differing circumstances. Given the nature of Discrete Event Simulation, variability already included, modifying the simulation to account for these differing circumstances is easy. The equations postulated by (Biskup 2007) describe how schedules effect the learning within the Emergency Department. Changes to the Emergency Department’s staff scheduling might be able to improve expedite the learning process.

(Biskup 2007), suggests that the processing time associated with a job can have an effect on the learning process. Managing that processing time can have a positive effect on the performance of the system as a whole. The priority based system does provide help to the sickest of patients first, most of which already require longer processing times. Additionally the scheduling referenced by (Biskup 2007) is for known processes, with precise processing times, and a set schedule of events to proceed and follow them. Unfortunately the processing times are not known to the Emergency Department Staff at the patient's time of arrival. The conditions present in the Emergency Department make scheduling sets of tasks with regards to patients are nearly impossible due to the high variability.

Some of the functions that are used are the most common power function for a learning curve.

$$P_{[k]} = P_{[1]}k^{a} \tag{2.1}$$

Where $P_{[k]}$ is the processing time for the k^{th} unit, or in our case the for the k^{th} process. The variable a is defined by the learning rate (LR), which is described below.

$$LR = \frac{P_{[2k]}}{P_{[k]}} = \frac{(2k)^{a}P_{[1]}}{k^{a}P_{[1]}} = 2^{a} \tag{2.2}$$

Or it can be described directly as

$$a = \frac{\log LR}{\log 2} = \log_2 LR \tag{2.3}$$

Using these equations we can calculate all of the relevant values of the learning curve. A lot of things need to be considered before we can apply this to the emergency department. A major factor in the stress and workload for emergency department staff is the large amount of variation in processing times caused by the variety of patients, procedures, staff availability, and overall workload. The most practical use for this formula will be to generalize the effects of learning by new staff members. With this we can model the effect of staff turnover, new hires, medical students, and the effect of residents who are specifically assigned to the emergency department or on standard rotations. Unfortunately the data required to add a learning curve modeled after equations 2.1, 2.2, and 2.3 to the model is not readily available, and goes beyond the scope of this thesis. Additional research would need to be done to see if working a non-standard shift (not between 07:00 and 16:00) has any adverse effects on the learning process. Another area of interest might be the effect of fatigue on a staff member's ability to learn. Applying this formula might not be the simplest way to account for the effects of learning, but it does not necessarily mean they should be discounted entirely.

(Biskup 2007) talks about position based learning. Specifically about how scheduling a process to happen on a specific machine of a group of identical machines, given that the learning curve for each machine (usually run by different operators), is independent of the others. When applying this idea to the Emergency Department, we must realize that each of the "machines" is a nurse, doctor, resident, or another member of the emergency department. There are going to high levels of variations between the staff but modeling can be used to show the impact, but more than likely we will assume that the processing times average out.

$$p_{ir} = p_i * r^a \qquad (2.4)$$

With i = 1, 2, 3…, n, being a job, and r being the position in the scheduled position of the job. So together the term p_{ir} represents the processing time for job i on a specific machine at the scheduled position r. When the process is fully automated, the processing time is assumed to be a constant, with a negligible standard deviation and variance. With full automation, learning cannot happen during the processing time, because the human element isn't present. Learning can still occur, but its impact is limited to the setup times, scheduled maintenance times, and material handling times, that are required for the machine. With this idea, we can modify the previous equation to account for setup time specifically using the equation below.

$$p_{ir} = S_i * r^a + V_i \qquad (2.5)$$

In this new formula, the processing time for job i at position r for the a^{th} machine am based on Setup time S_i and a fixed processing time V_i. With regards to the fixed processing time, in the health care context of the Emergency Department, we can set V_i equal to distribution the better describes our process. With this approach we can account for the effects of the learning curve with regards to setup times and processing times to add another source or variability. Although the final model created in this thesis does not account for set up times, it could take into consideration in future studies. (Biskup 2007) goes on to describe equations that account for job dependent position based learning, which also becomes too granular for out purposes. We do not want to model n types of procedures, and attempt to account to m number of attempts for each procedure to develop competency. Modeling the Emergency Department in that much detail would make the simulation unnecessarily complicated, increasing the computation time. Setup times in the Emergency Department are generally small, and are therefore combined into the processing time of the process that they would precede.

Another paper titled "A new approach to the learning effect: Beyond the learning curve restrictions" by Adam Janiak starts out with a revelation that the scheduling field as a whole is becoming increasingly interested in how to model the learning effect and how it pertains to scheduling. Janiak references Biskup, and uses one of the learning curve below. Biskup originally chose the following equation to describe the learning curve's effect on processing time.

$$p_j(v) = a_j(v)^{-\alpha} \qquad (2.6)$$

This equation works with values of v and j that are integers representing the v^{th} position and the j^{th} job. Meanwhile a_j is the processing time for the specific job and alpha is the common learning rate of all the jobs which is greater than zero. This notation is used throughout the paper, although it is the same formula from the first paper.

Many papers were reviewed in an attempt to apply learning curves to processes in the emergency department but unfortunately most followed an approached around successive attempts to success or morbidity. (Richard J. Novick 1999) (Keir J. Warner 2010) (Rade B. Vurkmir 2010) For example, (Mulcaster 2003)studied Laryngosopic Intubation procedure is performed after Cardiac Arrest, and should be used for Asthma and COPD because it deals with establishing an Air-Way. Mulcaster suggests that it should not take longer than 12 minutes because the result is the death of the patient. After 47 attempts, the subject reaches a 90% probability of a good result, but they still required assistance. After 57 attempts, the subject reaches a 90% probability of a good result. While Mulcaster's paper and many papers like it are very useful to others, they are not helpful in the context of process modeling. This shortcoming leads to the suggestion that as hospital strive to be more efficient; they will need to change the focus of their studies to include process time much like manufacturing industries.

To the best of our knowledge the most common areas addressed in Emergency Medicine centered around cardiac arrest, asthma and COPD, trauma, and charting and training. Interviews with the physicians in the Emergency Department at the Kansas University Medical Center have determined that during Trauma Code, the Emergency Department Physician's primary goal is to establish the airway. During a Trauma Activation specialists from different departments will be on hand to facilitate other needs. Additionally the primary concern for Cardiac Arrest is to establish the airway, leading to the consolidation of three of the most common tasks; cardiac arrest, asthma and COPD, into a single learning curve. Now there are only two areas; training and charting without a learning curve.

Charting in the Emergency Department at the Kansas University Medical Center is done through the previously discussed EpicCare System. In short, the EpicCare System is similar to the electronic medical records system described in by (Alexander J. McLeod Jr. 2008). His study of learning while adapting to the introduction of an electronic medical record system provided the following information which yields a curve described in Figure 2:6 Computer Charting Learning CurveFigure 2:6 below.

- Height Initial = 24.87 $_{T1}$
- Days to Stabilize 537 n
- Stable time 23.85 T_{537}
- β = -.0066621147

$$T_n = T_1 * n^{\beta} \tag{2.7}$$

$$\beta = \frac{\frac{\ln T_n}{\ln T_1}}{\ln n} \tag{2.8}$$

Figure 2:6 Computer Charting Learning Curve

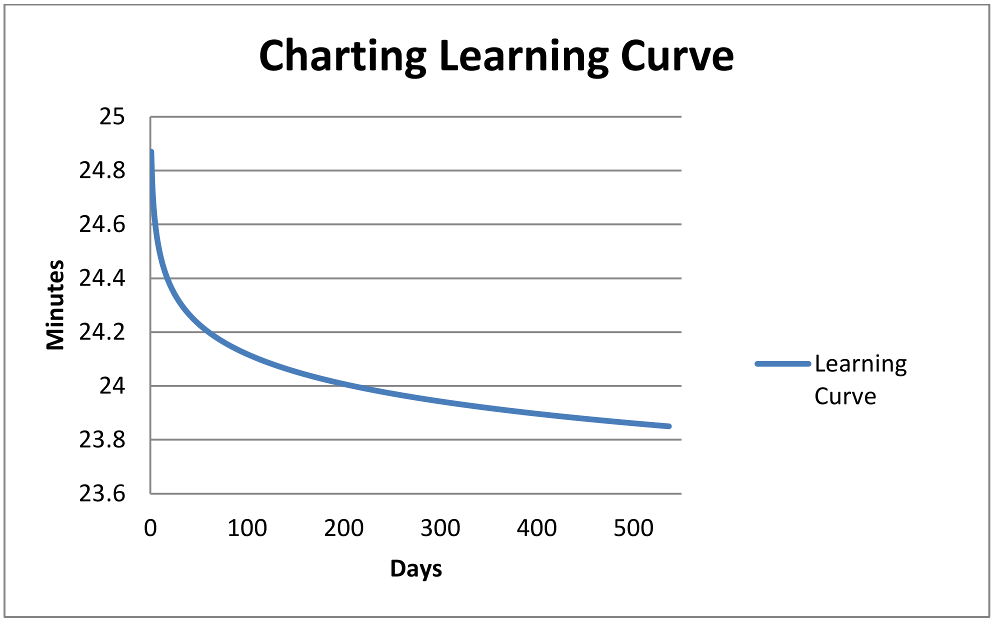


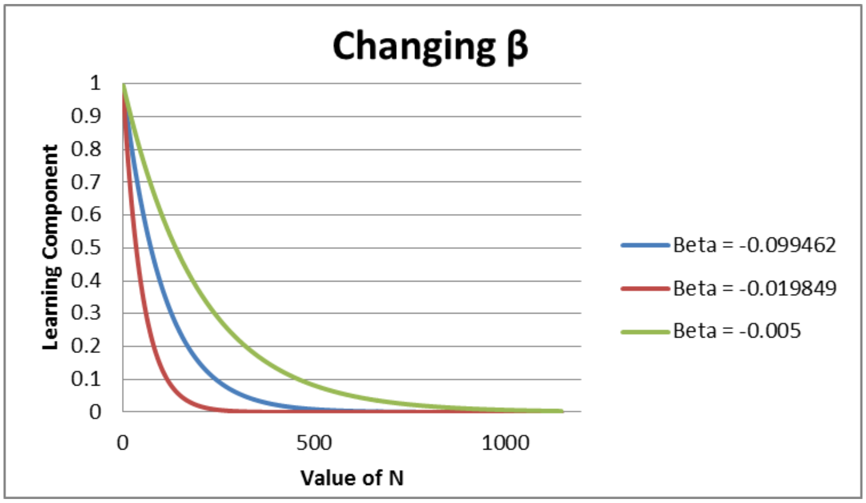
Figure 5 shows that after 537 days the expected time for charting has decreased by about 1 minute. Although every minute is precious in the Emergency Department, a saving of 1 minute is not worth incorporating into the Model. The learning curve associated with time spent charting, will not be considered as it is represents very little amount of time. After looking at the information available from the literature review, the only useable learning curves come from Cardiac Arrest, Asthma and COPD and Charting. Due to their common method of treatment, Intubation, they can all be summarized as a single learning curve.

After examining several examples of Learning Curves in recent literature, a generalized form was determined to be the best approach because it would translate better to the theoretical nature of the project. The generalized form of the Learning Curve that is used follows the equation below:

$$T_n = D(1 + (e^{-\beta n})) \tag{2.9}$$

From this equation, we see that as n increases, the component from learning decreases. As n increases, the term $e^{-\beta n}$ approaches 1. At the beginning of the simulation, the term is roughly zero, meaning that the initial processing time is T_1*(1 + 1), which equals $2T_1$. This means that the residents are expected to take twice as long as normal physicians at the beginning of their residency. The term β represents the time required for the term to reach 0, which will make equation $T_n = T_1$ meaning that the resident is preforming at the same level as the doctor. Changes can be made to β to allow the term $e^{-\beta n}$ to take more or less time to approach zero allowing the model to take into account changes to learning. Figure 2:7 shows how the smaller negative values of b elongate the shape of the curve.

Figure 2:7 Change β in the Learning Curve



In equation 2.10, the value of alpha is based on the assumption that the residents require twice as much time to perform the equivalent task. This equation can be scaled to any justifiable level by the addition of a coefficient α. Using different values of α differing, starting levels can be evaluated.

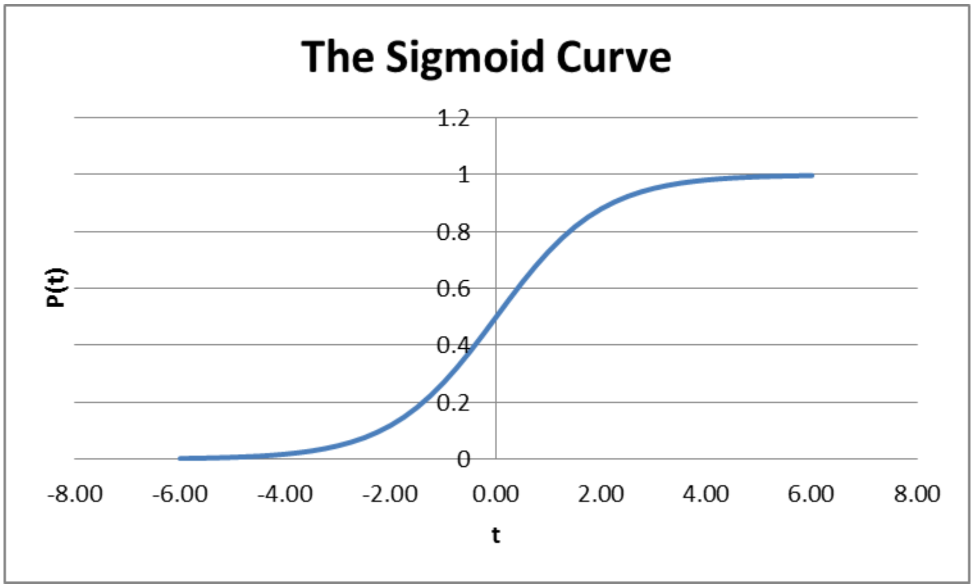
$$T_n = T_1(1 + \alpha(e^{-\beta n})) \qquad (2.10)$$

2.2.1 The Sigmoid Curve

A Sigmoid Curve is mathematical formula that resembles the letter S and is defined by the equation below. Figure 2:8 shows that as t approaches negative infinity, the value of P_t approaches zero. As t approaches zero P_t approaches a value of one half. Since the Sigmoid curve is symmetrical around one half, it can be useful if we want to assume that the resident's learning is half over at the halfway point. In equation 2.11 as t approaches positive infinity, P_t approaches one. For our purposes we will want the opposite effect using $1 - P_t$ as a contribution of learning to the processing times of the residents, which will be described by equation 2.12.

$$P_t = \frac{1}{1 + e^{-t}} \qquad (2.11)$$

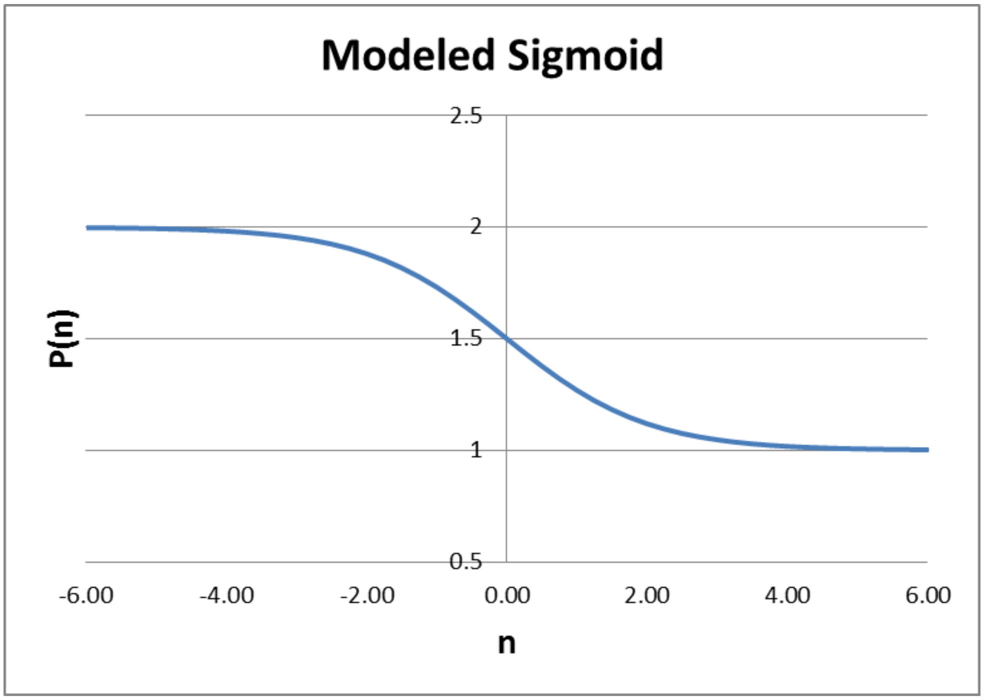
Figure 2:8 The Sigmoid Curve



In Figure 2:8 the sigmoid uses the example value of t to proceed from $P(t) = 0$ at $t = -6$, to $P(t) = 1$ at $t = 6$. For the purpose of the model, we needed to modify the basic sigmoid function as shown in equation 2.12 below. The resulting curve can be seen graphically in Figure 2:9, and shows the value $P(\mathrm{n}) = 1$ at $t = -6$ and $P(t) = 0$ at $t = 6$. When looking at both Figure 2:8 above and Figure 2:9 below, we see that the sigmoid function is centered around 0 on their respective horizontal axis. It's also very important to note that the step size used in the model for this function is not one. In all other models, the step size for the learning curve is one, and it is increased after each shift. Due to the odd scale of the sigmoid curve, and the ease of model changing, we scaled the step size to fit our period. All other models used a period 0 to 1092; representing the number of shifts a resident would perform over the course of the four year residency. In the sigmoid model, we used an incremental step size to fit the period from -6 to 6. The resulting step size for this model is thus 12 ÷ 1092 = 0.01099. With this new step size, the model required very few modifications and maintained the base assumptions of improving incrementally after each shift over four years.

$$P_n = D(1 + \left(1 - \frac{1}{1 + e^{-n}}\right)) \qquad (2.12)$$

Figure 2:9 Modeled Sigmoid Curve



2.2.2 The Gompertz Function

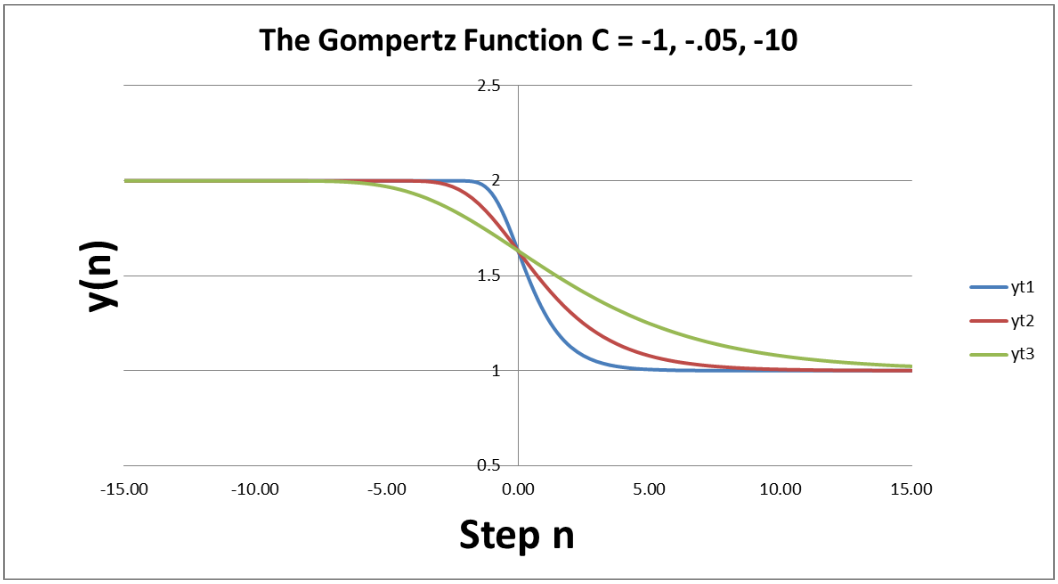
The Gompertz Function is a Sigmoid Function that can be easily modified to fit different benchmarks described by data. Using the Gompertz Function, the learning curve can be tailored to meet almost any shape described by the data. Shown in the figures below are some modifications to the Gompertz function graphed in Microsoft Excel. Manipulating the value of *a* will have similar results as manipulating α in the generalized learning curve.

$$Sigmoid\colon\ P_t = \frac{1}{1+e^{-t}} \qquad\qquad Gompertz\colon\ y_t = ae^{be^{ct}} \tag{2.13}$$

- *t* is the step
- *a* is the upper limit
- *b* determines the displacement of *t*
- *c* establishes the steepness of the function

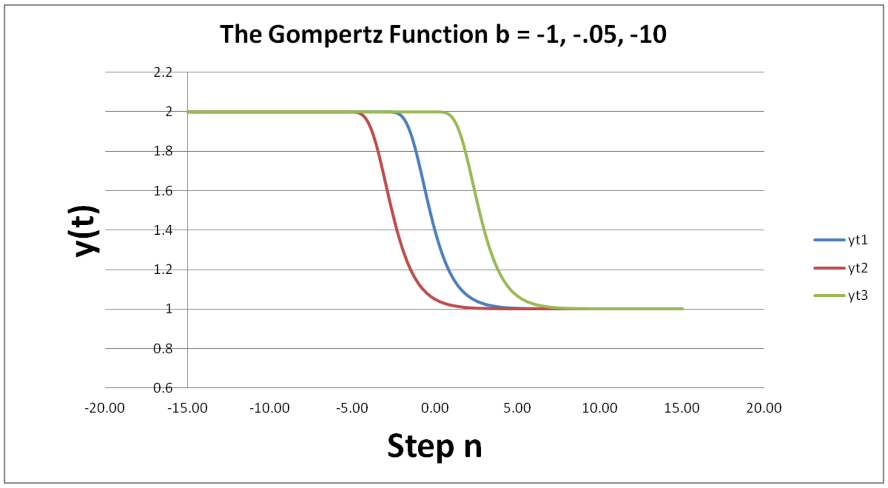
Modifying the Gompertz function to fit the slope of a learning curve can be done easily by changing the value of *c*. Figure 2:10 shows the effect that changing c has on the shape of the Gompertz function. It's important to notice that neither of the horizontal asymptotes is affected by the change in *c*. In our simulation model, we prefer to keep the value of the learning curve between 1 and 0 to keep the logic simple.

Figure 2:10 Gompertz Changes in *c*



(Humphrys n.d.) suggests that Gompertz function is very flexible which makes it a good candidate to be incorporated into a Discrete Event Simulation Model. Future models should begin with the Gompertz function in mind, because when collecting data, the researchers can identify benchmarks in the learning process. After collecting the correct data, the Gompertz function can be modified to the fit the approximate shape described by benchmarks. Figure 2:11 shows the effects of changing b which is used to shift the function horizontally, changing where the function crosses the y-axis. Changes to b do not provide any benefit for our model. As the residents learn, they progress along the function with the end result of reaching the value of 1 at the upper horizontal asymptote.

Figure 2:11 Gompertz Changes in *b*



So how is this useful? Hospitals with established residency programs or those that want to start their one, can use the Gompertz function to fit establish their expected learning curve. For hospitals without residency programs, the attending physicians can be used to establish a level of performance that they expect. Either way, the emergency department will know have a good tool to evaluate their residents.

Chapter 3 - Model of The Current State

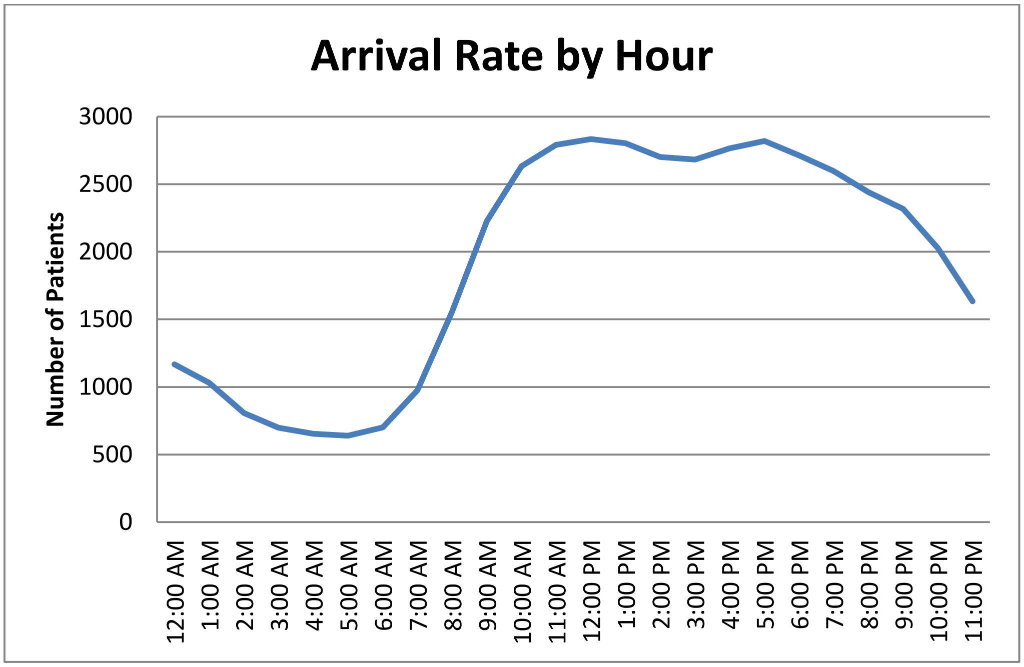
3.1 Modeling Details

This chapter provides an in-depth explanation of how the major parts of the simulation work. Some of the less important parts of the model are not included. Specific information about the processing times and generated revenue has been intentionally excluded as that information is considered to be the property of the Kansas University Medical Center. The Simulation model was created in Rockwell Software's Arena version 13.9.

3.1.1 Patient Creation

The simulation starts using the data provided by the EpicCare electronic medical record system. Figure 3:1 was generated by EpicCare and is used as a scheduled arrival rate for patients. In the model the patients are assigned an acuity level of one to five immediately being created. In reality patients don't receive an acuity level until they've been seen in triage. In reality, the patient's acuity level is not known until they have gone through triage, but assigning the acuity level early allows us more accurately quantify the patients who Leave Without Being Seen (LWBS). The model also decided which patients will require any tests in the emergency department. Patients are assigned lab tests based on their acuity level, meaning that the more severe the patient, the higher the chance that they will be assigned lab tests. The lab tests come in three types, general lab work, X-Ray Lab, and a combination of both. With the exception of trauma patients, all patients will now proceed to triage.

Figure 3:1 ED Average Hourly Arrival Rate in 2010



3.1.2 Triage

When patients arrive in the Emergency Department they check-in and wait to be triaged. The concept of triage was developed by the French during World War I. In short, medics on the battle field divided wounded soldiers into three categories; those who would live regardless of treatment, those who would die regardless of treatment, and those patients whose chances for survival would drastically improve if they received immediate attention. This methodology has been modified and applied to Emergency Departments around the world. (Mitchell 2008)

When a patient is seen in triage, they are evaluated by a registered nurse (RN). This nurse commonly referred to as the triage nurse, has had sufficient experience to provide the first medical screening. They will ask the patient about the history of the present illness, symptoms they've experienced and other general questions. Based on the patient's response to chief complaint questions the triage nurse will assign them an acuity level. Acuity level 1 patients are the most severe, and typically are in the process of dying requiring immediate medical intervention. Patients are categorized as acuity level 2 if they are experiencing chest pains, major respiratory problems and blunt force trauma. Almost all patients seen in trauma rooms are given an acuity level of 1 or 2. Patients with less severe conditions such as abdominal pain, minor cuts, broken bones and joint problems that require two or more medical resources indicated in classified as acuity level 3. Acuity level 3 Patients are the most common, and typically stay in the Emergency Department the longest. Unfortunately the level 3 patients are not critical enough to get priority, and their conditions are not simple enough to be seen in Fast Track.

Table 3:1 Resources for Triage System

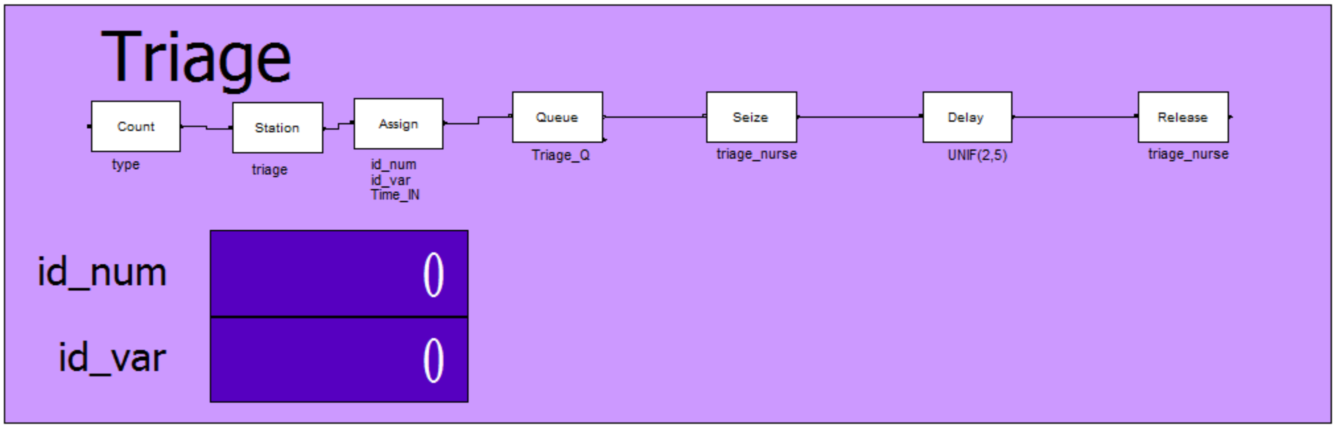
Resources	Not Resources
Labs (blood, urine)	History & physical (including pelvic)
ECG, X-Raysm CT-MRI-Ultrasond	Point-of-care testing
IV fluids (hydration)	Saline or heplock
IV, IM or nebulized medications	PO medications
Specialty consultation	Phone call to PCP
Simple procedure = 1 (lac repair, Foley cath) Complex procedure = 2 (conscious sedation)	Simple wound care (dressings, recheck) Crutches, splints, slings

Acuity level 4 and 5 patients are patients that typically require minor or minimal medical attention. If one resource from Table 3.1 is required, the patient is assessed as the acuity level 4, otherwise, it is assigned to acuity level 5. These patients have stable general health conditions and have an extremely remote chance from dying, and are thus considered the lowest priority. Over the years emergency departments throughout the world have been inundated with low acuity patients using the emergency departments as their primary care facilities. These patients cause long waits in emergency departments, and are a drain on critical medical resources in their respective communities. Because they are low acuity, they typically end up waiting the longest. Their congestion causes more severe patients to leave without being seen due to the expected waiting time. This has led to the adoption of Fast Tracks treatment concept. The idea is that level 4 and 5 patients can be seen in designated area called the "Fast Track" rooms utilizing a few registered nurses and providers (typically, physician assistance or nurse practitioners). This policy helps relieve overcrowded regular exam rooms and in the general waiting areas in emergency departments and will be discussed in more detail in section 3.1.3.

A screen shot from the triage section of the model is shown in In it, patients pass through a station block that gives them a current location in the hospital. They are assigned an identification number as an attribute named "id_num" which can be used to identify the patent later in the model. They then wait in a Queue that represents the waiting room, to see the triage nurse. After going through triage, the patient proceeds to the Room Assignment section of the model.

Figure 3:2. In it, patients pass through a station block that gives them a current location in the hospital. They are assigned an identification number as an attribute named "id_num" which can be used to identify the patent later in the model. They then wait in a Queue that represents the waiting room, to see the triage nurse. After going through triage, the patient proceeds to the Room Assignment section of the model.

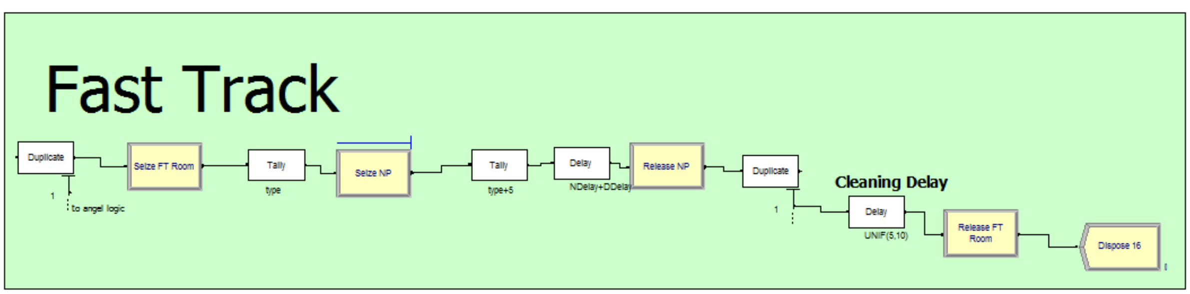
Figure 3:2 Modeling Triage



3.1.3 The Fast Track

The Kansas University Medical Center's Emergency Department has rooms set aside for the treatment of the less severe patients called the Fast Track. Patients seen here in the Fast Track must have an acuity level of 4 or 5, and must be seen between 11:00am and 11:00pm. During its operating hours, patients are sent to the fast track after they have finished being triaged in the triage section of the model. Figure 3:3 shows how the model handles patients in the Fast Track. Patients must first wait to get a Fast Track room before they can be seen by a nurse practitioner. In reality, nurse practitioners act like doctors, but have limited authority to prescribe controlled medicines. The probabilities that patients with an acuity level of 4 or 5 get admitted to the inpatient are of the hospital is insignificant, therefore all patients in the Fast Track are discharged after being seen by the nurse practitioner.

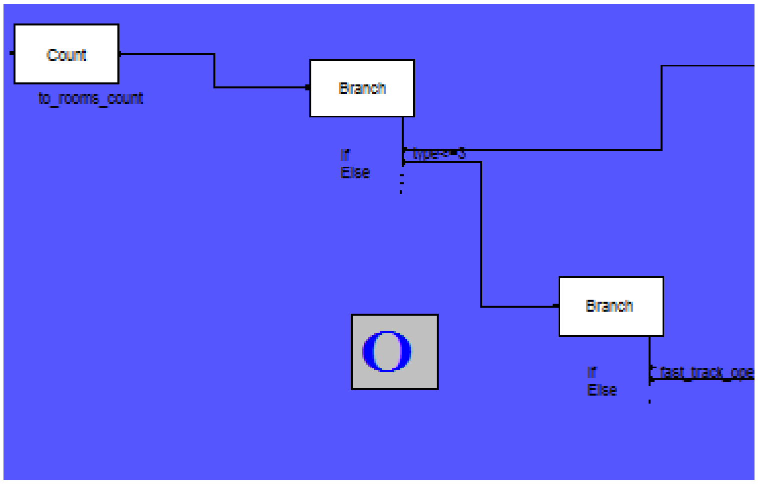
Figure 3:3 The Fast Track



3.1.4 Room Assignment

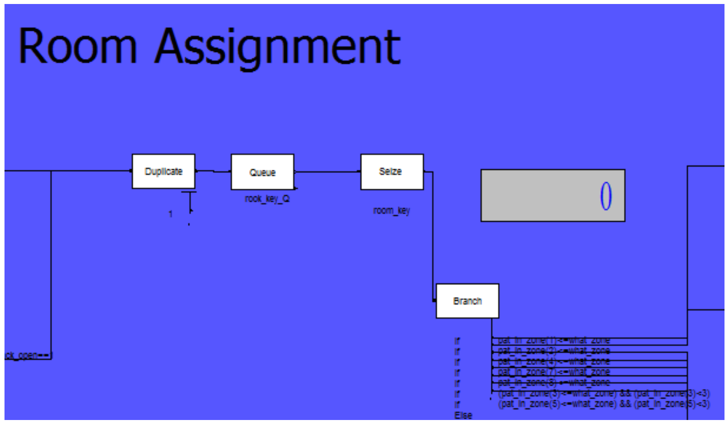
The Room Assignment section of the model is a fairly complex part of the model because of how the KUMC Emergency Department zones their staff. In reality the concept is very simple and easy to apply, but modeling it requires a bit of creativity. When filling the rooms, the Charge Nurse try to keep a balanced number of patients assigned to each nurse. Figure 3:4 below shows how patients enter the room assignment logic. First the level 4's and 5's are given the opportunity to go through the Fast Track. If the Fast Track is open, they will be sent there, but if it's not, they proceed on to the waiting room to with all of the other patients. The queue is based on priority, meaning patients with the higher acuity level (1 being high) are seen first.

Figure 3:4 Fast Track Path



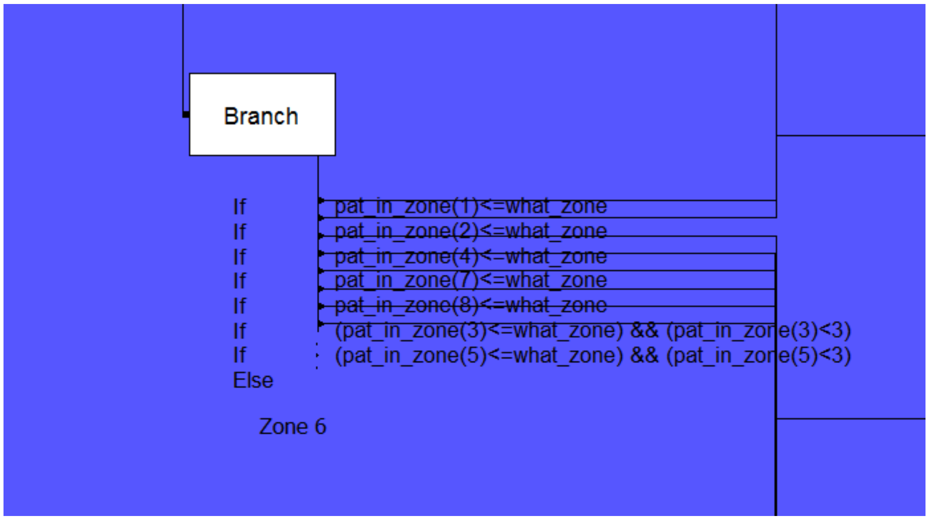
In this model, the Room Queue is a major improvement from the 2008-9 model mentioned in section 2.3.1. The previous model used different queues for each of the five acuity levels. This required more complex Left Without Being Seen (LWBS) logic, which is why in Figure 3:5 all patients duplicated before they wait for a room to become available. Additionally the previous model was not concerned with order in which the beds were filled. Each of the beds had access to all of the nurses and all of the doctors because the zones were not a concern in that model. In the new model, patients wait for a "bed key" which is an imaginary resource. There are thirty bed keys in the model, one bed key for each of bed. This method keeps all of the patients waiting in a single queue for a bed to open up. If this device wasn't in place, patients would wait in one of eight different zone queues and they would fill the Emergency Department haphazardly.

Figure 3:5 Modeling Room Assignments



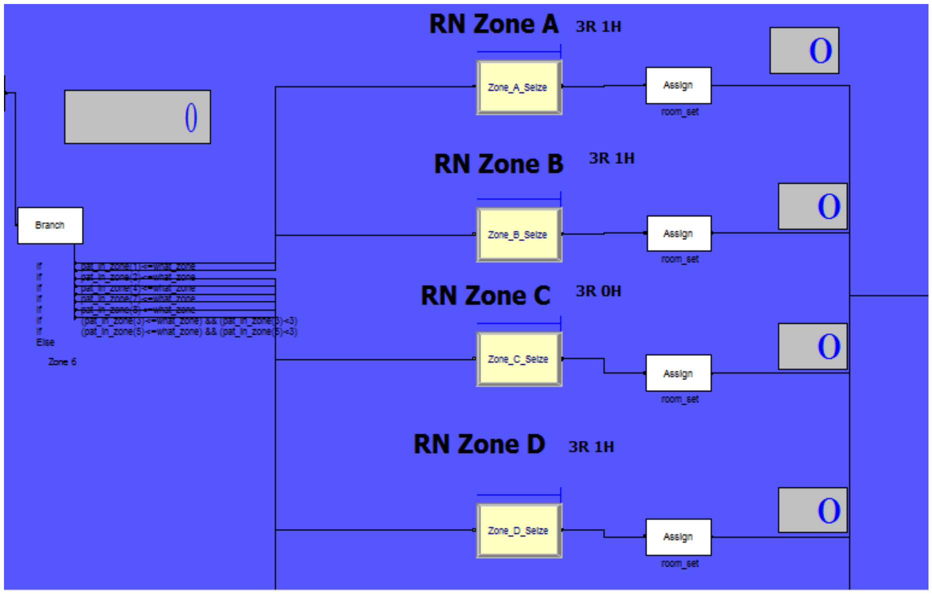
In reality the Nurses are each responsible for a zone that has between three and four beds in it. In all there are eight zones, and we want them to fill evenly so that no one nurse is completely overwhelmed. Knowing that the Emergency Department has a total of thirty beds when full allows model to fill a specific zone based on how many beds are in use. An expression called "what_zone" holds the value of the zone with the least patients in it. Figure 3:6 shows the different paths that a patient will take to fill a bed in the zone that is the least full. The model fills the rooms starting from the zone closest to the Triage Room. Assigning what zone the patient enters is only half of the battle. Because the simulation handles each of the beds as individual resource for animation purposes there could potentially be thirty different seize blocks, so the model needed a way group the beds by their zones. Early versions of this simulation model used at least ten branch blocks, and after many revisions, the final version of this model does it with just one.

Figure 3:6 Filling Zones



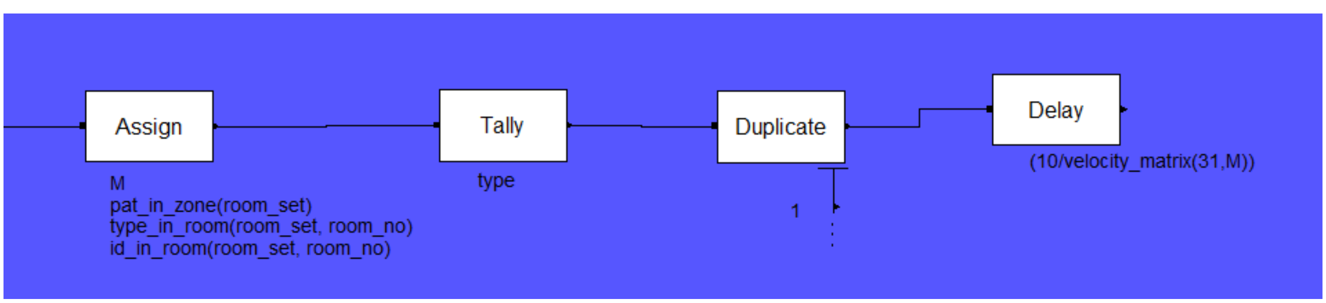
The reduction is only possible because of the creative use of variables and resource sets. Eight resource sets were created to model each zone consisting of three to four beds. Each of the eight zones corresponds to one of eighth seize blocks where the beds in the sets are seized in a preferred order. The preferred order allows meaning that the beds in the ED rooms were always seized before the overflow beds in the hallways. In order to release the correct bed later in the model when a patient is discharged from ED, each patient is assigned an attribute called “room_no” corresponding to the specific bed that they seized in that set. Because all of the sets have three to four beds, all patients will receive a room_no between one and four. Afterwards they are assigned an attribute called “room_set” which refers to the zone that they are staying in. Figure 3:7 shows a few of the seize blocks tied to the zones.

Figure 3:7 Assigning Patient Location



In the modeling software (Arena v13.9) there is a default attribute called "M" which keeps track of an entity's location. Our model uses this default variably by assigning location at an assign block. Since we can use variables in the assign block, we only need to use one assign block, where most simulations models would use a station for each location. This was accomplished by using both the "room_set" and "room_no" attributes previously assigned to the patients. A variable array consisting of thirty-two numbers was used to assign the patient a location. Additionally the assign block kept track of how many patients were a specific zone, what acuity level was in each bed, and the identification number of the patient in the room. The entire process happens in the one Assign block shown in the Figure 3:8. Once all of the data is recorded by the model, a copy of the patient is sent to the nurse logic to keep track of the nursing workload.

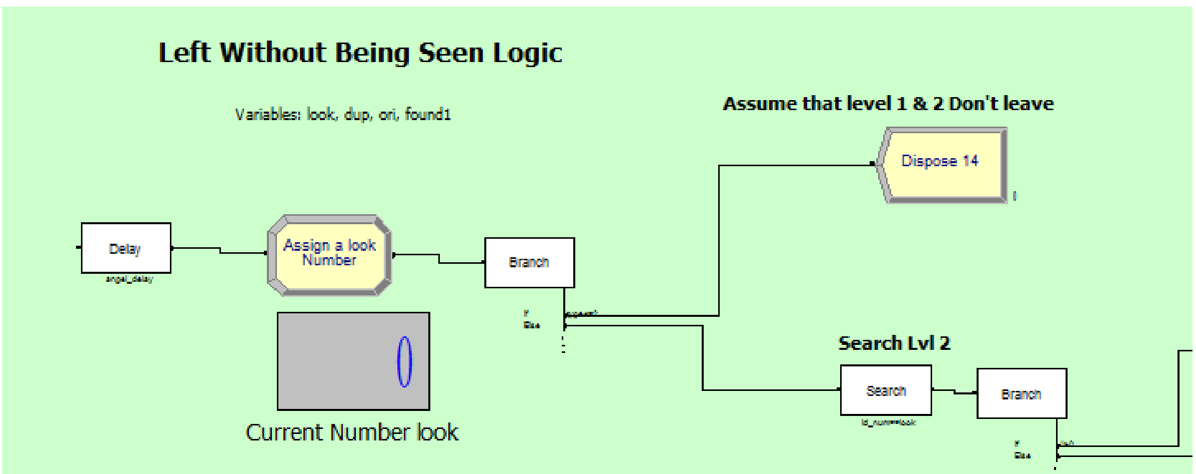
Figure 3:8 Managing Room Assignments



3.1.5 Angel Logic

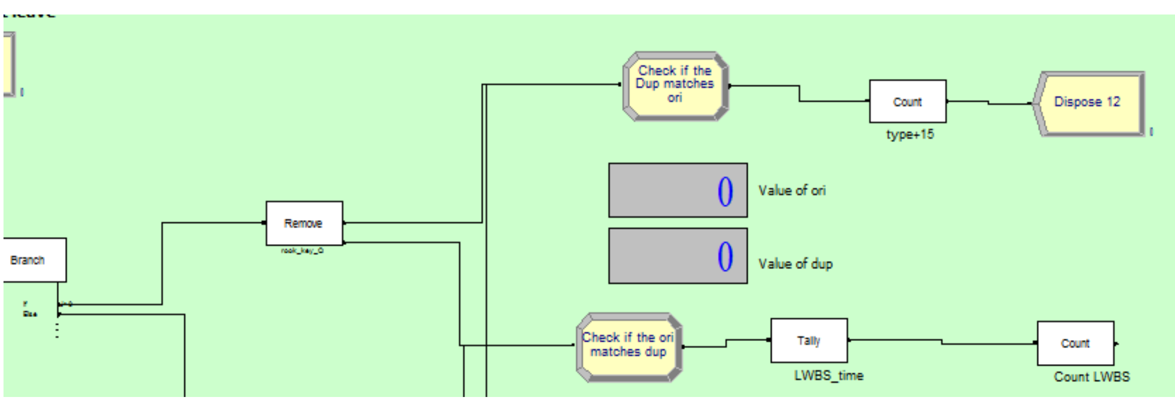
At the beginning of the Room Assignment section of the model, a duplicate was created and sent to the Angel Logic section. The purpose of this section is to simulate the patients who Leave Without Being Seen. This section follows the same process as the 2008-9 model, but it has been greatly simplified. A duplicated copy of the patient enters this section through and waits for a specified amount of time that was calibrated to approximate the amount of time at a patient is willing to wait for a room to become available. It is assumed that patients with acuity levels of 1 and 2 do not leave because of the severity of their illness. In Figure 3:9 the level 1 and 2 duplicates that have waited they are immediately thrown away. Everyone else is sent through the LWBS Logic. Then the model scans the waiting room for the original patient that from which the duplicate was made. If the original isn't in the waiting room, the duplicate is thrown away. If the model finds the patient with the matching identification number in the waiting room, then it proceeds to send the patient home.

Figure 3:9 Angel Logic (LWBS)



Once the original patient has been found, it is removed from the waiting room, and sent here. Figure 3:10 shows the path that the original patient and the duplicate take to finish the LWBS process. Both the duplicate and the original's information are recorded by the model. Once the model's taken note of the important metrics original entity is sent to the exit, while the duplicate is thrown way.

Figure 3:10 Counting the LWBS



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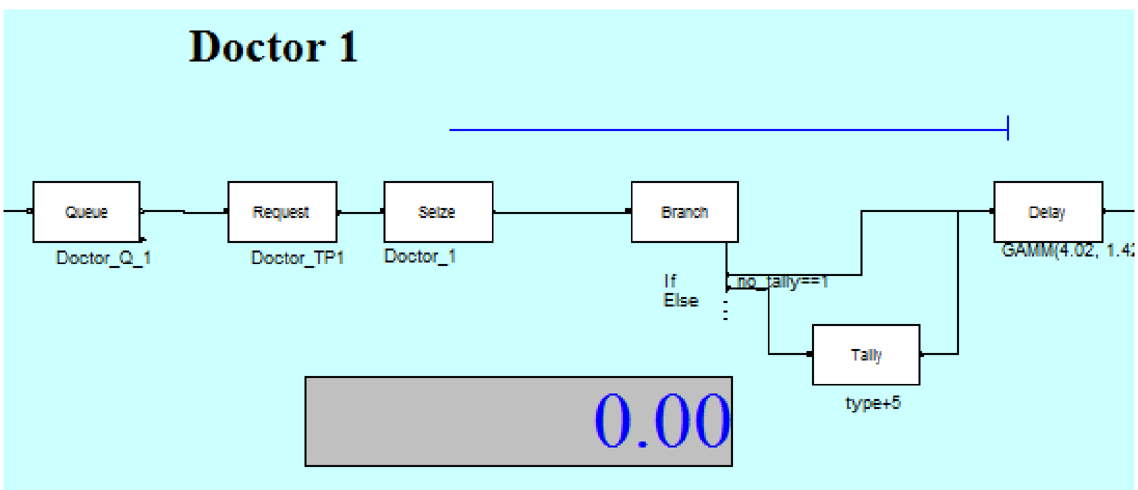
3.1.6 Simulating Walking Distances

Both the nurses and the doctors use the same travel logic to simulate the travel time in the model. This section shows the commonly used combination of are used to simulate the travel time. In the modeling software Arena resources are used to model a physical thing that can be used to process an entity. Often resources are used to model machines or employees. In this model, doctors, nurses, tech, and nurse practitioners are modeled as resources. Our model also aims to describe the movement of our resources through the use of transporters.

Each resource that could travel was paired with a transporter unit that would move along the desired travel distance. Figure 3:11 below shows how this concept was modeled in the doctor logic section of the model. Tasks that the doctor will perform enter on the left side of Figure 3:111 where the task must wait in a queue for its turn to be performed by the doctor. When the doctor decides that it's time to perform the specific task, the model signals the doctor to move to the location associated with the task at the request block. Once the doctor has moved from wherever it was located to the location of the task the doctor can begin preforming the task. If the task is a patient related task, the model records the data associated with the door to doctor metric before the process begins.

Figure 3:11 Simulated Travel



After the doctor is finished with his or her task, model must tell the doctor to what to do next. If the doctor has another task that needs to be performed, then the new task signals the doctor transporter right away, if not the model must tell the doctor to return to the physician's area until needed. Just like in section 3.1.5, this uses a duplicate copy of the task so that the original task can move on without being effected. Once the duplicated copy of the task has told the doctor to go to the physician's area, it can be thrown away.

In the physician's area, attending physicians chart information and review lab results, so often the doctor is already waiting in the room where he or she is needed. Overall this allows us to separate the time a doctor spends traveling from the time he or she spends working with patients. This concludes how the patient interacts with the doctors, nurses, and nurse practitioners as resources and transporters but there is a much more complicated process happening behind the scenes.

There are a total of forty different station locations in this model. Each corresponds with a meaningful location in the Emergency Department. Most of them are rooms, while others are administrative places like the nursing stations. The model uses about 800 different distances linking stations to one another. This creates a very labor intensive and error prone process of entering all of these distances into the software. Additionally if a layout change was to be modeled, the process would need to be repeated. To help simplify this all of the distances between stations are set uniformly to 10 feet. To get the correct time spend traveling, the velocity is altered by the location of each task using the “velocity_matrix” variable.

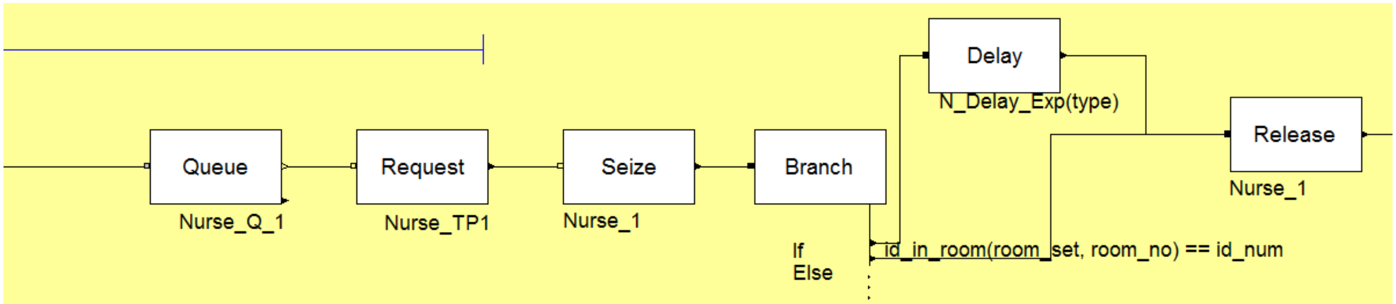
Since each task in the model has a location assigned to it, the “velocity_matrix” variable can be referenced using the location of the location of the task and the location of the nurse or doctor. For example, say that nurse 4 is at the left nurse station (station 37) has a task that is in room 6 (station 6), model would reference the value stored at [6, 37] in the “velocity_matrix”. The referenced value then determines the velocity a transporter has to travel at in order to simulate the time spent traveling the desired distance. At the end of the model, the total time spent traveling can be modified to describe the actual distance the doctor traveled. Currently the matrix is created in excel and then input directly into Arena. In the future the simulation will read in the file at the beginning of the replication if it is required.

3.1.7 Nurse Logic

The Nurse Logic section of the model is a lot like the Angel Logic section that was previously described in section 3.1.5. Because the other areas of the model use interconnected and highly dependent logic, only duplicated or copied entities are used in the Nurse Logic. These duplicated represent the patient and are entities that can be thrown away when they’re no longer needed. The duplicated entities enter the section through a Delay block that simulates the time between nurse visits. This time the duplicated entries wait is based on the data gathered during the room observations mentioned in section 2.1.2, and relates to the patient’s acuity level.

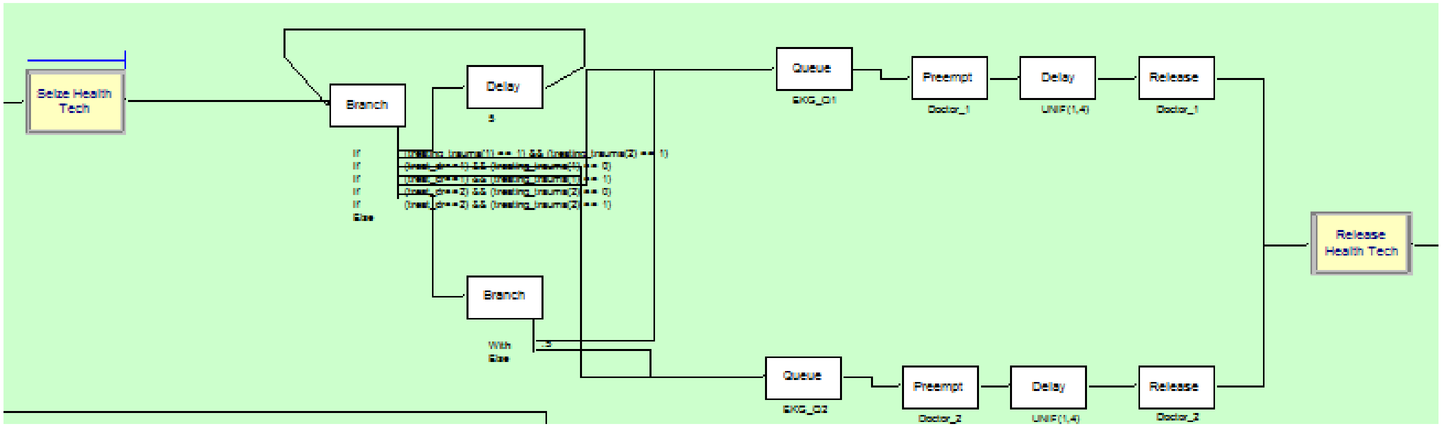
Most importantly, since the duplicates are just copies of the original patient or task, we need to be sure that the patient hasn’t tired too leave the system yet. Before each duplicate is processed, the model checks to verify that the original entity (the patient) is still in the room. Figure 3:12 show how tasks flow through the nurses logic section of the model. If the patient is still in the room, then the duplicate waits to be processed in order of the acuity level of the patient. When the duplicate becomes the current task for the respective nurse, the nurse proceeds to the location of the duplicate and begins to perform the task. It’s important to note that the nurses travel in the exact same way as a doctor, which is described in the Simulated Travel section. The model performs an additional check before the nurse begins to process the task to make sure that the patient hasn't slipped out. Once the nurse has finished the task described by the duplicate, it is sent back to the beginning to start the process over. The duplicate repeats this loop until the original patient leaves the room. This method allows the nurse to be requested independently from the doctor, and allows the original entity to wait in the Doctor Logic Section area.

Figure 3:12 Nurse Task Logic



Additionally there is another section of the model that follows a similar loop called the EKG Interruptions section. In reality most patients with acuity level 2 suffering from chest pains require Electro Cardiograms (EKG) be taken at regular intervals. There are two basic schedules, once an hour or once every two hours. There isn't a lot of data on how those are assigned, so for the purpose of this simulation, it is assumed that half of all level 2 patients need an EKG taken every ninety minutes. Current Policy at the Kansas University Medical Center Emergency Department requires that all EKG readouts be signed by a doctor within five minutes. For our model, this means a doctor must be interrupted to perform this task. When the doctors are preempted, they stop working on whatever they were doing, to sign the EKG readout. This is a major source of interruptions in reality, but it is a required part of the process based on KUMC policy. Modeling it was straightforward, as shown in Figure 3:13

Figure 3:13 EKG Interruptions



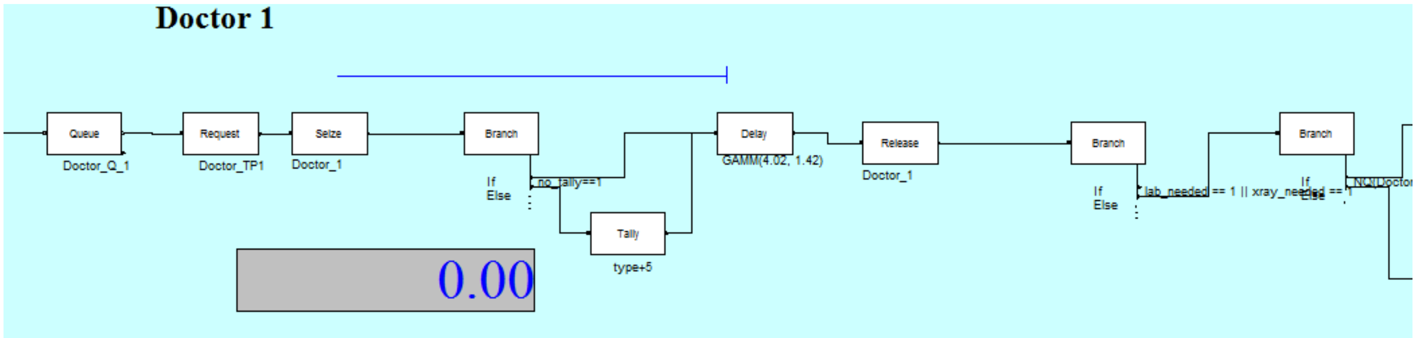
3.1.8 Doctors Logic

The Doctors Logic section of the model is somewhat misleading because it also includes the residents. A resident is assumed to follow all of the same processes as the doctor but they can only handle a few patients that are low acuity and processes take longer to complete. This mirrors reality, except that the doctor would typically help the resident when the doctor had spare time while charting. It is assumed in the model that the doctor provides assistance during downtime.

There are always two doctors staffed in the KUMC Emergency Department. When entering the Doctors Logic section of the model, the patient's provider is chosen based on several on the conditions in the system. If Doctor 1 has more patients than Doctor 2, then Doctor 2 gets the new patient. If the patient has an acuity level of 3, 4, or 5, they will be sent to the resident if they aren't too busy. Typically the load on the doctors evens out, but due to the changing conditions, over course of a year one doctor may end up seeing a few more patients than the other.

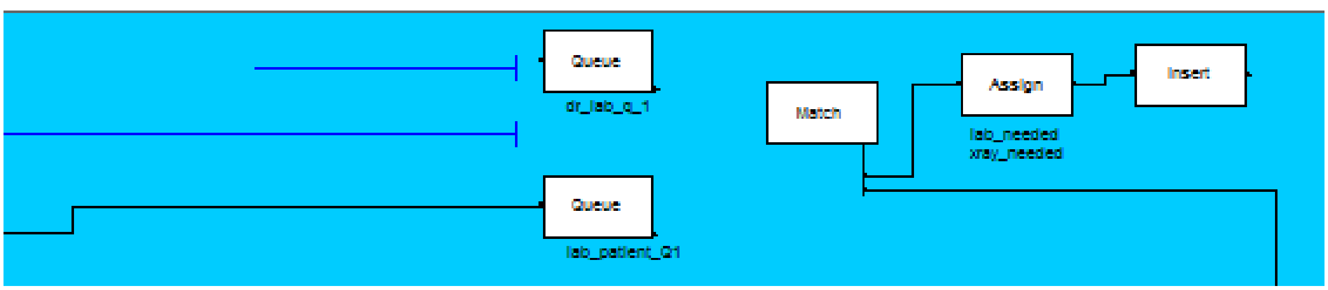
Figure 3:14 show where the tasks wait for the doctor to become available. After being assigned a doctor, the patient waits for the respective doctor based on acuity level. Just as in Figure 3:11, Figure 3:14 shows the Simulated Travel process is used before the doctor can begin a task. Once the doctors have finished their task, they either move onto the next patient, or back to the physician's area. The patient now presented with two different paths. Some patients will require a lab test, an X-Ray or both before they can be discharged from the emergency department.

Figure 3:14 Activity Based in Doctors Logic



If the patient needs a lab test, they are sent through a copy is made, while the original patient is left to wait in the room. A duplicate for each test is then sent to the Lab Area which processes Labs and X-Rays. Once the all the duplicates representing the labs for a patient have been processed they are sent back as a single task to wait for the doctor. The combined labs have been given location which will trigger the doctor to go back to the physician's area to view them. This simulates the doctor's reality of viewing lab results in the Epic information system. Once the doctor has reviewed the results, the duplicate representing the labs are then paired up with the original patient to simulate the doctor reviewing the results with the patient. The process is shown in Figure 3:15

Figure 3:15 Matching Doctors and Results



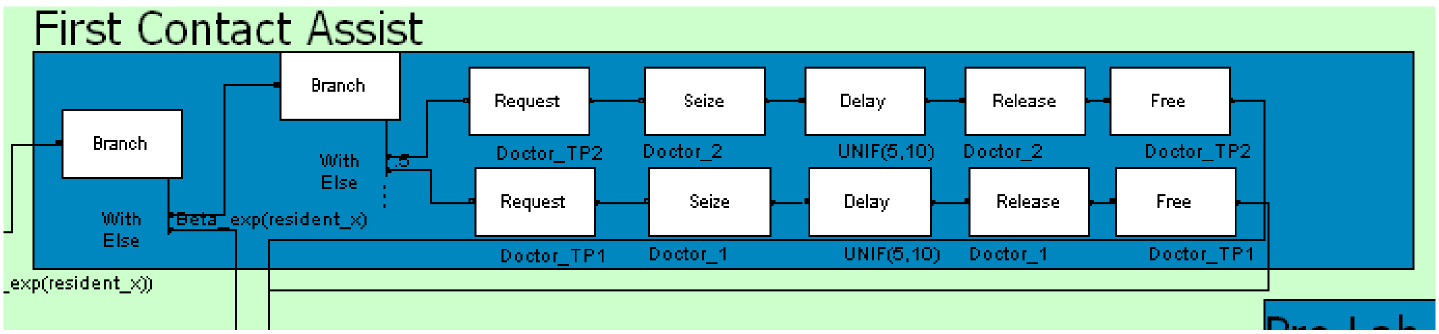
Once the duplicated lab entity is in the queue it is matched with its original patient based on the identification number it was assigned in the Triage section. The duplicate lab is disposed, while the original is inserted into the Doctor's Queue at the front of the line. Now the doctor will travel to the room where the patient is at, and simulate the doctor discussing the results with the patient. Once this is complete the patient release the doctor resource and doctor transporter in the manner previously described. From here the patient is either discharged or admitted.

3.1.9 Resident Logic

The Resident's Logic works similarly to the Doctor's Logic as described in section 3.1.8 above. Everything is the same, except that the Residents occasionally require help from the attending physicians at three points, initial contact with the patient, before labs are drawn, and before the discharge can be ordered. This thesis only models these interruptions because they were the most common observed over the summer of 2010. The relative frequency of these interruptions is governed by the learning curve that affects the Resident's processing times. As the simulation progresses, the number of times that a Resident requires assistance decreases. This decrease in required assistance represents the Residents becoming more self-sufficient.

Figure 3:16 shows an example of one of the interruptions. This specific example is for the first contact assist, where the resident might require assistance with things like a patient's physical evaluation or the collaboration of the patient's medical history. It is assumed that the Residents will require this help based on their position on the learning curve because we don't have information on how often they actually require assistance. Each Resident's learning curve already returns a value between zero and one, and works well as a probability of requiring assistance. If the learning curve is changed, it can be scaled much like a unit vector and a magnitude, so that its value is between zero and one.

Figure 3:16 The Resident's Logic



Once it has been determined that the task requires the assistance of the attending physician, the task arrives at a request block that requests the assisting doctor's transporter. Remember that the request block and doctor transporter allows the model to accurately simulate the travel time associated with the corresponding doctors. When the assisting doctor is available he or she travels to the task's location, and begins the assisting process. The duration of the process is assumed to be a uniform distribution between five and seven minutes. This process delay assumption is based on observations of interactions of the residents during the old residency program. If the Emergency Department conducts a detailed study the simulation can be modified easily to fit to match their results.

3.1.10 Admission Logic

One way or another all of the patients created will end up in the Exit section of the simulation. All patients need to be counted, and have their attributes recorded before they can be destroyed. This area of the model also includes the Bed Release logic. Basically a duplicate entity is created after the patient leaves, and is sent to a cleanup delay. Once the duplicate has been delayed for the average amount of time it takes for the housekeeping staff to clean the room, the duplicate releases the bed. Then the duplicate entity is destroyed.

Only a few entities will end up going through the Admission Logic located in the Exit section of the model. This area of the model is kind of tricky in that it doesn't use a set number of resources. In fact this part of the model creates and destroys resources every day. The inpatient beds are part of the Kansas University Medical Center and should not be confused with the beds in the Emergency Department. Because these beds don't belong to the Emergency Department we don't have much say in how they're utilized. All we know is how many are available on an average day. Typically when a resource is seized, we intend to release it and use it again, but that's not the case with the inpatient beds. They are needed for only one very important purpose, to get a few people out of the Emergency Department. Based on the information that we have available, a patient being admitted into the inpatient area of the hospital generates a substantially higher amount of revenue. The longer patients wait to get into the inpatient area, the fewer patients the Emergency Department can see. So the faster we can get them into the inpatient, the more patients we can see in the Emergency Department, and hopefully the more we can admit to the inpatient area. For modeling purposes, each day the average number of beds is created. Then as patients seize them, release them, and then the inpatient bed is destroyed.

3.2 Validating the Model

All in all the results from the new model are very similar to the results from the 2008-9 model. The new model incorporates a much finer level of detail than the previous model while maintaining a similar level of accuracy. A comparison from the actual data and the simulated data is shown in the Table 3:2. It is important to note that the major discrepancies are in the number of admission and the number of patients who Leave Without Being Seen (LWBS). The reason that the simulation numbers match is because that the numbers provided to us do not actually add up. From the data we received, there is difference of about 1,000 patients who are not counted. This presents a slight problem, in that in the simulation, the patients have to go somewhere. It was decided that we would model the worst case scenario for the processing in the Emergency Department, and add 60% of the absentee patients to LWBS and 40% to the admissions. It represents the worst case scenario because patients, who need to be admitted, take up more time in the emergency department, and patients who leave without being seen don't generate revenue. In the model described in Table 3:2 we generated about 2.4% more patients than the data provided, and sent a little more than 1000 extra patients to the admissions. The additional 1,102 that were randomly generated were split between the admissions and the leave without being seen. When comparing the percentages between the model and the actual, the percentages are a bit off. When comparing the actual numbers, model is very close to actual data. It is important to note that the residents are not included in this model.

Table 3:2 Model Validation

Metric	Actual	Simulation	Percent Difference	# different
Admissions	10,931	11739	7.39%	808
Discharge	31,832	31673	-0.50%	(159)
LWBS	3,399	3852	13.33%	453
Total Patients	46,162	47264	2.39%	1,102

Something we wanted to in this simulation was the amount of time a doctor travels in the model is very close to the amount of time recorded by the observed data. The Table 3:3 shows simulated data regarding the utilization of the doctors. The observations provided data suggesting that on average a doctor spends 16.5 minutes traveling each day. The results below support the correctness of the model's Simulated Travel section. It is a bit more difficult to accurately verify is the overall utilization.

Table 3:3 Validated Travel

	Time Walking	Utilization	Time With Patients
Doctor 1	18.375	64.10%	307.68
Doctor 2	15.79	58.20%	279.36 *time in

3.2.1 Door To Bed

In the 2008-9 model, metrics like the Door To Bed Times were used to help validate the results. These times represent the amount of time that it takes for a patient to enter the Emergency Department to get into a bed. Table 3:4, shown below, has the results from the model. It's important to note that the minimum amount time for a patient to be triages is 2 minutes, which is why the minimum value for all of the acuity levels is roughly the same.

Table 3:4 represents only patients seen in the main Emergency Department beds, and not those who were seen in Fast Track. On average, it takes the patient about 11.64 minutes to get to a bed. Remember that the numbers in the table above are averages, and the average of the averages is not the same as the actual average. The times represent the entire day, so the maximum numbers typically come from the peak periods around 11am and 5pm. All in all the numbers come in as we would expect. Patients with acuity level 3 typically wait the longest because they can't be seen in Fast Track and they're not considered high priority. It is also important to note the patients who Leave Without Being Seen are estimated to only wait about 128.5 minutes. In the simulation model, we approximate that with a function based on a normal distribution. The Leave Without Being Seen Logic will keep the all of the Door to Bed times from getting much higher.

Table 3:4 Door To Bed Validation

Metric	Average	Min	Max
DTB 1	10.704	2.01	57.28
DTB 2	16.816	2.00	121.04
DTB 3	24.547	2.00	142.47
DTB 4	18.908	2.00	137.70
DTB 5	18.052	2.01	119.45

*time in minutes

3.2.2 Door To Doctor

In emergency medicine, there is a commonly used term called the "Golden Hour." It's based on the idea that the patient's condition slowly deteriorates and needs to be managed by a medical professional within the first hour. Ideally, seeing patients within an hour of their injury could help prevent the onset of shock or identify internal bleeding sooner. Some doctors do question the validity of the "Golden Hour" because it isn't based on concrete statistics, and more of a rule of thumb. They do agree that the sooner they can see the patient, the better. The table below shows the times it takes for a patient to enter the Emergency Department, to the time they can see the doctor.

Looking at the data in the table, it's clear that sometimes the golden hour isn't always achieved. For patients with acuity levels 1 and 2 that's a problem, while the rest really aren't a concern. The problem with this section of the model is that there isn't anything like Left Without Being Seen Logic to keep people from waiting in the bed forever. The average values are very acceptable; however the maximum values seem a bit high. Patients who are less severe will end up waiting longer because patients are seen based on their Acuity. Higher than expected numbers are reasonable considering how the priories are modeled. Unfortunately we don't have any data on how long a patient is willing to wait in there bed to be seen by a doctor.

Table 3:5 Door to Doctor Validation

Metric	Average	Min	Max
DTD 1	14.046	2.422	69.27
DTD 2	20.587	2.289	183.48
DTD 3	31.803	2.087	1002.9
DTD 4	30.932	2.019	854.07
DTD 5	33.085	2.025	804.14

*time in minutes

3.2.3 Length of Stay

The numbers generated by the model, might seem a bit on the high side, but it is important to remember that on average, only 28 people are admitted to the inpatient area of the

Kansas University Medical Center. This means that the 29th person that wants to be admitted on a given day could wait a very long time. Table 3:6 shows the times that the simulation produced. We haven't received much data on the breakdown of admissions for this model, so we are using data from the previous project. The highest times belong to the patients with an acuity level of 1 because they the most likely to be admitted. About 90% of all level 1 patients are admitted into the inpatient area. Additionally level 1 patients account for less than 1% of the total patients seen in the Emergency Department over the course of a year.

Table 3:6 Length of Stay Validation

Metric	Average	Min	Max
LOS 1	589.944	62.316	954.34
LOS 2	413.684	2.6944	1042.98
LOS 3	305.194	2.6125	1141.73
LOS 4	63.964	2.8632	1037.23
LOS 5	54.212	3.2415	904.76

*time in minutes

Chapter 4 - Analysis of Output

4.1 The ED without the Residents

In order to evaluate the true impact that the Residents have on the Emergency Department, we must first establish what the Emergency Department can do without them. In section 3.2, the model compared to the actual numbers provided by the University of Kansas Medical Center Emergency Department was base model with the residents logic turned off.

During normal conditions, the base model has eight residents that work three eight hour shifts every four days. In the base model, there is two of each of the first, second, third and fourth year residents. A variable was created in the base model to adjust the number of patients that could be seen by the Residents called "Num_Pats" which will be used more in section 4.2. In all versions of the base model, the value of "Num_Pats" is set to four, meaning the two residents on duty can see a maximum of four patients between at any time. Modeling the Emergency Department without Residents was accomplished by setting the value of "Num_Pats" to zero. This essentially turned off the Residents Logic, making the attending physicians the only resources available to treat patents in the Emergency Department. This section provides a few highlights of the results while the entire output can be seen in the appendix.

In order to provide an accurate assessment of this and other scenarios we used Rockwell Software's Arena simulation software. Twenty replications of the both simulation models, the base model and the variation model, were completed before performing any analysis. Analysis was done in one of Arena's accessory programs called Output Analyzer. Output Analyzer was able to provide a two-sample t-test that compared the two means generated by the base and variation models for all metrics. The metrics that were compared were Door to Bed (DTB), Door to Doctor (DTD), Length of Stay (LOS), Length of Stay to Admission (LOSA), and the number of patients who Leave Without Being Seen (LWBS). Relevant differences are shown in this section while the results for each comparison are shown in Appendix A through Appendix G.

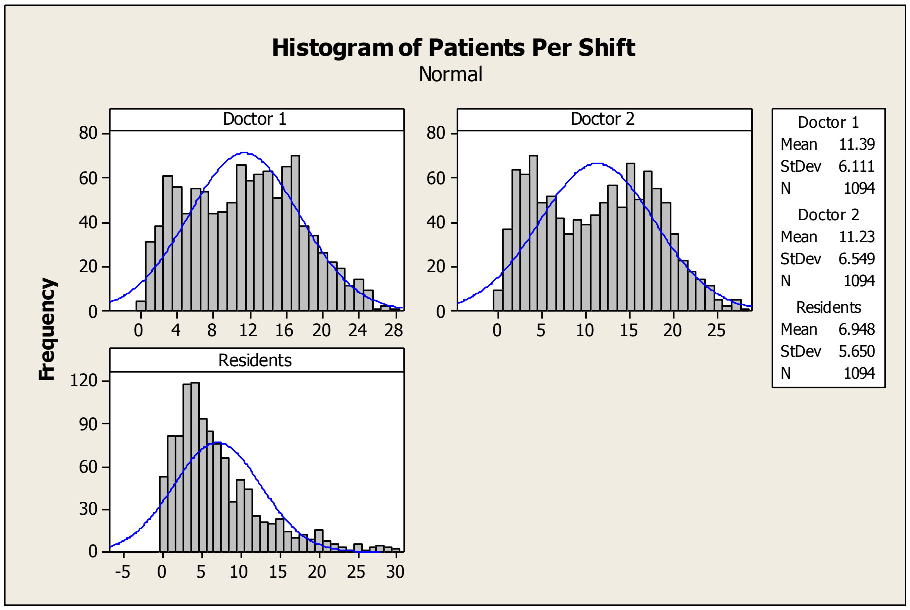
A common metric of evaluating the workload in the emergency department is the number of patients physicians see during three and five hour periods. When the model is running, it records the number of patients that are being treated by two attending physicians (Doctor 1 and Doctor 2) and the two on duty residents. Table 4:1 shows the average numbers for each of the providers. It is important to note the in Table 4:1 the number of patients seen by the residents split between 2 residents. Looking at the Patients per Shift Column, this means that an individual resident sees about 3.5 patients not 7. In an article examining patient interruption (Carey D. Chisholm 2000) found an average between three different sized emergency departments, a doctor will see 5.1 patients per 180 minutes, with a standard deviation of 2.1 patients. Without residents, 4.3 patients per hour puts KUMC in the 35th percentile, meaning their doctors see fewer patients. One of the hospitals studied in (Carey D. Chisholm 2000) was considered an Urban Site, and had an annual census of 82,500 patients. Although the larger emergency department sees more patients, their doctors see 4.1 patients during a 180 minute period, with a standard deviation of 1.6. One thing that might make our numbers lower than the national standard is that the model does not count the attending physicians as seeing a patient if a resident requires assistance.

Table 4:1 Average Hourly Patients

	Patients per 3 Hours			Patients per 5 Hours			Patients Per Shift		
	Doctor 1	Doctor 2	Residents	Doctor 1	Doctor 2	Residents	Doctor 1	Doctor 2	Residents
With Residents	3.22	3.22	2.00	6.43	6.43	4.00	11.38	11.23	6.94
Without Residents	4.30	4.30	0.00	8.60	8.60	0.00	15.17	15.19	0.00

When looking at the number of patients a physician sees per shift in Table 4:1, were interested in the seeing variability in the model. Figure 4:1 shows the variability in the number of patients that a physician sees per shift. Over the course of one year there are around 1094 shifts per provider to fill. That is why all of the graphs within Figure 4:1 have 1094 observations. It is important reiterate that the numbers for the residents are split between the two that are on duty. Looking at the data, there is a very large standard deviation that is cause of the difference in patient arrival patterns between the shifts. Looking back at Figure 3:1 ED Average Hourly Arrival Rate in 2010, the average number of patients arriving during the middle of the night is much smaller in comparison to those who arrive between 7am-5pm. Together the residents see about 7 patients per shift with a standard deviation of about 6 patients. We can see that on average the doctors see about 11 patients per shift with a standard deviation of about 6 patients. Using a two sample t-tests, shown in Appendix H, the p-value associated with the null hypothesis that the samples are the same is $p = 0.000$. These results suggest that we reject the null hypothesis at the $\alpha = 5\%$ level. These results suggest that the addition of the residents does reduce the number of patients seen per shift.

Figure 4:1 Patients Per Shift



Due their teaching/training burden, the presence of the residents hinders the performance of the attending physicians. (A. Roy Magnusson 1999) suggests that 89% to 98% of the resident's educational experience in the emergency department are facilitated by an attending physician. Table 4:2 shows the effect of adding residents on the door-to-doctor (DTD) metric. It's important to reiterate, the base model uses eight residents total, two first year residents, two second year residents, two third year residents and two fourth year residents. The DTD times are about 2 to 4 minutes longer for all acuity levels in the base model. In this metric the residents have a statically significant negative impact, although small, on the emergency department's performance. All of the differences were statistically different at the p = 0.05 level, meaning that the means for the two models are different. Other metrics were much more affected by their presence.

Table 4:2 Base vs. No Residents DTB

Metric	No Residents	Base Model	% difference	Significant
DTB1	10.704	12.976	21.23%	Yes
DTB2	16.816	18.254	8.55%	Yes
DTB3	24.547	26.057	6.15%	Yes
DTB4	18.908	14.593	-22.82%	Yes
DTB5	18.052	13.238	-26.67%	Yes

Just as above, Table 4:3 below shows the effects of the residents have on the door to doctor (DTD) metric. The addition of the residents has caused much longer DTD times for the most critical patients. Although the DTD times for acuity level 1, 2, and 3 patients increase, the

DTD times for acuity levels 4 and 5 by about 10%. Only the DTD times for patients with an acuity of 2 was not found to be statistically different at the p = 0.05 level. Part of this result stems from the additional time taken from the attending physicians by the residents needing help with the lower level patients. Since the attending physicians are the only ones able to see level 1 and 2 patients, they are the ones to suffer longest delay. Patients with acuity levels 4 and 5 have benefit because there are additional resources that aren't tied down with more sever patients.

Table 4:3 Base vs. No Residents DTD

Metric	No Residents	Base Model	% difference	Significant
DTD1	14.046	47.286	236.65%	Yes
DTD2	20.587	46.049	123.68%	No
DTD3	31.803	44.399	39.61%	Yes
DTD4	30.932	28.102	-9.15%	Yes
DTD5	33.085	30.12	-8.96%	Yes

Table 4:4 shows the effect that residents have on the number of patients who leave without being seen (LWBS). The results are not positive for the residents; however we had expected to see a lot more patients become tired of waiting. In comparison the residents only caused an increase of 187 patients or an increase of 4%. Although it appears that the residents lowered the total number LWBS acuity level three patients, the result was not statistically different from those of the model without residents at the p = 0.05 level.

Table 4:4 Base Model vs. Residents LWBS

Metric	No Residents	Base Model	% difference	Significant
LWBS3	1748	1672	-4.35%	No
LWBS4	1836	2068	12.64%	Yes
LWBS5	268	299	11.57%	Yes

Given that residents had a negative effect on the emergency department as a whole, we would expect the hospital admissions to be lower. Surprisingly that was not the case. Although the numbers presented in Table 4:5 that the number of admissions was higher without the residents, the discrepancy is not statistically different at the p = 0.05 level.

Table 4:5 Base Model vs. Residents Admissions

Metric	No Residents	Base Model	% difference	Significant
Admit 1	346	340	-1.73%	No
Admit 2	5778	5752	-0.45%	No
Admit 3	5615	5624	0.16%	No

This leads us to the question, are we really surprised by these results? If the Residents didn't have questions, or require assistance with proper policies and procedures, they wouldn't be a hindrance to the system. But then again, that's what residents have to do in order to become an attending physician. In reality the added burden to their emergency department may not entirely be a bad thing, because the residents definitely help relive the load on the attending physicians. Also policies are in place to prevent the residents from having the full load of the emergency department bearing down upon them. This line of thinking leads us to the next section, how many patient can we realistically give the residents?

4.2 Allowing the Residents to see More Patients

As mentioned previously in section 4.1, in the simulation model the maximum number of patients Residents are allowed to see at any given time is governed by the variable "Num_Pats" which has a default value of four. In this section, "Num_Pats" is changed to various levels to see what effect it has on the system. The figures and tables below are some of the most improved metrics, while the results of changing "Num_Pats" can be seen in their entirety in the appendix. In this section, there was high variability in the results, with only on really noticeable trend. All of the metrics in the tables that were found to be statistically significant at the $\alpha = 5\%$ level were marked as bold. Results that were significant we also marked by an up arrow (↑) and a down arrow (↓) for an increase or a decrease in the metric when compared to the base model.

When allowing the residents to see more patients, the door to bed (DTB) times remains almost unchanged with the exception of variability. Table 4:6 show the small variations in the DTB times as the number of patients increase. There appears to be a decreasing trend in the DTB times for patients with an acuity level of 3, but the results were not significant.

Table 4:6 More Patients DTB

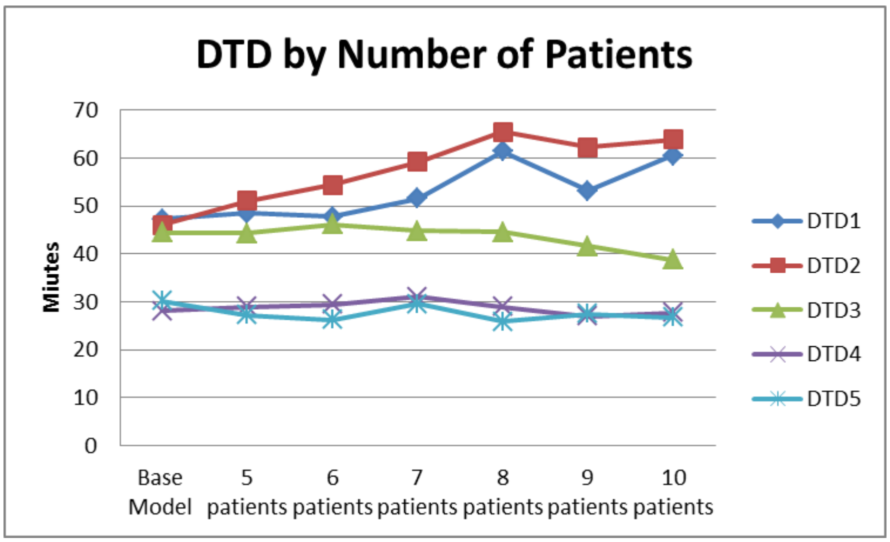
Name	Base Model	6 patients	8 patients	10 patients
DTB1	12.976	12.119	*↓ **10.622**	11.845
DTB2	18.254	17.117	15.512	*↓ **16.399**
DTB3	26.057	27.984	26.415	25.396
DTB4	14.593	*↑ **15.453**	15.613	*↑ **16.697**
DTB5	13.238	13.556	13.485	15.768

When looking at the door to doctor (DTD) times in Table 4:7 we begin to see a trend start to for as the number of patients that the residents should be allowed to see increases. **Error! Reference source not found.** shows the trends described in Table 4:7 more clearly. As the number of patients that the residents are allow to see at once increases, so does the amount of time that patients wait to be seen by a doctor. Most interestingly about **Error! Reference source not found.**, is that it shows the DTD times for acuity level 3 patients decreasing but it is not found to be statistically significant until the residents are allowed to see 10 patients at a time. This is because the acuity level 1 and 2 patients are not be seen by the residents, and don't have to wait as long for treatment due to their lower acuity. Compounding the matter is that the residents interrupt the doctors causing the DTD times for the higher acuity level patients to increase. Some might argue that since acuity level 3 patients make up a larger portion, this might be considered as an improvement.

Table 4:7 More Patients DTD

Name	Base Model	6 patients		8 patients		10 patients
DTD1	47.286		47.777	*↑ **61.429**	*↑	**60.470**
DTD2	46.049		54.359	65.446		63.790
DTD3	44.399		46.084	44.493	*↓	**38.810**
DTD4	28.102	*↑	**29.385**	28.882		27.654
DTD5	30.120		26.186	25.878		26.732

Figure 4:2 DTD By Number of Patients



Increasing the maximum number of patients that the residents can see at a given time starts to develop a trend when we look at the length of stay (LOS) times as shown in Table 4:8. Patients with acuity levels of 1 and 3 start to see a reduction in the amount of time they spend in the emergency department. Unfortunately patients with acuity levels 2 and 4 begin to wait longer. These changes are significant, but come with mix feelings. Decreasing the LOS times for patients with an acuity level of 3 is great news because they make up about 51% of the patients seen in the Emergency Department. Putting that into perspective, patients with an acuity level of 2 only account for about 18%, but their conditions are more serious

Table 4:8 More Patients LOS

Name	Base Model	6 patients		8 patients		10 patients	
LOS1	591.315		586.501	*↓	**569.826**	*↓	**583.323**
LOS2	395.441	*↑	**406.468**	*↑	**408.459**	*↑	**411.143**
LOS3	344.085		342.478	*↓	**335.059**	*↓	**321.704**
LOS4	72.010		73.712	*↑	**74.473**	*↑	**73.770**
LOS5	58.923		56.058		57.079		58.119

With regards to the numbers of patients who leave without being seen, the results can be seen Table 4:9. Noting that most of the numbers are not statistically significant except the LWBS times and admission numbers for acuity level 3 patients. Although they don't appear to form any sort of trend.

Table 4:9 More Patients Admission and LWBS

Name	Base Model	6 patients		8 patients		10 patients	
Admit 1	340		342		332		341
Admit 2	5752		5783		5728		5783
Admit 3	5624		5574		5629	*↓	**5584**
LWBS3	1672	*↓	**1800**		1589		1655
LWBS4	2068		2187		2002		1865
LWBS5	299		316		288		267

4.3 Changing the value of α

Referring back to the formula 2.10 discussed previously in the literature review;

$$T_n = D(1 + \alpha(e^{-\beta n}))$$

The value of α is designed to be a changeable parameter. α can be thought of as a scaling factor for the processing time of the residents. The initial intent was to discretely increase α so that the residents would take longer to process than the base model, where α is equal to 1. Despite its original purpose, changing of α had a very limited effect. So much so that the only metrics in Table 4:10 identified as being statistically significant at the α = 0.05 level were the DTD 1 times shown in green. The average change between all of the metrics 3%. Additionally there was no apparent trend to discuss.

Table 4:10 Combine changes in α

Metric	Base Model (1)	α = 2	α = 3	α = 4	α = 5	α = 6
DTB1	12.65	*↓ **12.13**	11.95	11.84	12.50	*↓ **12.80**
DTB2	18.39	18.22	18.09	17.58	17.65	18.65
DTB3	26.30	25.73	25.82	26.60	25.62	26.03
DTB4	14.73	14.62	15.11	14.98	14.61	15.61
DTB5	13.18	13.35	13.30	12.99	13.32	14.15
DTD1	47.59	35.08	39.94	41.16	37.87	35.47
DTD2	46.86	48.70	45.38	46.09	45.52	45.16
DTD3	44.67	45.21	43.36	45.10	43.42	43.49
DTD4	28.06	29.00	27.79	28.14	27.87	28.68
DTD5	29.45	29.10	26.96	27.97	27.51	28.97
LWBS3	1714	1696	1735	1718	1645	1788
LWBS4	2068	1992	1994	2092	1994	2042
LWBS5	299	289	297	310	298	290

In reality, the residents were taking more time with patients, but alpha has a very limited effect because the ($e^{-\beta n}$) portion of equation 2.10 approaches zero very quickly. The equation is so steep, that after about 1 years' worth of working, the ($e^{-\beta n}$) portion has reached about 4%, meaning that even with the multiplier α, very little has changed. All 6 of the residents that are past their first year were barely affected by α. Another factor that contributed to the better results, were that while α was high, and the younger residents were working, the attending physicians picked up more patients. So really the effect of changing α has become negligible with this learning curve function. Applying the same reasoning to sigmoid we see a similar effect as described below. The difference between each of the models can be dismissed due to variability.

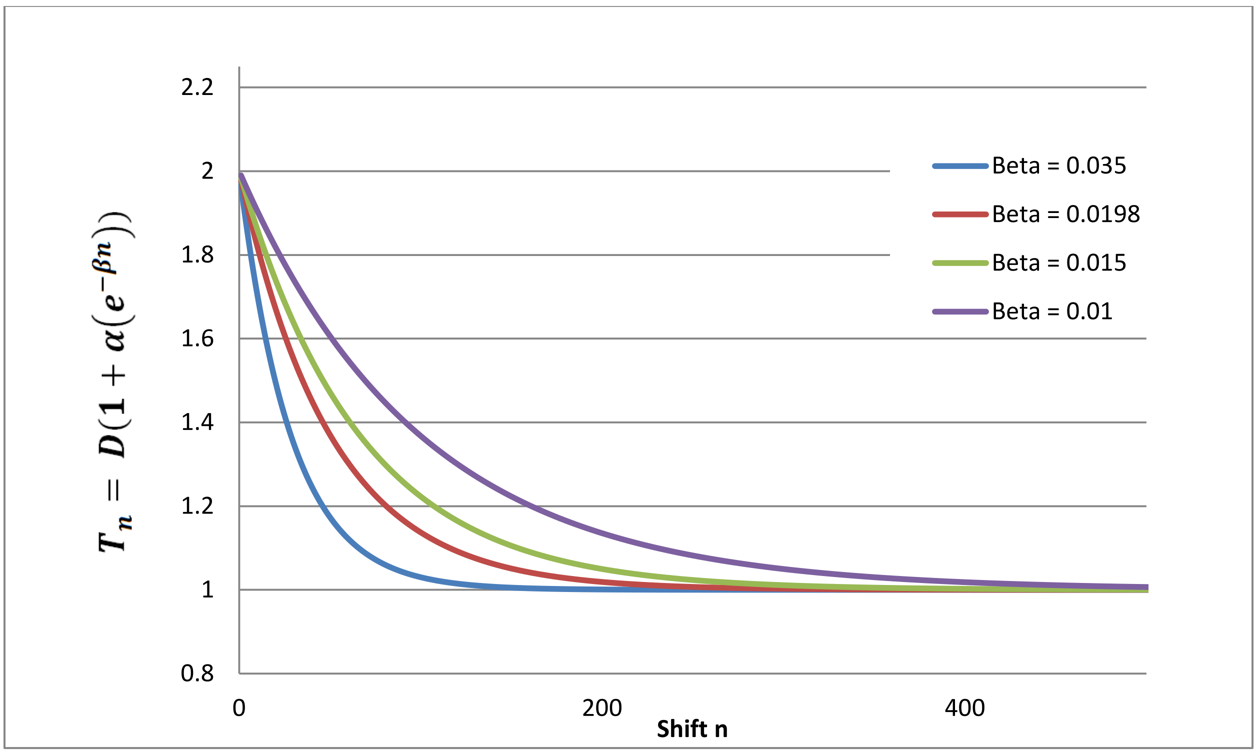
The unexpected results suggest that the residents have a limited contribution in the Emergency Department. For the sake of this model, they have been limited to 4 patients between the 2 residents working at any given time. This assumption is based on direct observations in the Kansas University Medical Center's Emergency Department. Additionally the residents cannot see the most severe patients (Acuity 1 and 2), and during part of the day cannot see patients that were sent to the Fast Track. Since the inception of their residency program, these limitations may have changed, and should be reevaluated if this study is continued.

4.4 Changing the Value of β

After seeing the limited effects that changes α had on the model, the focus of the study switched to the shape of the learning curve. Still following equation 2.10, the rate at which the curve approaches zero is defined by beta. β was an assumed value, based on the assumption that it takes four years for the residents to perform as well as the attending physicians.

Figure 4:3 below shows the effect that changing β has on the learning curve. In this figure we use a step size is in shifts (n). After the resident completes a shift, their position on the learning curve is advanced by one step. Examining Figure 4:3 more closely, we can see that larger the value of β, the faster the learning curve approaches 1, therefore β can be thought of a measure of competency. This leads the instance where large values or β cause the residents to perform like attending physicians sooner than the assumed four year period. This in turn tells the model that the residents need much less help, effectively making the two residents equivalent to attending physicians that can only see four patients at a time. When applied in reality, emergency departments want residents with larger values of β because they are more competent. This leads us to ask what happens if all of the residents don't actually reach the level of an attending physician after four years? To examine this question, we evaluated smaller values of β to see what the affects were on the emergency department.

Figure 4:3 Values of β



It is important to understand that changes to beta will cause the rate of learning to change, and therefore change the period that it takes for residents to reach proficiency. Simply put, changes to β greatly affect the model. Table 4:11 shows that the closer the value of β is to zero while remaining negative, the worse the door to bed (DTB) and door to doctor (DTD) times become. The base model uses β = 0.0198. It's important to note that patients with acuity levels 4 and 5 are still mostly seen in the fast track, and therefore the changes to β have a limited effect on them.

Table 4:11 Changes to β DTB and DTD

Beta	0.0001	0.0005	0.001	0.0015	0.0025	0.003	Base Model
DTB1	51.732	54.534	48.891	44.435	39.826	37.128	12.165
DTB2	78.088	76.597	72.84	68.6	60.245	57.698	18.39
DTB3	38.455	37.335	37.552	36.528	35.012	33.056	25.849
DTB4	16.063	15.659	15.818	15.714	14.778	14.381	15.106
DTB5	12.444	12.725	12.325	12.358	11.915	11.524	13.727
DTD1	149.789	158.454	141.701	133.362	119.969	118.55	41.839
DTD2	178.133	177.17	168.452	158.372	144.214	139.781	46.759
DTD3	134.81	132.782	126.639	121.928	108.452	105.356	44.195
DTD4	62.621	62.715	60.545	59.277	53.043	52.571	29.231
DTD5	62.823	62.821	60.735	60.301	49.434	52.917	28.989

Changes to β also have a large effect on the number of patients who leave without being seen, as shown in Table 4:12. With smaller values of β residents take longer to become as proficient as an attending physician. This means that they all of the residents, including the third and fourth year residents, require more help, more often. This slows down the doctors, which makes the system worse for the most severe patients.

Table 4:12 Changes to β and LWBS

Beta	0.0001	0.0005	0.001	0.0015	0.0025	0.003	Base Model
LWBS3	5483	5353	5130	4882	4331	4150	1747
LWBS4	3767	3647	3630	3535	3318	3117	2062
LWBS5	546	530	521	503	474	453	306

So what can we gather from changing β? Once β has been defined, it can be use a predictor for how well the residents perform from year to year. The direct implications of β can be applied retrospectively as well. Say you have a residency program that has limited positions available and you want to know which ones which residents to keep for the next year. You can use each resident's performance on the benchmark tasks to determine their own value of β using the learning curve formula that fits your expected learning. Anyone that has a β smaller than your expected β, might have difficulty meeting the level of expectation in the emergency department.

4.5 Modeling with the Sigmoid Function

Knowing that the Sigmoid Function follows a much different shape than the generalized learning curve, we expected a noticeable difference between the two models. Looking at Table 4:13 Base vs. SigmoidTable 4:13, we can see that the Sigmoid model performed slightly better in the door to doctor (DTD) times for patients with acuity levels of 1, 2 and 3, and slightly worse for patients with acuity levels 4 and 5, in comparison to the base model. At first glance this suggests that when using the sigmoid function, residents were more helpful to the system. When we examine the door to doctor times the effect becomes more apparent. All time related metrics such as DTD, DTB, and LOS proved to be statistically significant, however the sigmoid function failed to improve the number of LWBS and admissions.

Table 4:13 Base vs. Sigmoid

Alpha	Base Model	Sigmoid	% differece
DTB1	12.65	11.08	-12.36%
DTB2	18.39	16.67	-9.37%
DTB3	26.30	24.08	-8.43%
DTB4	14.73	16.94	15.06%
DTB5	13.18	16.24	23.19%

In Table 4:14 shows the door to doctor (DTD) times generated by the simulation model. The difference is surprisingly better for patients with acuity levels 1, 2 and 3, while only about 5 minutes better for the acuity level 4 and 5 patients. This suggests that the residents are taking up less of the attending physicians' time because. The leave without being seen numbers are about 11% higher and can be seen with the rest of the generated output in Appendix D.

Table 4:14 Base vs. Sigmoid DTD

Alpha	Base Model	Sigmoid	% differece
DTD1	47.59	15.21	-68.03%
DTD2	46.86	22.44	-52.11%
DTD3	44.67	29.85	-33.19%
DTD4	28.06	23.82	-15.13%
DTD5	29.45	24.80	-15.79%

So the question arose, what happens if α were increased on the sigmoid function? Would the model slow down with a larger initial handicap? In short, no, the percentage of interruptions seems to have the largest effect on the performance of the model, which is determined by the learning curve. The results from the simulation are shown In Appendix D: Sigmoid Curve with Changes to the Variable α between 5 and 10. In Table 4:15 we can see what is negative effect due to and increasing value of α. A closer look provides better insight. With an α of greater than 5, it is assumed that any task an attending physician 1 minute to perform, it takes a first year resident takes 5 minutes to perform. This assumption could be justified by more data collection, however the other end of Table 4:15 the value of α is at 10. There is no evidence to support that the actual value of α isn't that high, but experience in the emergency department suggests that it is less than that. Once again, the shape of the curve has proved to be most influential factor.

Table 4:15 Sigmoid Changing α

Alpha	Alpha 5	Alpha 6	Alpha 7	Alpha 8	Alpha 9	Alpha 10
DTB1	13.208	11.142	13.301	11.946	13.387	15.072
DTB2	19.511	16.591	18.626	18.248	19.535	20.426
DTB3	24.256	22.397	27.476	26.508	26.534	25.815
DTB4	17.866	17.343	15.61	15.453	15.443	15.965
DTB5	17.203	15.187	13.926	14.054	13.315	14.932
DTD1	17.615	13.592	38.187	37.47	43.648	42.5
DTD2	24.721	21.213	45.334	42.909	47.506	48.313
DTD3	29.394	27.604	45.612	42.456	44.39	42.956
DTD4	24.779	24.152	29.499	28.269	28.814	29.597
DTD5	24.691	22.729	28.4	26.436	26.325	28.074

4.6 Changing the Resident Population

As the Emergency Department starts the Residency Program, they will have a different population over four years. The question is how will the inclusion of two residents each year affect the performance of the emergency department? Using the "no residents" model as the comparison, and the base model as the final steady state, we simulated the years in between that the Emergency Department would experience. In each of the following tables, the year columns refers to the year the after the start of the residency program. In column "year 1" there are only two residents, both are first year residents. In the column "year 2" there are four residents, two first year and two second year residents. The pattern continues until the "Base Model" column where the full roster of residents is incorporated. Table 4:16 shows the effects that the startup of the new residency program will have on the Kansas University Medical Center's Emergency Department's door to bed (DTB) times. The residency program will have a negative impact on the DTB times for patients with acuity levels of 1, 2, 3 and a positive impact on acuity levels 4 and 5. All of the significant changes have been marked at the α = 5% level.

Table 4:16 Adding Residents DTB

Name	No Residents	year 1	year 2	year 3	Base Model
DTB1	10.704	***↑ 12.115**	***↑ 12.663**	***↑ 13.884**	***↑ 12.976**
DTB2	16.816	***↑ 18.439**	***↑ 19.113**	***↑ 19.524**	***↑ 18.254**
DTB3	24.547	25.286	24.759	24.381	***↑ 26.057**
DTB4	18.908	***↓ 15.175**	***↓ 15.337**	15.083	***↓ 14.593**
DTB5	18.052	***↓ 13.093**	***↓ 13.257**	14.055	***↓ 13.238**

When examining the effects of the new residency program on the door to doctor (DTD) times Table 4:17 shows that there are some good and bad effects. During the first year of the residency program, all door to doctor times are significantly longer at the α = 5% level. After the first year, the residents have start having a positive impact on the patients with acuity levels of 4 and 5. This reduction is because they are no longer waiting for the patients with acuity levels 1, 2, and 3 to be processed by the doctors. Unfortunately for the patients with acuity levels 1, 2, and 3, their wait becomes longer due to the amount of assistance that the residents require.

Table 4:17 Adding Residents DTD

Name	No Residents	year 1	year 2	year 3	Base Model
DTD1	14.046	***↑ 26.698**	***↑ 32.886**	***↑ 32.233**	***↑ 47.286**
DTD2	20.587	***↑ 34.919**	***↑ 39.399**	***↑ 41.274**	46.049
DTD3	31.803	***↑ 48.329**	***↑ 43.606**	***↑ 37.431**	***↑ 44.399**
DTD4	30.932	***↑ 37.541**	32.726	***↓ 25.938**	***↓ 28.102**
DTD5	33.085	***↑ 38.866**	31.481	***↓ 25.092**	***↓ 30.121**

When looking at the patient's average length of stay (LOS) we see surprising results. Although door to bed and door to doctor times for patients with acuity levels 1 and 2 have been significantly longer as the residents have been added in, their length of stay actually decreases during the first two years of the residency program. Although the results are surprising Table 4:18 shows that as the residents reach the steady state described by the Base Model, the results are no longer statistically significant. The only permanent effect of adding the residents shown in Table 4:18 is the increased length of stay of patients with acuity level 3.

Table 4:18 Adding Residents LOS

Name	No Residents	year 1	year 2	year 3	Base Model
LOS1	589.944	***↓ 544.608**	***↓ 572.904**	588.322	591.315
LOS2	413.684	***↓ 367.438**	393.969	402.064	395.441
LOS3	305.194	***↑ 358.666**	***↑ 339.402**	***↑ 329.303**	***↑ 344.085**
LOS4	63.964	***↑ 83.064**	***↑ 71.962**	65.471	72.011
LOS5	54.212	***↑ 67.177**	56.517	***↓ 49.997**	58.923

So what effect does the new residency program have on the Emergency Department as a whole? In Table 4:19 we can see the metrics affect the revenue in the emergency department. Although there is a slight variation in the number of patients admitted and who leave without being (LWBS) seen during the first year, there is very little effect on the emergency department due to the residency program. In al it still sees about the same number of patients up until it reaches stead state as described by the base model.

Table 4:19 Adding Residents Admissions and LWBS

Name	No Residents	year 1	year 2	year 3	Base Model
Admit 1	346	345	340	347	340
Admit 2	5778	5787	5792	5786	5752
Admit 3	5615	***↓ 5568**	5575	5600	5624
LWBS3	1748	1640	1769	1636	1672
LWBS4	1836	1906	1917	1876	***↑ 2068**
LWBS5	268	***↑ 289**	276	279	***↑ 299**

We suspect the diversity between the resident's levels of experience can affect the performance of the Emergency Department. A question was purposed: what if all the residents had the same level of experience? The base model assumes that there are 8 residents total. Only two residents work at the same time. There are 2 residents from each of the 4 experience levels of post graduate year 1, 2, 3 and 4. Changing model is as simple as changing the starting position on the learning curve for all of the residents. The outputs were compiled after running the simulation for 20 replications. Highlights of the complied results are shown below, while the rest of the metrics can be seen in Appendix G.

When all of the residents are performing as Post Graduate year 1 Residents, the effect on the system is noticeable. The total number of LWBS increases as well as all of the wait times. Conversely, simulations featuring residents behaving as though they were more experienced than Post Graduate Year 1, show a decrease in LWBS and wait times. Table 4:20 below shows an example of the decreases.

Table 4:20 Homogenous Resident Populations

Residents	Base	All PG 1	All PG 2	All PG 3	All PG 4
DTB1	13.719	23.769	7.052	6.881	7.011
DTB2	21.436	34.903	8.434	7.549	7.68
DTB3	12.784	13.343	12.376	12.525	12.871
DTB4	7.848	8.169	7.505	7.604	7.731
DTB5	6.977	6.982	6.662	6.672	6.686

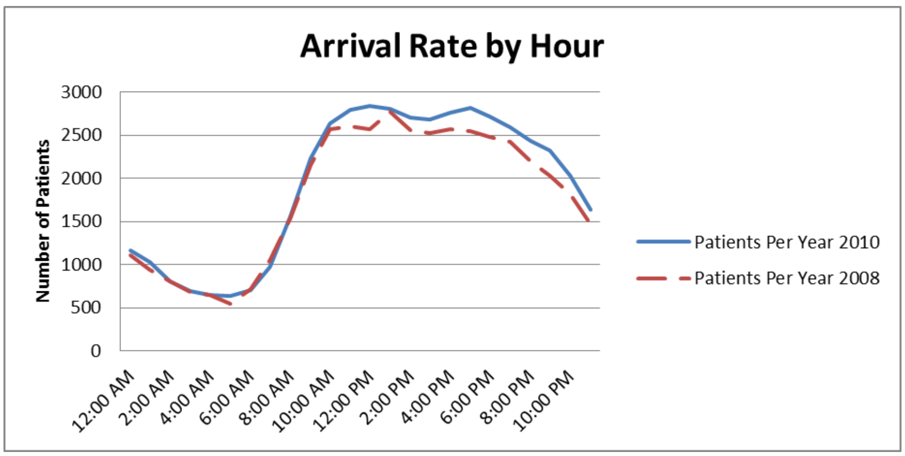
This could because by the equation the $(e^{-\beta n})$ portion of equation 2.10 causes the learning curve to approach 1 very quickly. Using the standard learning curve, after their 1st year, the Residents behave almost as if they were attending physicians. All other metrics behaved in this manner and can be seen in the appendix. Most importantly there is another way to look at this data.

If an emergency department was considering developing a residency program, and all of their residents were first year (PSG 1), then their first year with a residency program would have a large negative effect. After the first year, however, all of their residents are PG 2, assuming they've all stayed. Reexamining Table 4:20 you'll notice that the PG 2 performs better than the base model.

4.7 The Increasing Population at KUMC

Historically speaking, the number of patients entering the Emergency Department at the Kansas University Medical Center has increased by about 4% each year. Between the 2008 and 20010 projects there was an increase of 4.9%, which is shown in Figure 4:4. In the figure, the 2010 Simulation Model show the large increase in the number of patients who leave without being seen (LWB) alongside two of their suggested alternatives from section 2.1.4. In Figure 4:4, the suggested alternatives reduce the number of LWBS. The question becomes, how will the addition of regular residents affect the system? Several of the more interesting sets of data are shown below in terms of percent increase over the base model. All of the information that the simulation was able to produce is show in its entirety on pages in the appendix.

Figure 4:4 KUMC 2010 Patient Sustainability



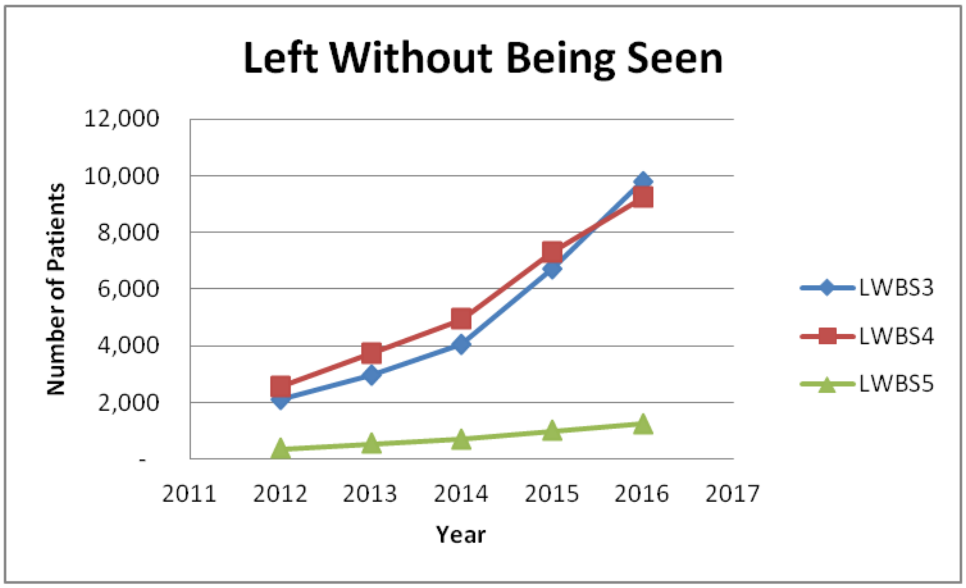
From the administrative perspective, reducing the number of patients that "Leave Without Being Seen" (LWBS) has been major focus in Emergency Departments across the United States. These potential patients represent lost opportunity for the hospital to gain revenue, and for the patient to receive a medical screening. The increasing trend can be seen numerically in Table 4:21 and graphically in Figure 4:5.

Table 4:21 Increase of LWBS with 4% Population Growth

Year	Base	2012	2013	2014	2015	2016
Population	100.0%	104.0%	108.2%	112.5%	121.7%	131.6%
LWBS3	1,672	2,115	2,954	4,039	6,710	9,789
LWBS4	2,068	2,556	3,721	4,919	7,296	9,226
LWBS5	299	371	540	692	1,006	1,246

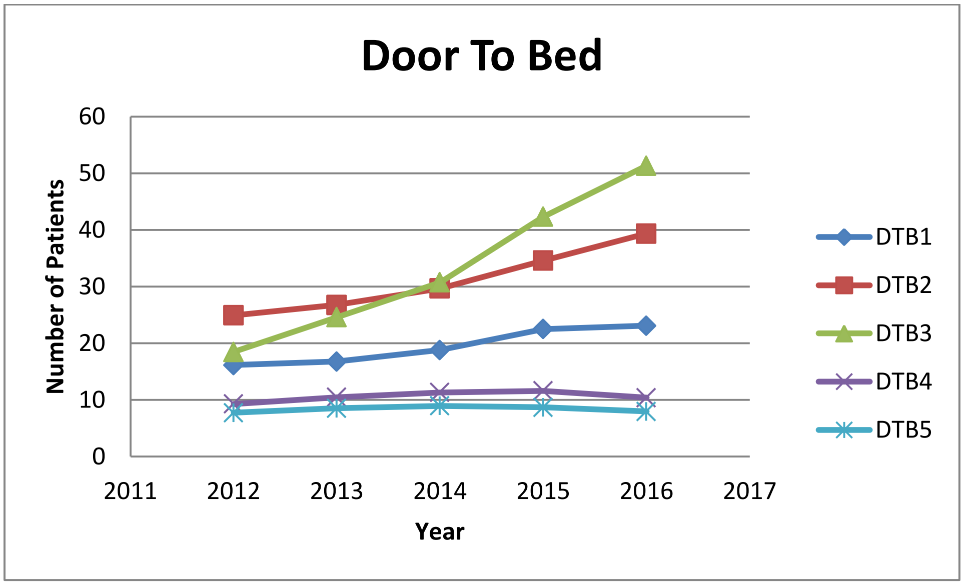
Included in this highlight are the LWBS numbers for patients with the lower acuity levels 3, 4, and 5. Some will argue that most of the patients that Leave Without Being Seen are the lower acuities, and are not considered to be severe and are therefore not as important of a demographic to consider. First, it stands to reason that anyone seeking a medical screening is in need of a service, and that excessive wait times have prevent some for obtaining it. Secondly, patients with acuity levels of 3, 4, and 5 make up roughly 81% of the patient population at the Kansas University Medical Center Emergency Department. Amazingly, after 5 years of continuous growth, the number of Acuity 3 LWBS increases to 7.64 times its base model value. Those numbers translate to an increase from about 1,300 people to 9,800. Although the numbers are alarming, they are still based on some assumptions that are easily changeable. The increasing trend can be seen clearly in Figure 4:5. Restrictions on the number of patients that the residents can see can help, but so could adding another attending physician.

Figure 4:5 LWBS Population Increase



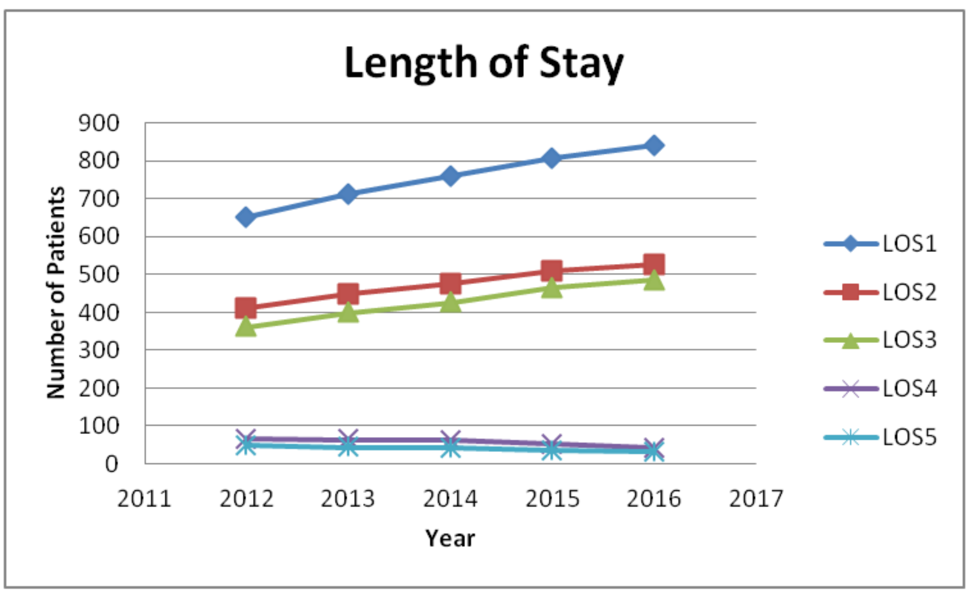
By far, the largest portion of the population is Acuity 3, consisting of roughly 51% of all of the patients seen in the emergency department. As the number of patients increases by 4% each year, Acuity 3 patients suffer the most. Patients with Acuity 4 and 5 have the benefit of the Fast Track, meaning during normal hours, they have a separate set of resources available to them. Meanwhile, patients with higher severity Acuity 1 and 2 have higher priority over the acuity level 3 patients. Looking at Figure 4:6 we can see that as the population increases, the amount of time that the acuity level 3 patients wait to be seen by doctor increases to about 4.22 times the base level, which is about 51 minutes. It is important to note, that the LWBS section of the model's logic prevents the numbers from excessively high, because patients won't wait forever.

Figure 4:6 DTB Population Increase



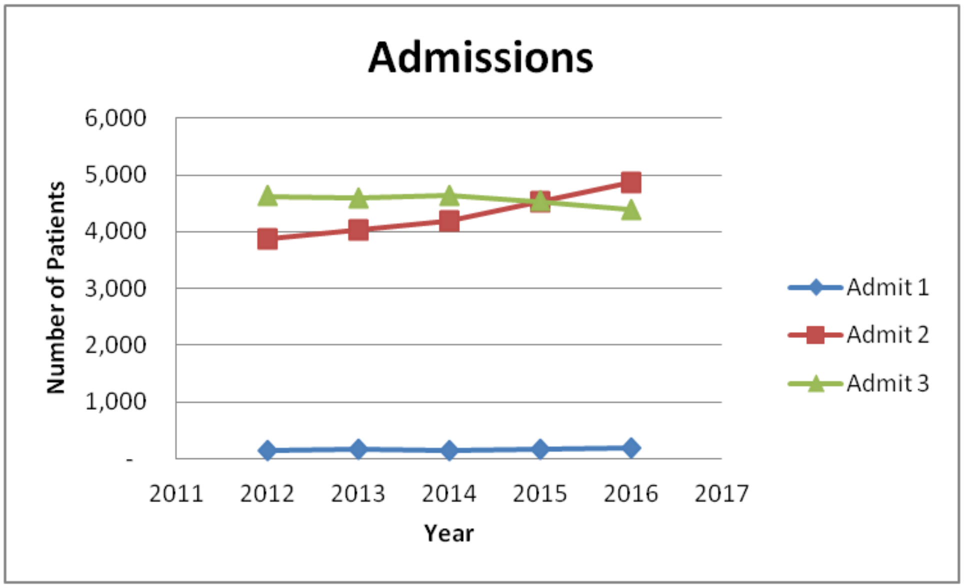
Looking into the Length of Stay Metric (LOS) and the Discharge Statistics, the increased number of LWBS has had an unexpected side effect. Figure 4:7 shows that while the most severe patients do end up waiting longer, the only patients with lowest acuity levels that stay are the ones that can be seen while the system isn't full. Since the system isn't full, there are less people to wait on, therefore the LOS times for Acuity 4 and 5 patients decrease.

Figure 4:7 LOS Population Increase



There isn't much surprise in the number of admissions. Looking at Figure 4:8 we can see the number of admissions steadily increases as the number of patients arriving to the Emergency Department increases. After three years of the steady 4% growth, the number of patients with higher Acuity 1 and 2, start to affect the availability of resources available for Acuity 3 patients. Because the Emergency Department is lacking the resources necessary to process the Acuity 3 patients, more and more will become frustrated and Leave Without Being Seen, causing the number of acuity level 3 patient admissions to decrease.

Figure 4:8 Admissions Population Increase



Chapter 5 - Conclusion

5.1 Conclusions and Recommendations

The main objectives of this thesis are to provide informed insight into the adoption of a residency program in Kansas University Medical Center's Emergency Department (KUMC) and other emergency departments like it. KUMC's Emergency Department's fundamental question is if by adding residents in their new residency program negatively impact their operations? Additionally, will the addition of the residents add too much stress to the already strained attending physicians? Since the residency program at KUMC is new, they had no historical data form which to draw upon. Lacking data led us to peruse a study of literature about medical residents to find any useful data. After evaluating the relevance of literature in discussed in section 2.2, we decided that learning curves could be used to extrapolate the residents' performance.

When developing a basis of information for the use of learning curves to determine the effects of residents on the emergency department several key sources of literature were identified. (Adam Janiak 2008) (Biskup 2007) (David T. Wong 2003) Issues regarding high turnover rates, fatigue and levels of stress (Peter C. Winword 2006) (Linda D. Scott 2006) were referenced in order to avoid suggesting alternative that would have unintended effects. Using the data provide by the attending physicians, used a generalized learning curve described in section 2.2 to develop a base ling level of performance for the residents. The information gathered in this thesis provides a foundation for future studies in the application or evaluation of learning curves in medical residency programs.

Before applying learning curves and residents, a Discrete Event Simulation model was created that generates accurate data for the Kansas University Medical Center's Emergency Department as described in section 3.2. In conjuncture with the review of literature, a new model including residents and their contribution to the emergency department was established using the generalized learning curve describe in equation 2.10. Using a two sample t-test comparison of the means, it was proven that the difference between the model without residents and the model with residents was statistically significant at the 5% level. The model generates common metrics used to evaluate emergency departments consisting of Door to Bed (DTB), Door to Doctor (DTD), Length of Stay (LOS), and the number of patients who Leave Without Being Seen (LWBS). The supplemental analysis was performed on these metrics.

The main contributions of this thesis are;

The main contributions of this thesis are;

1. Determined the impact of different learning curves, and what significant parameters dominate the effects of learning
2. Suggested that residency programs develop a baseline level of performance by which to evaluate the progression of their residents
3. Studied the operational impact that residents and their learning have on the operations in the emergency department
    a. How long the impact lasted
    b. How the addition of the residents will perform with an increasing population
4. Established a foundation for future studies

In section 4.5 the study showed the effects of changing the shape of the learning curve by switching to a different function. When studying the comparison between the generalized learning curve to that of a sigmoid curve, the model failed to produce metrics that were statistically different form the generalized learning curve. Later in section 4.5, we show that the residents still provide a benefit regardless of the actual shape of the learning curve. In section 2.2 the study reviewed the Gompertz function and found that it is easily modifiable version of the sigmoid function. In conjuncture with the conclusion that the shape does not affect the performance of the emergency department, the study supports the suggestion that a Gompertz function might be considered if an emergency department wants to develop a learning curve based on specific benchmarks.

The effects of learning on the resident's processing time and competency can be seen in the scaling parameter α and the learning parameter β respectively, in equation 2.10. The scaling parameter α, was used in the generalized learning curve provide the initial competency of a resident. The base model used α to scale the initial difference between the resident's performance and that of the attending. Low values of α represented higher levels of competency while higher values of α relate to high levels of incompetency. When analyzed in detail in section 4.3, high values of α failed to produce data that was statistically different that the base model. In section 4.4, the residents' learning competency parameter β was reduced to show that high levels of incompetency (slower than expected learners) have a negative impact on the emergency department. Section 4.4 shows that β is the statistically dominating parameter of the generalized learning.

Sections 4.3 and 4.4 lead the study to suggest that residency programs consider their ideal value of β when adopting a residency program. Knowing that each resident will follow their own value of β, residency programs can develop their own measure to evaluate the residents using standardized value of β. Initially some residents will be slower than others as described by variations to α, while others will be faster with a lower α. It's important to reiterate that Section 4.4 showed that differences in α had no significant effect. This supports the notion that no matter how large a resident's processing time is initially, a sufficient value of β (learning competency) should still yield a competent attending physician after four years. This study suggests that a residency program should evaluate a resident's progress base on their value of β. Residents whose value of beta is smaller than the β determined by the administration might have trouble performing at the expected level and should be the focus of their training efforts. (Adler 1990)

From the analysis of our data, we can draw a few conclusions. In the base model using a generalized learning curve defined β with a period of four years does not greatly hinder the operations in the emergency department. Although section 4.1 showed that the addition of residents caused longer wait times for the most emergency department patients, the number of admissions was not greatly diminished when evaluated at the 5% significance level. This showed that the residency program has negative impact on wait times, but did not decrease the number of admitted patients and only increase the number of patients who leave without being seen by 4%.

Section 4.6 found that although first year residents have a negative effect on system as a whole, the more experienced residents provide much needed relief to the attending physicians. A resident population consisting of only first year residents negatively affects the emergency department, but residents with homogenous populations with more than one year of experience had a positive impact on the emergency department. The positive effect is supported in section 4.1 regarding the number of patients that the attending physicians see during a full shift, 3 hour, and 5 hour period. The data provided from these sections suggests that only the first year residents negatively affect the performance in the emergency department.

Section 4.7 shows the effect that the potential patient population growth has on the Kansas University Medical Center's Emergency Department. Simply put, KUMC's Emergency department with the residency program describe by the base model was not able to keep up with the increasing demand. It is not suggested that the residency program caused this shortcoming, but it is clear that the residency program needs to be considered when planning for the future demands of the Emergency Department.

5.2 Future Research and Limitations

In all, this thesis provided a very stable model capable of examining the effects of learning, but it did so by extrapolating the needed data. The simulation model is founded on assumptions that provide the best approximations that we could find. To the best of our knowledge, this thesis is only known examination of the effects of learning on emergency department residents using a Discrete Event Simulation. Applying learning curves in medical residency programs requires more in-depth studies. The Kansas University Medical Center and other hospital like it will need to devote more resources to monitoring the performance of both their attending physicians and their new residents in order to maintain their expected level of service. Future studies should follow the adoption of a medical residency program with the goal of collecting processing time specific data. With the collection of that data, researchers can develop a more precise learning curve with relevant benchmarks in order to evaluate a resident's performance.

In sub-section 2.2.2 we examined the Gompertz function. Because it is easily modifiable, it would make an interesting candidate for future study. Future studies could apply Discrete Event Simulation Software to test the dominating parameters of the Gompertz function. Their work could draw comparisons to the generalized learning curve function describe by equation 2.10. There are other functions that provide curves of varying shapes. This thesis only examined two of those functions. If data collected on the tasks performed by residents does not fit the functions described in this study, researchers should examine other curves to find an appropriate match. There also exists the possibility that the learning follows a piecewise linear function. Evidence of this might be seen after a residency program establishes a baseline level of performance as suggested in the paper.

One area that was not discussed in this thesis was the use of progressive steps along the learning curve as a contributing factor. In all models presented in this thesis steps along the learning curve were assumed to happen after a resident finished their shift. Although there is nothing wrong with this assumption, there exists the possibility to model the resident's progression after each task completed. This change would cause residents working late shifts with fewer tasks to learn slower than residents working the day shifts with more tasks. The difficulties presented by this approach are that of a standardized step size. Future researchers would need to determining the number of tasks that a resident is expected to perform within the four year period to reaching the level of performance of an attending physician. This number might be more difficult to determine, and require a study on the tasks residents typically perform, as well as their relative frequency.

Another area of future research is scaling the number of patients that residents are allowed to see on an individual basis. The number of patients the residents were allowed to see was based on observations of their old residency program. An additional question follows, should third or fourth year residents be allowed to see more acute patients? Another consideration might include having more or fewer residents? Some aspects that were not looked but could be included in future studies are the effects of cumulated fatigue, stress and the possibility of recovery time. It has been suggested that insufficient personal recovery time coupled with nonstandard shift work (the night shifts) negatively affected medical personnel's ability to perform. (Peter C. Winword 2006) Future models might look into the effects caused by the scheduling of the residents in addition to the learning curve.

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Appendix A: No Residents

Name	Base Mod	No Residents
reps	20	20
run length	525600	525600
Num Pats	4	0
LWBS1	0	0
LWBS2	0	0
LWBS3	1672	1748
LWBS4	2068	1836
LWBS5	299	268
DTB1	12.976	10.704
DTB2	18.254	16.816
DTB3	26.057	24.547
DTB4	14.593	18.908
DTB5	13.238	18.052
DTD1	47.286	14.046
DTD2	46.049	20.587
DTD3	44.399	31.803
DTD4	28.102	30.932
DTD5	30.12	33.085
LOS1	591.315	589.944
LOS2	395.441	413.684
LOS3	344.085	305.194
LOS4	72.01	63.964
LOS5	58.923	54.212
Type_In_1	367	373
Type_In_2	8536	8564
Type_In_3	24050	23959
Type_In_4	12693	12708
Type_In_5	1694	1660
Admit 1	340	346
Admit 2	5752	5778
Admit 3	5624	5615
Admit ICU	1469	1474
Discharge	26	27
Discharge	2780	2783
Discharge	16742	16583
Discharge	6125	6375
Discharge	786	812
Dr 1 Util	0.443	0.47
Dr 2 Util	0.381	0.469
Res Util 1	0.297	0
Res Util 2	0.086	0
Res Util 3	0.173	0
Res Util 4	0.029	0
Res Util 5	0.294	0
Res Util 6	0.048	0
Res Util 7	0.131	0
Res Util 8	0.026	0

Appendix B: Varying the number of patients

Name	Base Model	5 patients	6 patients	7 patients	8 patients	9 patients	10 patients
reps	20	20	20	20	20	20	20
run length	525600	525600	525600	525600	525600	525600	525600
Num Pats	4	5	6	7	8	9	10
LWBS1	0	0	0	0	0	0	0
LWBS2	0	0	0	0	0	0	0
LWBS3	1672	1616	1800	1726	1589	1649	1655
LWBS4	2068	1934	2187	2040	2002	2040	1865
LWBS5	299	277	316	303	288	304	267
DTB1	12.976	10.978	12.119	10.754	10.622	10.932	11.845
DTB2	18.254	16.052	17.117	16.049	15.512	15.972	16.399
DTB3	26.057	25.291	27.984	27.041	26.415	26.711	25.396
DTB4	14.593	14.67	15.453	16.388	15.613	15.809	16.697
DTB5	13.238	13.456	13.556	14.629	13.485	14.926	15.768
DTD1	47.286	48.455	47.777	51.59	61.429	53.134	60.47
DTD2	46.049	51.049	54.359	59.183	65.446	62.22	63.79
DTD3	44.399	44.342	46.084	44.791	44.493	41.597	38.81
DTD4	28.102	28.934	29.385	31.005	28.882	26.909	27.654
DTD5	30.12	27.247	26.186	29.503	25.878	27.436	26.732
LOS1	591.315	564.347	586.501	559.689	569.826	582.579	583.323
LOS2	395.441	391.141	406.468	406.656	408.459	409.782	411.143
LOS3	344.085	333.069	342.478	330.553	335.059	334.338	321.704
LOS4	72.01	73.016	73.712	76.333	74.473	73.859	73.77
LOS5	58.923	54.746	56.058	62.177	57.079	61.317	58.119
Type_In_1	367	366	367	379	362	364	369
Type_In_2	8536	8587	8608	8553	8506	8555	8589
Type_In_3	24050	23940	24029	23963	23978	24028	23814
Type_In_4	12693	12760	12761	12728	12682	12781	12725
Type_In_5	1694	1690	1668	1727	1688	1685	1676
Admit 1	340	340	342	353	332	339	341
Admit 2	5752	5794	5783	5764	5728	5764	5783
Admit 3	5624	5579	5574	5596	5629	5614	5584
Admit ICU	1469	1480	1467	1473	1448	1475	1470
Discharge 1	26	26	25	26	29	25	28
Discharge 2	2780	2789	2821	2784	2774	2787	2802
Discharge 3	16742	16733	16640	16629	16748	16751	16562
Discharge 4	6125	6292	6043	6152	6166	6208	6343
Discharge 5	786	820	760	810	800	784	808
Dr 1 Util	0.443	0.426	0.411	0.4	0.396	0.376	0.361
Dr 2 Util	0.381	0.36	0.338	0.313	0.306	0.29	0.261
Res Util 1	0.297	0.354	0.379	0.425	0.449	0.46	0.488
Res Util 2	0.086	0.119	0.147	0.18	0.206	0.219	0.245
Res Util 3	0.173	0.211	0.242	0.275	0.296	0.314	0.343
Res Util 4	0.029	0.047	0.059	0.083	0.095	0.106	0.126
Res Util 5	0.294	0.349	0.383	0.423	0.445	0.46	0.486
Res Util 6	0.048	0.071	0.096	0.127	0.144	0.159	0.183
Res Util 7	0.131	0.165	0.189	0.222	0.24	0.256	0.284
Res Util 8	0.026	0.043	0.057	0.078	0.092	0.103	0.123

Appendix C: Changing the value of α

reps	20	20	20	20	20	20
run length	525600	525600	525600	525600	525600	525600
Alpha	1	2	3	4	5	6
LWBS1	0	0	0	0	0	0
LWBS2	0	0	0	0	0	0
LWBS3	1714	1696	1735	1718	1645	1788
LWBS4	2068	1992	1994	2092	1994	2042
LWBS5	299	289	297	310	298	290
DTB1	12.646	12.132	11.953	11.84	12.5	12.808
DTB2	18.391	18.222	18.089	17.583	17.647	18.649
DTB3	26.3	25.729	25.823	26.601	25.619	26.029
DTB4	14.725	14.618	15.107	14.975	14.61	15.606
DTB5	13.179	13.351	13.297	12.993	13.323	14.148
DTD1	47.593	35.08	39.944	41.156	37.866	35.466
DTD2	46.862	48.703	45.376	46.09	45.522	45.162
DTD3	44.674	45.214	43.359	45.098	43.419	43.485
DTD4	28.062	28.999	27.791	28.142	27.869	28.68
DTD5	29.449	29.103	26.96	27.972	27.513	28.965
LOS1	597.976	576.409	586.894	586.059	583.532	579.055
LOS2	398.047	395.053	397.532	398.776	393.291	400.608
LOS3	345.261	342.029	337.78	344.487	337.677	336.238
LOS4	71.883	72.806	70.734	72.289	71.786	72.057
LOS5	58.869	57.803	55.166	55.615	56.811	58.035
LOSA1	144107.3	141333.8	140755.5	145928.349	143095.4	143064.6
LOSA2	59027.52	58974	59198.9	58634.846	59294.78	58739.71
LOSA3	438.313	436.862	446.214	445.417	434.206	457.754
Type_In_1	371	371	370	365	371	365
Type_In_2	8570	8552	8592	8568	8587	8566
Type_In_3	24001	23955	23967	23970	23941	23962
Type_In_4	12722	12695	12745	12705	12725	12735
Type_In_5	1682	1668	1686	1685	1682	1681
Admit 1	345	343	343	335	342	336
Admit 2	5769	5777	5789	5791	5777	5788
Admit 3	5605	5591	5573	5572	5587	5577
Admit ICU	1476	1472	1469	1470	1479	1463
Discharge 1	26	28	27	30	29	29
Discharge 2	2796	2771	2800	2773	2806	2774
Discharge 3	16667	16656	16649	16667	16697	16585
Discharge 4	6137	6220	6217	6112	6213	6184
Discharge 5	783	783	796	776	791	790
Dr 1 Util	0.442	0.442	0.433	0.438	0.437	0.427
Dr 2 Util	0.382	0.382	0.38	0.382	0.382	0.376
Res Util 1	0.297	0.306	0.31	0.319	0.322	0.329
Res Util 2	0.086	0.09	0.088	0.087	0.091	0.092
Res Util 3	0.172	0.174	0.177	0.172	0.175	0.18
Res Util 4	0.029	0.029	0.03	0.029	0.029	0.031
Res Util 5	0.294	0.308	0.31	0.316	0.32	0.332
Res Util 6	0.047	0.05	0.049	0.05	0.05	0.053
Res Util 7	0.13	0.13	0.133	0.131	0.131	0.134
Res Util 8	0.027	0.027	0.028	0.027	0.028	0.03

Appendix D: Sigmoid Curve with Changes to the Variable α

	Base Model	year 1	year 2	year 3	year 4	year 5	Sigmoid
Num Reps	20	20	20	20	20	20	20
% increase	4	1.04	1.0816	1.1249	1.2167	1.3159	---
LWBS1	0	-	-	-	-	-	-
LWBS2	0	-	-	-	-	-	-
LWBS3	1672	2,115.00	2,954.00	4,039.00	6,710.00	9,789.00	748.00
LWBS4	2068	2,556.00	3,721.00	4,919.00	7,296.00	9,226.00	1,317.00
LWBS5	299	371.00	540.00	692.00	1,006.00	1,246.00	198.00
DTB1	12.976	16.15	16.78	18.82	22.51	23.08	7.89
DTB2	18.254	24.92	26.77	29.68	34.58	39.37	8.46
DTB3	26.057	18.46	24.60	30.74	42.32	51.32	12.52
DTB4	14.593	9.28	10.47	11.33	11.61	10.39	7.44
DTB5	13.238	7.73	8.52	8.95	8.69	7.97	6.62
DTD1	47.286	21.58	21.57	23.41	27.79	27.58	11.69
DTD2	46.049	31.48	32.66	35.53	40.11	44.74	12.49
DTD3	44.399	24.62	30.31	36.29	47.33	56.30	16.24
DTD4	28.102	15.77	15.84	16.33	15.24	13.03	11.25
DTD5	30.12	15.83	15.13	14.91	12.64	10.64	10.99
LOS1	591.315	652.04	712.69	759.50	808.96	840.66	554.51
LOS2	395.441	411.62	447.96	475.23	508.44	526.77	341.08
LOS3	344.085	362.36	399.38	426.66	465.81	486.99	305.78
LOS4	72.01	64.78	63.95	61.56	52.55	42.57	56.10
LOS5	58.923	47.70	43.96	42.68	34.81	30.44	39.73
Type_In_1	367	381.00	404.00	407.00	452.00	489.00	371.00
Type_In_2	8536	8,948.00	9,289.00	9,639.00	10,451.00	11,277.00	8,587.00
Type_In_3	24050	24,939.00	25,862.00	26,989.00	29,137.00	31,537.00	23,964.00
Type_In_4	12693	13,224.00	13,746.00	14,271.00	15,483.00	16,783.00	12,672.00
Type_In_5	1694	1,748.00	1,816.00	1,886.00	2,028.00	2,194.00	1,664.00
Admit 1	340	147.00	157.00	153.00	176.00	189.00	145.00
Admit 2	5752	3,872.00	4,029.00	4,187.00	4,518.00	4,872.00	3,724.00
Admit 3	5624	4,628.00	4,590.00	4,646.00	4,536.00	4,395.00	4,697.00
Discharge 1	26	43.00	45.00	43.00	49.00	54.00	42.00
Discharge 2	2780	3,727.00	3,849.00	3,981.00	4,348.00	4,713.00	3,571.00
Discharge 3	16742	18,179.00	18,300.00	18,283.00	17,868.00	17,331.00	18,507.00
Discharge 4	6125	5,988.00	5,163.00	4,295.00	2,733.00	1,664.00	6,859.00
Discharge 5	786	754.00	630.00	521.00	306.00	180.00	873.00
Dr 1 Util	0.443	0.403	0.433	0.402	0.416	0.443	0.442
Dr 2 Util	0.381	0.38	0.379	0.396	0.399	0.378	0.383
Res Util 1	0.297	0.26	0.23	0.21	0.19	0.18	0.18
Res Util 2	0.086	0.07	0.06	0.05	0.04	0.04	0.06
Res Util 3	0.173	0.14	0.13	0.11	0.10	0.10	0.17
Res Util 4	0.029	0.02	0.01	0.01	0.01	0.01	0.02
Res Util 5	0.294	0.25	0.23	0.21	0.19	0.18	0.18
Res Util 6	0.048	0.03	0.03	0.02	0.02	0.01	0.03
Res Util 7	0.131	0.10	0.09	0.09	0.08	0.07	0.13
Res Util 8	0.026	0.02	0.01	0.01	0.01	0.01	0.02

Appendix E: 4% Yearly Growth Output

	Base	year 1	year 2	year 3	year 4	year 5
Num Reps	20	20	20	20	20	20
% increase	---	1.04	1.0816	1.1249	1.2167	1.3159
LWBS1	-	-	-	-	-	-
LWBS2	-	-	-	-	-	-
LWBS3	1,282.00	2,115.00	2,954.00	4,039.00	6,710.00	9,789.00
LWBS4	1,440.00	2,556.00	3,721.00	4,919.00	7,296.00	9,226.00
LWBS5	219.00	371.00	540.00	692.00	1,006.00	1,246.00
DTB1	13.08	16.15	16.78	18.82	22.51	23.08
DTB2	20.44	24.92	26.77	29.68	34.58	39.37
DTB3	12.18	18.46	24.60	30.74	42.32	51.32
DTB4	7.61	9.28	10.47	11.33	11.61	10.39
DTB5	6.91	7.73	8.52	8.95	8.69	7.97
DTD1	20.19	21.58	21.57	23.41	27.79	27.58
DTD2	27.02	31.48	32.66	35.53	40.11	44.74
DTD3	18.44	24.62	30.31	36.29	47.33	56.30
DTD4	13.94	15.77	15.84	16.33	15.24	13.03
DTD5	14.97	15.83	15.13	14.91	12.64	10.64
LOS1	548.63	652.04	712.69	759.50	808.96	840.66
LOS2	353.37	411.62	447.96	475.23	508.44	526.77
LOS3	308.88	362.36	399.38	426.66	465.81	486.99
LOS4	61.88	64.78	63.95	61.56	52.55	42.57
LOS5	45.81	47.70	43.96	42.68	34.81	30.44
LOSA1	149,961.16	149,021.21	148,193.11	153,680.22	147,156.50	148,122.46
LOSA2	67,530.06	68,147.08	68,321.35	68,704.50	68,552.83	67,591.68
LOSA3	334.75	388.00	421.39	449.99	490.58	509.36
Type_In_1	369.00	381.00	404.00	407.00	452.00	489.00
Type_In_2	8,610.00	8,948.00	9,289.00	9,639.00	10,451.00	11,277.00
Type_In_3	23,915.00	24,939.00	25,862.00	26,989.00	29,137.00	31,537.00
Type_In_4	12,752.00	13,224.00	13,746.00	14,271.00	15,483.00	16,783.00
Type_In_5	1,665.00	1,748.00	1,816.00	1,886.00	2,028.00	2,194.00
Admit 1	142.00	147.00	157.00	153.00	176.00	189.00
Admit 2	3,723.00	3,872.00	4,029.00	4,187.00	4,518.00	4,872.00
Admit 3	4,558.00	4,628.00	4,590.00	4,646.00	4,536.00	4,395.00
Discharge 1	40.00	43.00	45.00	43.00	49.00	54.00
Discharge 2	3,588.00	3,727.00	3,849.00	3,981.00	4,348.00	4,713.00
Discharge 3	18,059.00	18,179.00	18,300.00	18,283.00	17,868.00	17,331.00
Discharge 4	6,750.00	5,988.00	5,163.00	4,295.00	2,733.00	1,664.00
Discharge 5	862.00	754.00	630.00	521.00	306.00	180.00
Dr 1 Util	0.60	0.63	0.64	0.65	0.66	0.66
Dr 2 Util	0.26	0.26	0.26	0.26	0.24	0.23
Res Util 1	0.29	0.26	0.23	0.21	0.19	0.18
Res Util 2	0.08	0.07	0.06	0.05	0.04	0.04
Res Util 3	0.17	0.14	0.13	0.11	0.10	0.10
Res Util 4	0.03	0.02	0.01	0.01	0.01	0.01
Res Util 5	0.29	0.25	0.23	0.21	0.19	0.18
Res Util 6	0.04	0.03	0.03	0.02	0.02	0.01
Res Util 7	0.12	0.10	0.09	0.09	0.08	0.07
Res Util 8	0.02	0.02	0.01	0.01	0.01	0.01

Appendix F: 4% Yearly Growth Output in Percentages

	Base	year 1	year 2	year 3	year 4	year 5
Num Reps	20	20	20	20	20	20
% increase		1.04	1.0816	1.1249	1.2167	1.3159
LWBS1						
LWBS2						
LWBS3	1.00	1.65	2.30	3.15	5.23	7.64
LWBS4	1.00	1.78	2.58	3.42	5.07	6.41
LWBS5	1.00	1.69	2.47	3.16	4.59	5.69
DTB1	1.00	1.23	1.28	1.44	1.72	1.76
DTB2	1.00	1.22	1.31	1.45	1.69	1.93
DTB3	1.00	1.52	2.02	2.52	3.48	4.22
DTB4	1.00	1.22	1.38	1.49	1.52	1.36
DTB5	1.00	1.12	1.23	1.30	1.26	1.15
DTD1	1.00	1.07	1.07	1.16	1.38	1.37
DTD2	1.00	1.17	1.21	1.31	1.48	1.66
DTD3	1.00	1.34	1.64	1.97	2.57	3.05
DTD4	1.00	1.13	1.14	1.17	1.09	0.93
DTD5	1.00	1.06	1.01	1.00	0.84	0.71
LOS1	1.00	1.19	1.30	1.38	1.47	1.53
LOS2	1.00	1.16	1.27	1.34	1.44	1.49
LOS3	1.00	1.17	1.29	1.38	1.51	1.58
LOS4	1.00	1.05	1.03	0.99	0.85	0.69
LOS5	1.00	1.04	0.96	0.93	0.76	0.66
LOSA1	1.00	0.99	0.99	1.02	0.98	0.99
LOSA2	1.00	1.01	1.01	1.02	1.02	1.00
LOSA3	1.00	1.16	1.26	1.34	1.47	1.52
Type_In_1	1.00	1.03	1.09	1.10	1.22	1.33
Type_In_2	1.00	1.04	1.08	1.12	1.21	1.31
Type_In_3	1.00	1.04	1.08	1.13	1.22	1.32
Type_In_4	1.00	1.04	1.08	1.12	1.21	1.32
Type_In_5	1.00	1.05	1.09	1.13	1.22	1.32
Admit 1	1.00	1.04	1.11	1.08	1.24	1.33
Admit 2	1.00	1.04	1.08	1.12	1.21	1.31
Admit 3	1.00	1.02	1.01	1.02	1.00	0.96
Discharge 1	1.00	1.08	1.13	1.08	1.23	1.35
Discharge 2	1.00	1.04	1.07	1.11	1.21	1.31
Discharge 3	1.00	1.01	1.01	1.01	0.99	0.96
Discharge 4	1.00	0.89	0.76	0.64	0.40	0.25
Discharge 5	1.00	0.87	0.73	0.60	0.35	0.21
Dr 1 Util	1.00	1.04	1.06	1.07	1.09	1.10
Dr 2 Util	1.00	1.02	1.01	0.99	0.92	0.90
Res Util 1	1.00	0.89	0.79	0.74	0.65	0.64
Res Util 2	1.00	0.85	0.70	0.59	0.50	0.45
Res Util 3	1.00	0.83	0.75	0.67	0.62	0.59
Res Util 4	1.00	0.72	0.56	0.48	0.36	0.32
Res Util 5	1.00	0.88	0.78	0.74	0.66	0.62
Res Util 6	1.00	0.73	0.59	0.48	0.34	0.30
Res Util 7	1.00	0.84	0.75	0.69	0.62	0.60
Res Util 8	1.00	0.71	0.58	0.46	0.33	0.29

Appendix G: Uniform Resident Population Output

	Base	All PG 1	All PG 2	All PG 3	All PG 4
Num Reps	20	20	20	20	20
LWBS1	-	-	-	-	-
LWBS2	-	-	-	-	-
LWBS3	1,348.00	1,803.00	741.00	702.00	724.00
LWBS4	1,518.00	1,713.00	1,283.00	1,302.00	1,377.00
LWBS5	229.00	249.00	193.00	194.00	208.00
DTB1	13.719	23.769	7.052	6.881	7.011
DTB2	21.436	34.903	8.434	7.549	7.68
DTB3	12.784	13.343	12.376	12.525	12.871
DTB4	7.848	8.169	7.505	7.604	7.731
DTB5	6.977	6.982	6.662	6.672	6.686
DTD1	19.94	32.843	10.532	10.359	10.573
DTD2	28.077	44.518	12.389	11.231	11.369
DTD3	19.076	23.839	16.001	15.854	16.224
DTD4	14.549	20.094	11.22	10.928	11.081
DTD5	15.771	22.325	10.719	10.405	10.543
LOS1	561.08	565.29	554.26	548.02	562.11
LOS2	359.80	368.26	339.89	340.49	345.07
LOS3	314.47	328.58	303.42	306.48	309.48
LOS4	62.62	72.43	56.77	55.95	56.81
LOS5	47.18	58.49	38.88	38.54	39.81
Type_In_1	369.00	369.00	370.00	363.00	373.00
Type_In_2	8,605.00	8,563.00	8,565.00	8,574.00	8,601.00
Type_In_3	23,973.00	23,944.00	23,967.00	23,896.00	23,922.00
Type_In_4	12,731.00	12,664.00	12,679.00	12,743.00	12,746.00
Type_In_5	1,675.00	1,680.00	1,680.00	1,689.00	1,680.00
Admit 1	143.00	142.00	143.00	141.00	145.00
Admit 2	3,735.00	3,709.00	3,695.00	3,712.00	3,729.00
Admit 3	4,569.00	4,482.00	4,694.00	4,679.00	4,674.00
Discharge 1	40.00	41.00	38.00	41.00	40.00
Discharge 2	3,576.00	3,569.00	3,575.00	3,572.00	3,580.00
Discharge 3	18,041.00	17,646.00	18,515.00	18,503.00	18,511.00
Discharge 4	6,676.00	6,471.00	6,913.00	6,941.00	6,860.00
Discharge 5	862.00	834.00	888.00	896.00	879.00
Dr 1 Util	35.2%	34.6%	33.6%	35.9%	34.6%
Dr 2 Util	34.7%	35.1%	31.8%	30.0%	34.3%
Res Util 1	28.4%	26.6%	17.7%	17.0%	16.8%
Res Util 2	7.9%	12.2%	6.3%	5.8%	5.8%
Res Util 3	16.6%	27.9%	17.9%	17.2%	16.9%
Res Util 4	2.5%	8.1%	2.5%	2.3%	2.2%
Res Util 5	28.6%	27.9%	17.8%	17.1%	16.8%
Res Util 6	4.3%	8.7%	2.4%	2.2%	2.2%
Res Util 7	12.2%	21.4%	13.4%	12.9%	12.7%
Res Util 8	2.4%	7.6%	2.2%	2.1%	2.0%

Appendix H: T-Test No Residents vs. Base Patients per hour

Two-Sample T-Test and CI: Doctor 1, Doctor 1 No Residents

```
Two-sample T for Doctor 1 vs Doctor 1 NR

                N   Mean  StDev  SE Mean
Doctor 1     1094  11.39   6.11     0.18
Doctor 1 NR  1095  -0.05   7.73     0.23


Difference = mu (Doctor 1) - mu (Doctor 1 NR)
Estimate for difference:  11.435
95% CI for difference:  (10.851, 12.019)
T-Test of difference = 0 (vs not =): T-Value = 38.40  P-Value = 0.000  DF =
     2077
```

Two-Sample T-Test and CI: Doctor 2, Doctor 2 No Residents

```
Two-sample T for Doctor 2 vs Doctor 2 NR

                N   Mean  StDev  SE Mean
Doctor 2     1094  11.23   6.55     0.20
Doctor 2 NR  1094  -0.00   7.30     0.22


Difference = mu (Doctor 2) - mu (Doctor 2 NR)
Estimate for difference:  11.228
95% CI for difference:  (10.646, 11.809)
T-Test of difference = 0 (vs not =): T-Value = 37.88  P-Value = 0.000  DF =
     2160
```

Appendix I: Yearly Increases of Residents

Name	No Residents	year 1	year 2	year 3	Base Model
reps	20	20	20	20	20
run length	525600	525600	525600	525600	525600
LWBS1	0	0	0	0	0
LWBS2	0	0	0	0	0
LWBS3	1748	1640	1769	1636	1672
LWBS4	1836	1906	1917	1876	2068
LWBS5	268	289	276	279	299
DTB1	10.704	12.115	12.663	13.884	12.976
DTB2	16.816	18.439	19.113	19.524	18.254
DTB3	24.547	25.286	24.759	24.38	26.057
DTB4	18.908	15.175	15.337	15.083	14.593
DTB5	18.052	13.093	13.257	14.055	13.238
DTD1	14.046	26.698	32.886	32.233	47.286
DTD2	20.587	34.919	39.399	41.274	46.049
DTD3	31.803	48.329	43.606	37.431	44.399
DTD4	30.932	37.541	32.726	25.938	28.102
DTD5	33.085	38.866	31.481	25.09	30.12
LOS1	589.944	544.608	572.904	588.322	591.315
LOS2	413.684	367.438	393.969	402.064	395.441
LOS3	305.194	358.666	339.402	329.303	344.085
LOS4	63.964	83.064	71.962	65.471	72.01
LOS5	54.212	67.177	56.517	49.997	58.923
Type_In_1	373	372	366	374	367
Type_In_2	8564	8596	8561	8587	8536
Type_In_3	23959	23889	23953	23929	24050
Type_In_4	12708	12704	12753	12676	12693
Type_In_5	1660	1679	1668	1683	1694
Admit 1	346	345	340	347	340
Admit 2	5778	5787	5792	5786	5752
Admit 3	5615	5568	5575	5600	5624
Admit ICU	1474	1475	1471	1489	1469
Discharge 1	27	28	27	27	26
Discharge 2	2783	2805	2765	2797	2780
Discharge 3	16583	16669	16593	16679	16742
Discharge 4	6375	6306	6315	6317	6125
Discharge 5	812	792	797	805	786
Dr 1 Util	0.47	0.482	0.443	0.415	0.443
Dr 2 Util	0.469	0.426	0.388	0.368	0.381
Res Util 1	0	0.428	0.345	0.298	0.297
Res Util 2	0	0	0.245	0.214	0.086
Res Util 3	0	0	0	0.13	0.173
Res Util 4	0	0	0	0	0.029
Res Util 5	0	0.256	0.164	0.066	0.294
Res Util 6	0	0	0.068	0.035	0.048
Res Util 7	0	0	0	0.017	0.131
Res Util 8	0	0	0	0	0.026