Optimizing Operational Flow in Emergency Departments via Simulation

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I. Abstract

Overcrowding has become a major issue in hospitals all over the country. Ever since the Affordable Care Act, there has been a new influx of patients, making it even more difficult for hospitals to manage a large volume of patients. In order to resolve this conflict, hospitals must develop creative ways to move patients through the system quickly and assign resources in a cost-saving manner. To purpose of this paper is to analyze various issues facing hospitals, examine the underlying issues and current strategies to relieve these problems, and develop a simulation model for Bellevue Hospital to improve their operations.

II. Importance of Hospital Optimization

Patient outcomes are heavily determined on the timely and effective care of hospital emergency departments. Hospital inefficiencies can lead to the reduction in the quality of care and cause severe discomfort among patients. This can eventually lead to a low patient satisfaction as well low scores for hospital emergency departments. While there are many reasons that could lead to a patient's dissatisfaction at hospitals, operational flow is one that can be altered by management[1].

When a patient arrives to a hospital emergency department, there are several steps that he or she must take in order to receive a bed. While this process varies from hospital to hospital, the general process a patient makes through a hospital involves arriving to a waiting room, filling out paperwork, waiting to be seen by a triage nurse, and finally, obtaining a spot in the emergency department. This general process can be time consuming for both the patient as well as the hospital. Patients waste time, energy, and feel discomfort during their waiting times while

[1] "Timely and Effective Care." *Timely and Effective Care*. Web. 20 Apr. 2016.

hospitals waste resources, space, and money. The nature of the ED should instead, allow patients to move freely through the system with as little wait time as possible and effectively manage hospital resources in order to optimize patient flow.

Hospital Emergency Departments across the world can analyze their specific patient flow and amount of resources available to them in order to create an optimal environment with as little wait time as possible. A smaller wait time allows patients to be seen faster and decrease a hospital's percentage of patients who leave the emergency department before being seen. Many hospitals do not have the resources to manage a high volume of patients, and due to this, many patients must leave without being seen. This creates an even higher risk for the patient and can lead to severe health outcomes. Effectively managing hospital resources can drive this percentage down and allow healthcare professionals to effectively evaluate patients' conditions.

While patients' conditions can worsen from leaving the hospital before getting evaluated, it is also the case where patients' can fall ill in the ED by waiting to be admitted into the hospital. It is imperative to the condition of the patient that he or she get admitted as soon as possible if he or she is in an urgent condition. When the average time spent in the emergency department before being admitted into the hospital is high, it may be a sign that the hospital is overcrowded or understaffed. Not only does this cause wait times to surge, but also the deterioration of quality of care. Reducing the time spent in the ED is vital in ensuring patient care as well as the health of the hospital[2].

These quality measures in hospital EDs can show how effective hospitals are at managing their resources. Long stays in hospital emergency departments and waiting areas puts the patient at risk. With hundreds of patients visiting the ED daily, the importance of effectively managing

[2] Ibid.

hospital resources remains high. This becomes increasingly important during seasons of high illnesses and the unscheduled nature of ED visits. Overcrowding can become an important issue in hospitals, but also one that can be resolved by employing tactics that can effectively manage resources.

Overcrowding can cause significant damage—not only on patients and hospitals, but also on physicians and other healthcare providers. According to a Johns Hopkins study in 2013, "more than one-quarter of hospital-based general practitioners…say their average patient load exceeds safe levels multiple times per month[3]." This creates stressful working conditions for nurses, physicians, and administrators. As the patient count increases over time, the demand for healthcare providers will only surge in the upcoming years. The Affordable Care Act has created an influx of new patients that has caused overcrowding to become an increasingly important issue that hospital managers need to address.

III. Solutions are scarce

While there has been active research and study in improving hospital operations, the process of dissemination of these ideas has been lacking. Patient data takes time to collect, and when Emergency Departments finally solve issues to some of their operational problems, the spread of ideas fails to occur, leaving the other 4,500 EDs in the nation left without solutions. In Shari Welch's "Using Data to Drive Emergency Department Design: A Metasynthesis," "ED

[3]Johns Hopkins Medicine. *Hospital Patient Loads Often at Unsafe Levels, Physician Survey Says*. *Http://www.hopkinsmedicine.org/*. 28 Jan. 2013. Web.

operations research is often slow to reach the front lines.[4]"

Welch mentions that there are few journals that look specifically at ED operations, something that would be useful in this area of study. Healthcare in the United States has taken several turns in the past few years, and with new policies and regulations being announced, the need to stay up-to-date increases.

IV. Challenges in Operational Research

Information is not as widespread as it should be—but also, it should also be noted that there are many challenges that come along with hospital operations research. According to Teresa Melo's research report on challenges and opportunities in operations research, she notes 6 specific challenges in hospital logistics[5]:

1. There is a clear conflict of interest between the patient, physician, and management. While management strives to achieve profits by cutting costs and improving resource management, physicians strive to provide quality care to patients. When conducting studies in operational research and restructuring hospital EDs, this can often lead to conflicting goals.
2. Hospital managers and physicians must often make decisions on resource allocation and operational efficiency. While having numerous other responsibilities as well, these groups often lack expertise in analytics and hospital operations research.
3. The lack of coordination between the ED and other departments make it difficult to enable operational changes in the hospital ED. For example, when nurses order prescriptions for patients within the ED, the time that it takes to get registered in the computer system and the

[4]Melo, Teresa. "A Note on Challenges and Opportunities for Operations Research in Hospital Logistics." *Saarland University of Applied Sciences (htw Saar), Saarland Business School* (2012). Web. <http://econstor.eu/bitstream/10419/98155/1/722231369.pdf>.
[5] Ibid.

time that the hospital pharmacy completes the order may be inefficient causing the patient to have a longer wait time.

4. Logistics in hospital EDs are underestimated and undervalued. Management often does not consider taking operations into decision making because it does not appear to have a large effect. However, patient satisfaction can become easily disrupted due to delays in administration and late deliveries.
5. There is a lack of information tools that allow clinicians to realize a gap in their operations. Information Technology is more focused on hospital information systems as opposed to operational research to reduce inefficiencies.
6. Hospitals are rewarded for how much care they deliver instead of their quality of care and efficiency in providing that care[6].

While there are definitely challenges in employing operational techniques, hospitals have a great deal to benefit from paying attention to gaps in their operational flow in order to cut costs, minimize waste of resources and overall improving patient care.

V. Introduction to Bellevue Hospital

Located in the Kips Bay neighborhood of New York City and founded in 1736, Bellevue Hospital is the oldest public hospital in the United States. Since then, the hospital has served as an academic medical institution and an incubator for innovations in public health, medical science, and medical education. Their state-of-the-art facilities include a 25-story patient facility with 800 beds, an Emergency Service and Trauma Center, and an Ambulatory Care Pavilion.

[6]Ibid.

Bellevue has a long history of serving the New York City population and maintains its policy of accepting every patient regardless of their ability to pay[7].

Bellevue remains of the largest hospitals in New York City and functions the only Level 1 trauma center in Manhattan south of 59th street. The hospital is also affiliated with the NYU School of Medicine as it offers a wide range of medical cases to students. While it is affiliated with the private hospital next door, the New York Health and Hospitals Corporation (HHC) assures its status as a public hospital that serves the needs of the New York City population[8].

Bellevue Hospital serves a diverse set of patients throughout New York City. As the largest hospital in the HHC group, Bellevue had 116,751 Emergency room visits and 479,788 clinic visits in 2014[9]. HHC group faced operating losses of about 263.3 million during the first quarter of fiscal 2015[10]. The loss that Bellevue Hospital as well as the other hospitals in the HHC face is driven by its waste of resources as well as Super Storm Sandy. Its lack of profit stems from its mix of payers as many of Bellevue's patients face socioeconomic challenges and have little access to healthcare. Due to Bellevue's open access policies, many patients from all over the five boroughs are served by them when in need of emergency care.

VI. Opportunities in Bellevue's Hospital Operations

Even though Bellevue Hospital faces tremendous patient flow compared to other hospitals in New York City, there is definitely room for improvement with regards to improving its

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[7] Gilman, Kurt, et al. Optimizing the Emergency Department Triage Process: Developing an Analytic Approach to Assign Patients to Work Groups in Bellevue Hospital's Emergency Department.
[8] Ibid.
[9] "About NYC Health Hospitals/Bellevue - Facts." *About NYC Health Hospitals/Bellevue - Facts*. Web. 29 Apr. 2016.
[10] "NYC Health and Hospitals' Operating Loss Soars." *Modern Healthcare*. Web. 23 Apr. 2016.

operational structure. Because of its open access policy, there will always be a need to ameliorate the overcrowding that is faced by the ED. By reducing the amount of time a patient stays in the waiting area and choosing the optimal amount of staff members working at a certain time, Bellevue Hospital can utilize its resources effectively to cut costs as well as improve patient flow.

According to Soroush Saghafian's research on how operations research impacts ED patient plow, operations management has had a significant impact on optimizing patient flow[11]. The processes that this includes are patient admission into ED, discharge from hospital, and admission into hospital. Long waiting times in the ED are partially caused by the mismatch between the supply of of healthcare providers and the capacity of patients that arrive to the ED. The increasing strain that hospitals face from overcrowding can be seen as an opportunity as opposed to a weakness. While the number of annual ED visits keeps increasing, from 90.3 million to 119.2 million from 1996 to 2006, the number of EDs in the United States decreased from 4019 to 3833. This strain places pressure on hospitals to remain in overcapacity over 50% of the time. While this issue is definitely multifaceted, hospitals can take a first step in correcting the operational issue via analysis of various throughput metrics.

As healthcare expenditures become a growing percentage of the United States Gross Domestic Product (GDP), there is a greater need to improve the market inefficiencies. These inefficiencies can have a large impact on U.S. healthcare expenditures as the ED is the first point of contact for most hospital admissions. That being said, there is ample opportunity in the growing market to improve operational decisions as they have the potential to impact an even

[11] Saghafian, Soroush, Garrett Austin, and Stephen Traub. "Operations Research Contributions to Emergency Department Patient Flow Optimization: Review and Research Prospects." *SSRN Electronic Journal SSRN Journal*. Web.

broader market. In order to utilize operational management research in hospital operations, Saghafian's team breaks it into three categories: "flow into the ED, flow within the ED, and flow out of the ED[12]." Within these categories, operations managers can look at specific triage activities, staffing, scheduling, and resource planning.

As mentioned earlier, there is ample research in the department, but implementation seems to be lacking due to the low level of collaboration between researchers, hospitals, various stakeholders. Involving managers as well as other hospital stakeholders early on in the process can prove to have ample progress in the field of hospital operations. There is a need to understand why and how overcrowding in hospitals is occurring and one of the many reasons why this information is not widespread is because it is not understood by many managers. Researchers use complex jargon and intricate mathematical models to describe hospital operations, which is not readily understood by most hospital stakeholders. This disconnect between the researchers and hospital stakeholders is one that can be seen as an opportunity to collaborate between the groups.

Research in operations management is cutting edge and can be used to solve many issues with overcrowding in the future. For example, reverse triage, a process towards the back end of the ED service process can be an important research direction. This methodology can be proven effective largely due to the fact that many hospitals act as a bottle neck for patients as they tend to exit the hospital less frequently than they enter the hospital—ultimately creating the overcrowding issue. Operations management researchers can utilize this tactic to focus on effective ways of moving the patients out of the ED without compromising quality of care.

Operations management research can also involve focusing on the arrival of patients as

[12] Ibid.

there is a strong correlation between ED and inpatient length of stay. This suggests that improving patient operations from the moment of their arrival can prove to correct inefficiencies down the line during the rest of their stay in the hospital. Improving hospital operations from the moment patients arrive can also be an effective starting point for operations researchers.

Bellevue Hospital has ample opportunity to improve their operational structure based on potential future research in this area. While most research involves optimizing patient flow in a single hospital, it can be beneficial that Bellevue hospital is affiliated with many other hospitals in New York City. This can potentially lead to future research in which advanced queuing models can represent multiple hospitals simultaneously.

VII. Simulation Analysis

Simulations are often used as a decision making tool to imitate the operations of a real-world process. Used in many contexts, simulations of hospitals with regards to hospital management can be proven to be useful when pinpointing specific inefficiencies. Simulations can be used to imitate inter-arrival times and service times in order to create a queuing model. Conducting an experiment of a real hospital Emergency Room would be impractical and difficult to carry out due to high costs of testing and obtaining consent from patients. Instead, creating a simulation of a hospital emergency department would require a few data inputs that can be then used to create a model in which one variable or more can be altered.

The ability to test a large number of patients in a small amount of time is one of the many benefits of simulation. When using the average arrival rates and service times, one can create a simulation of a hospital to determine the optimal amount of triage nurses or “servers” needed.

VIII. Data Received

In order to analyze Bellevue Hospital Operations and develop a simulation, data from the ED was collected over a time period of November 2013 to May 2015. The data contains information regarding volume metrics, throughput metrics, and median wait times. The amount of patients for which this data was collected was 123,104.

Table 1. Data Set Obtained from Bellevue Hospital

Metric	Average over 19 months (Nov 13-May 15)
Number of Patients Arrived to ED	8,536
Number of Patients Triaged	8,366
Number of Patients Claimed by a Provider	8,077
Percentage of Patients Left Without Being Seen	4.56%
Number of Patients Seen & Discharged	6,737
Number of Patients Who Were Admitted	1,111
Percentage of Patients Who Were Admitted	13.2%
Arrival to Triage (hh:mm)	00:08:32
Triage to First Provider (hh:mm:ss)	00:26:03
Arrival to First Provider (hh:mm:ss)	00:38:38
First Provider to Exit for Discharged Patients (hh:mm:ss)	1:52:57
Triage to Exit for for Discharged Patients (hh:mm:ss)	2:36:06
First Provider to Disposition for Admitted Patients (hh:mm:ss)	3:34:51
Dwell for Admitted Patients (hh:mm:ss)	2:53:38
First Provider to Exit for Admitted Patients (hh:mm:ss)	7:25:19
Triage to Exit for Admitted Patients (hh:mm:ss)	8:03:57
ED LOS for Discharged Patients (hh:mm:ss)	2:50:35
ED LOS for Admitted Patients (hh:mm:ss)	8:19:13

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IX. Limitations of the Data:

Moving forward with the data received from Bellevue Hospital, it is important to note that every set of data has limits and errors. Instead of specific times when patients arrive, the simulation created from this data set uses averages of times in order to obtain a result that can be comprehensive and represent the data set to the best of its ability. Using the average times and average number of patients allows for a comprehensive analysis over an entire year instead of a specific span of months. It should be noted that every season has a different amount of patient flow, but for simplicity reasons, they have been grouped together and averaged.

Hospitals collect a multitude of information from patients that pass through. As the patient goes through different levels in the hospital, various healthcare providers take down detailed information regarding patient health, socioeconomic status, family and medical history, and etc. However, due to HIPAA and several other restrictions, data researchers have limited access patient files and other factors that may have been useful when running a simulation. Confidentiality between patients and hospitals prevent data researchers from obtaining this information.

It is also important to note that specific operation plans of Bellevue Hospital were not provided. Specifically, the amount of staff that works in the ED, the number of nurses and physicians on call, and the number of administrators that are in the waiting area are unknown. Similarly, specific times to obtain medicine, laboratory testing, and radiology are not given. The data set obtained involves mainly that which is represented in Table 1.

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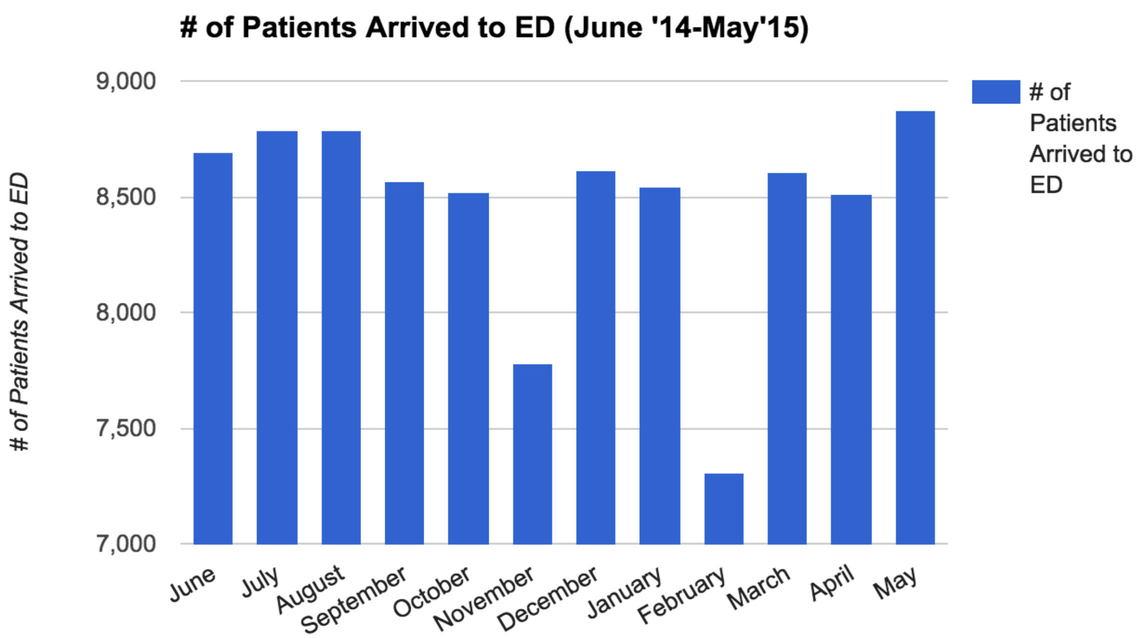
13 Bellevue Hospital Emergency Department Corporate Dashboard November 2013-June 2015. Raw data. Bellevue Hospital, New York City.

X. Descriptive Statistics

A data set with the number of patients arrived over the course of a year was obtained from Bellevue Hospital. Using this data, Graph 1 was created in order to get an idea of the number of patients that arrive over the course of a year, separated into months. According to the data set, there is some fluctuation between the number of patients that arrive to the ED per month. Over the course of this year May had the highest number of patients arrive at 8,877 patients while February had the lowest number of patients arrive at 7,310. The mean of the data set is 8,536 patients per month[14].

Graph 1. Patient Arrivals between June 2014 and May 2015



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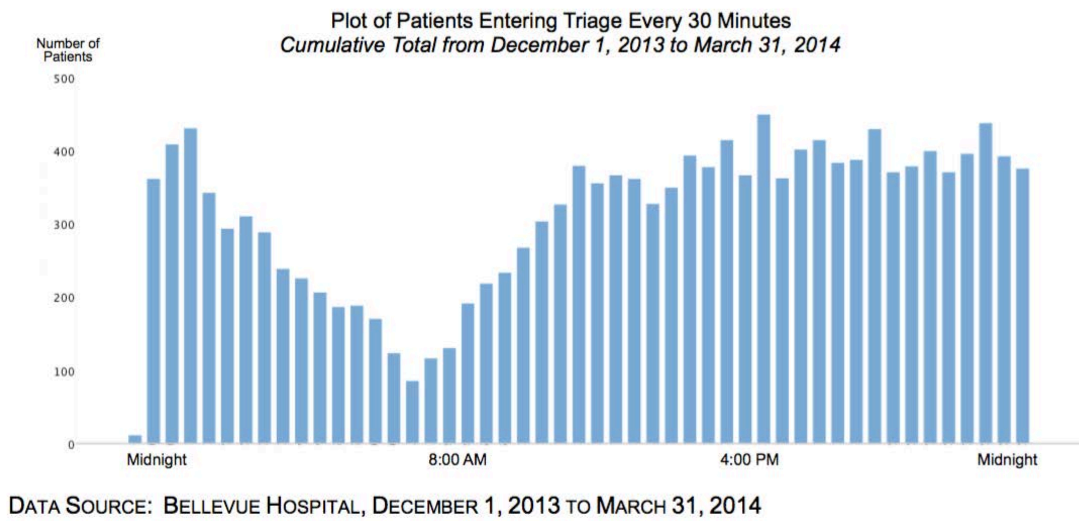
While Graph 1 depicts the number of patients arriving to the ED on a monthly basis, Graph 2 depicts the cumulative total number of patients that arrived to triage on a 30-minute basis. Comparing the two visuals, it is evident that while the amount of patients entering the ED

[14] Ibid.
[15] Ibid.

per month does not fluctuate very month, the amount of patients that enter triage throughout the day fluctuates greatly depending on the time. Observing the fluctuation patterns, it can be noted that a high point in patient arrivals starts around midnight and decreases steadily throughout the night up until 7am, the lowest point. From 7am, the number of patients that arrive into triage increases at a steady rate until noon. Throughout the afternoon hours and into the evening hours, the amount of patients that arrive remain relatively steady.



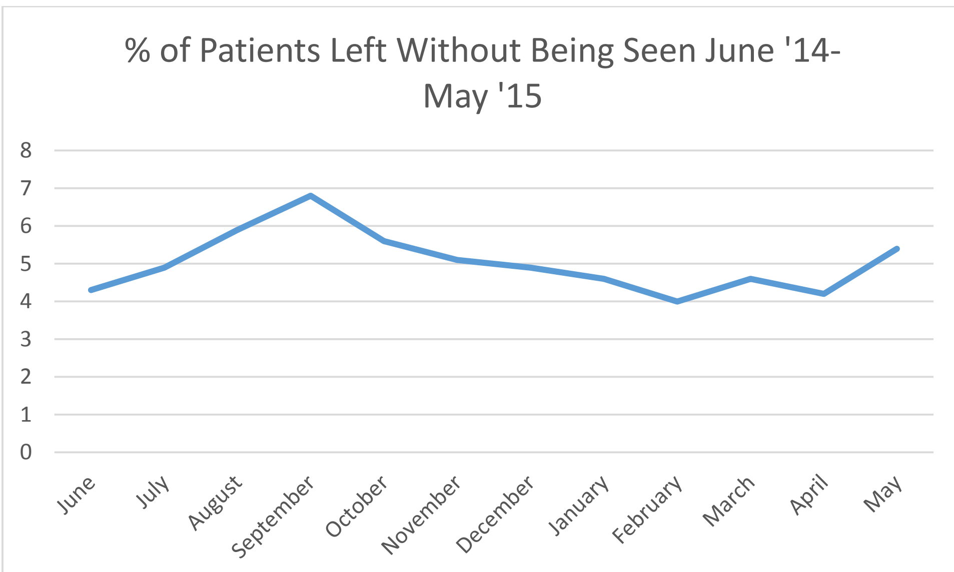
Graph 2. Plot of Patients Entering Triage Every 30 Minutes

Often times, patients come to the ED for a specific issue and due to various factors, they leave without being seen by a healthcare provider. According to a recent study, there are steps that a hospital can take in order to reduce the percentage of patients that leave the ED without being seen by a nurse or physician[16]. A high percentage is a sign that the hospital has failed to

[16] "A New Look at Leaving Without Being Seen in EDs." *Physicians Weekly for Medical News Journals Articles*. 2012. Web. 11 Apr. 2016.

provide care to patients and this can put the hospital at serious reputational risk. Not only is it crucial for hospitals to decrease this percentage, but also for the entire healthcare system as a whole. It places strain on the healthcare system as patients leave without being seen, spreading their illnesses to other people in the population and having little to no access to correct treatments. Hospitals can take initiative to lower these percentages as they cause harm to patients, hospitals, and the entire healthcare system.

Graph 3. Percentage of Patients that left the ED without being seen from June 2014-May 2015



[17]

Graph 3 depicts the percentage of patients that left the ED without being seen between the months of June 2014 and May 2015. In September 2014, 6.8% of patients that entered the ED left without being seen, the highest of the year. Contrastingly, February 2015 had about 4.0% of patients leave the ED without being seen. As seen in the graph, the percentage of patients that left the ED starts off low in June 2014 rising rapidly until its peak in September 2014. After

[17] Bellevue Hospital Emergency Department Corporate Dashboard November 2013-June 2015. Raw data. Bellevue Hospital, New York City.

September, the percentage decreases at a steady rate until February 2015 and then fluctuates up until May 2015.

There are many potential causes that patients would leave the Emergency Department—longer wait times, increased visits, or decreased supply. If there are increasing number of patients that leave the ED, it can often mean that access to healthcare issues are prominent amongst the population that comes to the hospital. This is crucial for all hospitals, but more specifically Bellevue Hospital because it sees patients from all over New York City regardless of their socioeconomic status and healthcare coverage.

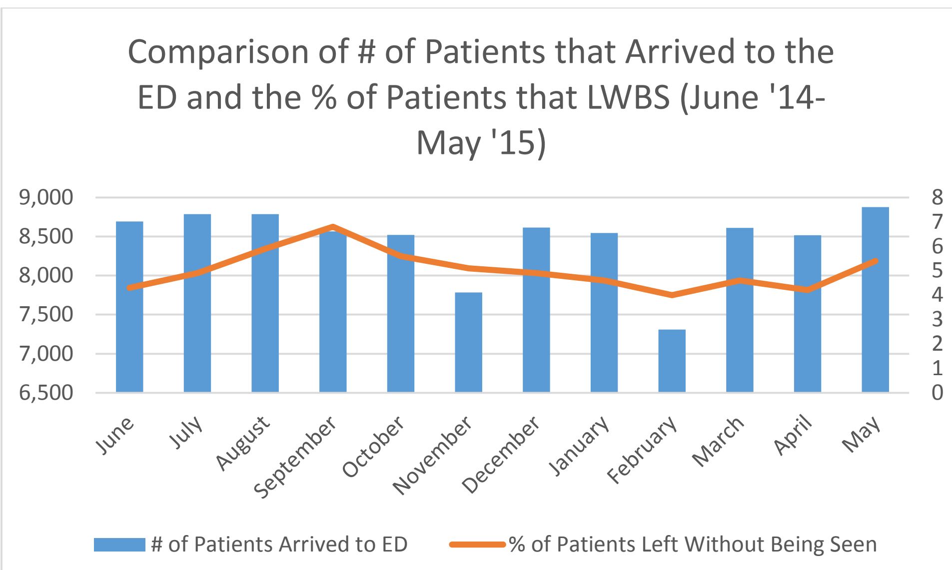
Compared to a select number of hospitals, Bellevue Hospital falls on the higher end of the spectrum of percentage of patients that leave the ED without being seen. According to the Annals of Emergency Medicine Study performed on 262 acute-care hospitals in California that involved about 9 million ED visits, the percentage of patients that left the ED ranged greatly from 0.1% to a high of 20.3%. The median was about 2.6% for a select few hospitals in California[18]. Comparing these statistics to the number of patients that left the ED without being seen in Bellevue Hospital, it is clear that they fall on the higher end of the spectrum. Even though Bellevue Hospital is located in New York City, while the study was performed in California, it is important to note the various similarities between the two cities with respect to the high population and diversity.

The average percentage of patients that left the ED without being seen at Bellevue Hospital between May 2014 and June 2015 was 4.56%. Studies show that national estimates of LWBS are about 1%. Bellevue's LWBS rate is about 3.56 percentage points above the national rate, and it will only rise if the management team does not change its operational structure. The

[18] "A New Look at Leaving Without Being Seen in EDs." *Physicians Weekly for Medical News Journals Articles*. 2012. Web. 11 Apr. 2016.

study examined the causes of such high variation even further and discovered that hospitals that are located in areas of high income tend to have lower LWBS percentages while hospitals that are located in areas serving patients in the bottom 10th percentile of income have high LWBS. The averages for both of these scenarios in the United States are 3.4% and 1.7% respectively[19]. Since Bellevue's open door policy allows patients to enter regardless of their healthcare coverage, the latter scenario of patients in the bottom 10th percentile of income describes Bellevue Hospital. Even so Bellevue Hospital's LWBS percentage falls 1.1 percentage points higher than the average, once again proving its greater need to improve their operational structure.

Graph 4. Number of Patients that Arrived to the ED vs. % Patients that LWBS



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While there are many possible reasons for a the high LWBS rate at Bellevue Hospital, it can be useful to compare the amount of patient influx to the LWBS rate. Graph 4 shows a

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[19] Ibid.
[20] Bellevue Hospital Emergency Department Corporate Dashboard November 2013-June 2015. Raw data. Bellevue Hospital, New York City.

comparison of the number of patients that arrived to the ED versus the percentage of patients that left without being seen (LWBS). The number of patients that entered the ED between June-September stayed relatively constant with slight fluctuations while the % of patients that LWBS increased rapidly. During the months of September and November, the number of the patients that entered the ED decreased while the % of patients that LWBS also decreased. December and January had a similar patient flow as June-September while the LWBS rate slowly decreased. In February, both the number of patients and the LWBS rate hit a low point. This correlation could stem from the fact that since the amount of patient flow was minimal, more patients were able to be seen, decreasing the LWBS rate. The number of patients increased from March to May as did the LWBS rate for those months. While the number of patients that entered the ED and the LWBS rate do not correlate exactly on a month by month basis, it can be noted that there are slight patterns that hint at a correlation.

The correlation implies that high patient flow can sometimes lead to a high LWBS rate, one which hospitals should strive to keep as low as possible. While there are other factors that may lead to a high LWBS rate, the number of patients in a contributing cause and hospital managers can and should take steps to optimize their patient flow in order to decrease their LWBS rate.

XI. M/M/c queuing model

Queueing theory allows researchers to model or simulate real life scenarios by creating a mathematical system in which customers can move through. Using a multi-server model, arrivals form a single queue and are governed by a poisson process. With *c* amount of servers, and exponentially distributed service times and interarrival rates, one can determine the optimal amount of servers needed in a system. The model is also used to analyze current operational systems and pinpoint specific mismatches in businesses.

Applying queing theory to hospital operations can be proven useful to analyze the flow of patients in Emergency Departments. Due to of overcrowding, hospitals, patients, and healthcare providers are strained. In order to relieve this strain and move forward with an effcient operational plan, it is evident to analyze patient flow using a simulaetion model in which various variable can be adjusted.

Using the data obtained by Bellevue Hospital (Graph 2), we can calculate the number of patients that arrived in a three month span. For simplicity purposes, the number of patients can be divided by the number of days and hours to obtain the number of patients that enter the ED per minute. During the months from December 1, 2013 and March 31, 2014, there were approximately 15,635 patients that entered the ED. Based on the number of patients that arrived over the span of four months, the number of patients that arrived per minute was 0.0897.

After a patient arrives in the ED, the length of stay was calculated. This data was obtained from Bellevue Hospital and the square root of the length of stay was taken in order to get a normally distributed curve. Using the data, descriptive statistics were obtained. The mean of the square root of the length of stay was calculated to be 1.9698 and the standard deviation was calculated to be 0.648 (See Figures 1 & 2). This data can be inputted into a simulation in order to obtain random service times based on the normally distributed curve.

Using the inter-arrival times and the service times, the waiting time in the queue can be calculated. When patients arrive into the system, they receive a random number. Using the random number, the interarrival time is calculated using $\ln(1\text{-rand}(\ ))/\text{-}\lambda$ where λ is equal to the # of arrivals per minute. λ=0.897. The service times can be calculated based on the normally distributed curve and its descriptive statistics. Using the mean and the standard deviation, the values can be plugged into the formula that will calculate service times. (Norminv(rand( ), mean, stdev))^2 gives random service times in hours based on the normally distributed curve. This can be converted into minutes for simplicity purposes.

XII. Running the Simulation

An M/M/3 queue simulation was run for Bellevue hospital for three separate scenarios:

1. Simulation ran with 50 patients, 3 servers, interarrival times multiplied by 5 (Figure 3)
2. Simulation ran with 50 patients, 3 servers, interarrival times multiplied by 10 (Figure 4)
3. Simulation ran with 50 patients, 3 servers, interarrival times multiplied by 20 (Figure 5)

For simplicity purposes, inter-arrival times were multiplied by a factor instead of adding additional servers to the simulation. The action of multiplying the interarrival times by a factor serves the same function as adding additional servers. For example, the first simulation was run with 3 servers with the interarrival times multiplied by 5. Because the interarrival times were 5 times as long, the servers will have more time to see each individual patient. This is equivalent of having 15 servers. Similarly, if the interarrival times are multiplied by 10, there would be 30 servers, and so on.

XIII. Analysis of Simulation

From the simulation, we can see that the strain that Bellevue Hospital faces from its patient flow is very extreme. In the simulation where the interarrival times were multiplied by 5, the average waiting time was about 708 minutes and the average time in the system was about 966 minutes (See Figure 3). This data was calculated with about 50 patients entering the system arriving at a pace that was five times slower. The average wait time of about 708 minutes is the average time a patient waits before being seen. Since the number is drastically, we can see that amount of strain that must be present on the hospital staff.

In a second simulation, the interarrival times were multiplied by 10, meaning that the amount of time between each patient arriving slows down by ten times (See Figure 4). This simulation simulates a scenario where there are double the amount of servers than the first simulation. The simulation was ran with 50 patients and the average waiting time was 82 minutes while the average time in the system was 339 minutes. By spacing out the patients, equivalent to adding more servers, we can see that the waiting time and the time spent in the system turned out to be drastically lower than the first scenario where the interarrival times were only multiplied by 5.

The final simulation involved multiplying the interarrival times by an even high factor of 20, which is equivalent to adding an even greater amount of servers to the simulation (See Figure 5). In this simuation run with 50 patients, the average wait time was only about 8 minutes while the average time in the system was 270 minutes. By increasing the interarrival time dramatically, we can see that the average wait time for a patient decreased by a large amount. Adding more servers into the system can be seen as a method of decreasing the wait time.

XIV. Conclusion:

With over 116,000 hospital ED visits per year, a struggling financial status, and a limited amount of staff and resources, Bellevue hospital faces a continuing issue to improve its operational flow. Bellevue Hospital faces a tremendous amount of strain when it comes to patient flow. This is largely due to the fact that the hospital has an open door policy allowing patients to receive care regardless of their healthcare status. This places an even grater presure on

Bellevue hospital to create a more effcient method of routing their patients in order to handle their flow. Patients from all over the five bouroughs of New York City rely on Bellevue Hospital for medical care, so it is imperative that they begin the optimization process.

With a set number of healthcare providers, Bellevue Hospital can become easily clogged with patients. As patients are entering the ED at a higher rate than they are leaving, the system creates a bottleneck effect. Not only does this process clog the hospital with patients, but also it can create additional issuse down the line of care and in other departments of the hospital slowing down care for all patients. Often times, there is a mismatch between patients and providers that can also cause the clogging of patients in the hospital. Specifically looking at Bellevue Hospital, the mismatch of patients and providers is especially important due to the large volume of patients that arrive to the hospital ona daily basis. By looking at the simulations ran above and the operational structure and capacity of Bellevue Hospital's ED, hospital managers can develop a system of care in which patients and providers are matched with optimal effciency.

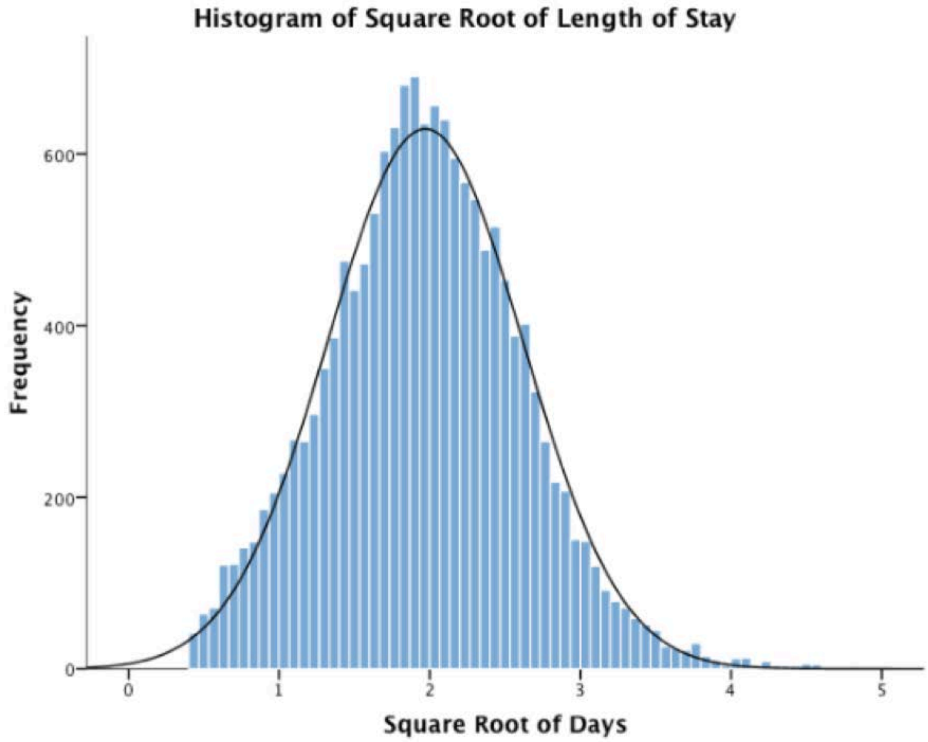
While it is important to have an optimal amount of healthcare providers to patients, it is also important to keep in mind the findings of Graph 2, the plot of patients entering triage every 30 minutes. The average of patients that arrive to the ED every day varies based on the time of day, month, and season. Calculating averages of this data over a span of a year or two can give the hospital vital information to implement into their operations plan. Utilizing the average number of patients that arrive at a given time on a given day, managers should implement a certain amount of staff that should be present on that specific day. Switching to a dynamic model of servers that adjusts based on patient flow may be more useful for Bellevue Hospital

A dynamic model would allow patients to remain in the system for a shorter span of time as well as reduce the amount of time a patient has to wait before being seen by a healthcare provider. This system will allow patients to enter the system with smaller wait times as well as decrease the metric “Leaving without being seen.” While hospital managers strive to achieve optimal effciciency, it is important to take into account quality of care. Quality of care should be minimally sacrificed while simultaneously reducing the strain that Bellevue Hospital faces.

Moving forward, Bellevue hospital should focus first on its patient flow and creating a dynamic model to improve their operational structure. By focusing on the first contact point a patient makes with a hospital, the rest of the structure will automatically shift towards improving efficiency. Using simulation as well as other analytical models can be proven useful with optimizing the ED process. Using the simulation done in this research, as well as refining the model continuously using updated data, will allow the ED to run efficiently. Bellevue can utilize their resources in an efficient way as well as reduce patients’ discomfort in EDs. Not only will these improvements benefit the current status of the hospital, but it will also be able to attract more privately-insured patients enabling it to improve its financial status.

Appendix

Figure 1. Histogram of the Square Root of the Length of Stay for Patients in the ED from December 1, 2013 to March 31, 2014



Data Source: Bellevue Hospital, Optimizing the Emergency Department Triage Process

Figure 2. Descriptive Statistics for the Square Root of the Length of Stay for Patients in the ED from December 1, 2013 to March 31, 2014

Square Root of Length of Stay	
Mean	1.9698
Standard Deviation	0.648
Variance	0.42
Skewness	-0.22
Standard Error of Skewness	0.02
Kurtosis	0.239
Standard Error of Kurtosis	0.04
Range	4.46
Minimum	0.41
Maximum	4.87

Data Source: Bellevue Hospital, Optimizing the Emergency Department Triage Process

Figure 3. Simulation Ran with 50 Patients, 3 servers, Multiplying the Interarrival times by 5

Number of times ran	Average waiting time	Average Time in System
1	241.8	483.8
2	659.4	886.7
3	1202.5	1471.8
4	421.6	677.9
5	813.4	1089.4
6	630.2	859.7
7	690.3	943.1
8	1425.3	1733.2
9	505.8	781
10	685.9	943
11	868.3	1107.9
12	638.6	902.3
13	679.8	921.5
14	416	676.1
15	710	967.6
16	306.2	536.7
17	826.9	1090.1
18	768.5	1049.5
19	703.1	954.4
20	962.2	1249.7
Average	**707.79**	**966.27**

Data Source: Bellevue Hospital

M/M/3 QUEUE SIMULATION FOR Bellevue Hospital
First available teller

	Random Number for arrival	Interarrival time	Clock (Arrival time)	Random Number for service	Service time	Teller 1 TS	Teller 1 TF	Teller 2 TS	Teller 2 TF	Teller 3 TS	Teller 3 TF	Waiting Time Wq	Time in System Ws	Which server ↓	Min work	Work 1	Work 2	Work 3
1	0.9330451	150.6552795	150.65528	0.0572669	53.82741	150.7	204.5					0.0	53.8	1				
2	0.1342895	8.035249712	158.69053	0.4642349	219.2595			158.7	378.0			0.0	219.3	2	0.0	204.5	0.0	0.0
3	0.3819467	26.81193364	185.50246	0.1971762	120.6205					185.5	306.1	0.0	120.6	3	0.0	204.5	378.0	0.0
4	0.8017571	90.1714012	275.67386	0.8726691	439.9751	275.7	715.6					0.0	440.0	1	204.5	204.5	378.0	306.1
5	0.4137256	29.75326877	305.42713	0.0491429	48.43947					306.1	354.6	0.7	49.1	3	306.1	715.6	378.0	306.1
6	0.2132144	13.36190002	318.78903	0.488007	228.2241					354.6	582.8	35.8	264.0	3	354.6	715.6	378.0	354.6
7	0.22863	14.4644887	333.25352	0.7147252	327.7987			378.0	705.7			44.7	372.5	2	378.0	715.6	378.0	582.8
8	0.9669015	189.9125796	523.1661	0.0801628	67.41887					582.8	650.2	59.6	127.0	3	582.8	715.6	705.7	582.8
9	0.7034198	67.72556185	590.89166	0.3098476	162.9956					650.2	813.2	59.3	222.3	3	650.2	715.6	705.7	650.2
10	0.4124281	29.63008447	620.52175	0.7500624	347.618			705.7	1053.4			85.2	432.8	2	705.7	715.6	705.7	813.2
11	0.4311563	31.4350567	651.9568	0.5323591	245.4106	715.6	961.1					63.7	309.1	1	715.6	715.6	1053.4	813.2
12	0.0129079	0.723923408	652.68073	0.5577742	255.599					813.2	1068.8	160.5	416.1	3	813.2	961.1	1053.4	813.2
13	0.0906739	5.296379085	657.97711	0.3151297	164.9135	961.1	1126.0					303.1	468.0	1	961.1	961.1	1053.4	1068.8
14	0.3761467	26.29146305	684.26857	0.8841723	452.0608			1053.4	1505.4			369.1	821.2	2	1053.4	1126.0	1053.4	1068.8
15	0.6475059	58.10162234	742.37019	0.5557199	254.7648					1068.8	1323.6	326.4	581.2	3	1068.8	1126.0	1505.4	1068.8
16	0.6974778	66.62023473	808.99043	0.3492542	177.2579	1126.0	1303.2					317.0	494.2	1	1126.0	1126.0	1505.4	1323.6
17	0.2770473	18.07657588	827.067	0.4793958	224.9596	1303.2	1528.2					476.2	701.1	1	1303.2	1303.2	1505.4	1323.6
18	0.7369845	74.41793347	901.48494	0.5984791	272.5769					1323.6	1596.1	422.1	694.7	3	1323.6	1528.2	1505.4	1323.6
19	0.0831938	4.839892157	906.32483	0.7468492	345.7341			1505.4	1851.2			599.1	944.8	2	1505.4	1528.2	1505.4	1596.1
20	0.3697808	25.7257583	932.05059	0.5948639	271.0315	1528.2	1799.2					596.1	867.2	1	1528.2	1528.2	1851.2	1596.1
21	0.9934038	279.7903288	1211.8409	0.9935094	768.8195					1596.1	2365.0	384.3	1153.1	3	1596.1	1799.2	1851.2	1596.1
22	0.8227584	96.41101313	1308.2519	0.1739403	111.2237	1799.2	1910.4					491.0	602.2	1	1799.2	1799.2	1851.2	2365.0
23	0.726697	72.28003173	1380.532	0.7853398	369.6046			1851.2	2220.8			470.6	840.2	2	1851.2	1910.4	1851.2	2365.0
24	0.5770264	47.94500558	1428.477	0.9736259	624.0226	1910.4	2534.5					482.0	1106.0	1	1910.4	1910.4	2220.8	2365.0
25	0.056963	3.268029136	1431.745	0.796042	376.8211			2220.8	2597.6			789.0	1165.8	2	2220.8	2534.5	2220.8	2365.0

Figure 4.

Simulation Ran with 50 Patients, 3 servers, Multiplying the Interarrival times by 10

Number of times ran	Average waiting time	Average Time in System
1	55	295.5
2	91.8	333.1
3	59.7	329.5
4	87	358
5	22.4	254.7
6	49.5	299.9
7	50.3	285
8	150.8	384.8
9	30.1	268.1
10	50.1	322.6
11	39.5	320.3
12	90.3	386.7
13	63.4	321.8
14	290.7	546.8
15	172.4	444.2
16	14.3	266.8
17	106.1	361.8
18	64.7	360.2
19	130.8	382.2
20	17.2	251.3
Average	**81.805**	**338.665**

Data Source: Bellevue Hospital

M/M/3 QUEUE SIMULATION FOR Bellevue Hospital
First available teller

	Random Number for arrival	Interarrival time	Clock (Arrival time)	Random Number for service	Service time	Teller 1		Teller 2		Teller 3		Waiting Time	Time in System	Which server				
						TS	TF	TS	TF	TS	TF	Wq	Ws	↓	Min work	Work 1	Work 2	Work 3
1	0.3219893	43.30560278	43.305603	0.9463185	544.7564	43.3	588.1					0.0	544.8	1				
2	0.5086522	79.19121809	122.49682	0.758763	352.8111			122.5	475.3			0.0	352.8	2	0.0	588.1	0.0	0.0
3	0.1700632	20.77347397	143.27029	0.0359237	38.72185					143.3	182.0	0.0	38.7	3	0.0	588.1	475.3	0.0
4	0.3227387	43.42884382	186.69914	0.5803528	264.9055					186.7	451.6	0.0	264.9	3	182.0	588.1	475.3	182.0
5	0.9164453	276.62806	463.3272	0.6746332	307.3184					463.3	770.6	0.0	307.3	3	451.6	588.1	475.3	451.6
6	0.8620293	220.7352933	684.06249	0.5579223	255.6592			684.1	939.7			0.0	255.7	2	475.3	588.1	475.3	770.6
7	0.1157771	13.71253523	697.77503	0.6951395	317.5617	697.8	1015.3					0.0	317.6	1	588.1	588.1	939.7	770.6
8	0.6510578	117.3318766	815.1069	0.489408	228.7573					815.1	1043.9	0.0	228.8	3	770.6	1015.3	939.7	770.6
9	0.6469888	116.0398977	931.1468	0.7912531	373.5564			939.7	1313.3			8.6	382.1	2	939.7	1015.3	939.7	1043.9
10	0.6433018	114.8819714	1046.0288	0.4708075	221.7235	1046.0	1267.8					0.0	221.7	1	1015.3	1015.3	1313.3	1043.9
11	0.8744511	231.2493657	1277.2781	0.0021826	0.903053					1277.3	1278.2	0.0	0.9	3	1043.9	1267.8	1313.3	1043.9
12	0.6641763	121.6023616	1398.8805	0.4275787	205.686	1398.9	1604.6					0.0	205.7	1	1267.8	1267.8	1313.3	1278.2
13	0.53954	86.42674405	1485.3072	0.0271496	31.34306					1485.3	1516.7	0.0	31.3	3	1278.2	1604.6	1313.3	1278.2
14	0.4907005	75.19222616	1560.4995	0.8870638	455.2583			1560.5	2015.8			0.0	455.3	2	1313.3	1604.6	1313.3	1516.7
15	0.4492876	66.48006903	1626.9795	0.7688438	359.0069					1627.0	1986.0	0.0	359.0	3	1516.7	1604.6	2015.8	1516.7
16	0.28748	37.7730625	1664.7526	0.4709525	221.778	1664.8	1886.5					0.0	221.8	1	1604.6	1604.6	2015.8	1986.0
17	0.4893739	74.9023177	1739.6549	0.8665674	433.934	1886.5	2320.5					146.9	580.8	1	1886.5	1886.5	2015.8	1986.0
18	0.9358249	306.0360797	2045.691	0.439148	209.9424					2045.7	2255.6	0.0	209.9	3	1986.0	2320.5	2015.8	1986.0
19	0.5958638	100.9670674	2146.6581	0.8763176	443.7048			2146.7	2590.4			0.0	443.7	2	2015.8	2320.5	2015.8	2255.6
20	0.3185138	42.73579746	2189.3939	0.1730544	110.8582					2255.6	2366.5	66.2	177.1	3	2255.6	2320.5	2590.4	2255.6
21	0.8079626	183.8870286	2373.2809	0.3552117	179.4091	2373.3	2552.7					0.0	179.4	1	2320.5	2320.5	2590.4	2366.5
22	0.444575	65.53047001	2438.8114	0.0661477	59.34034					2438.8	2498.2	0.0	59.3	3	2366.5	2552.7	2590.4	2366.5
23	0.6080528	104.3799656	2543.1913	0.4342329	208.1313					2543.2	2751.3	0.0	208.1	3	2498.2	2552.7	2590.4	2498.2
24	0.9157125	275.6549537	2818.8463	0.7498606	347.4991	2818.8	3166.3					0.0	347.5	1	2552.7	2552.7	2590.4	2751.3
25	0.6992488	133.8947765	2952.7411	0.0940283	74.83525			2952.7	3027.6			0.0	74.8	2	2590.4	3166.3	2590.4	2751.3

Figure 5. Simulation Ran with 50 Patients, 3 servers, Multiplying the Interarrival times by 20

Number of times ran	Average waiting time	Average Time in System
1	15.7	260
2	7.4	270
3	17.6	330.8
4	0.4	279.8
5	13.8	275.5
6	22.3	298.7
7	11.3	317.6
8	0	279.1
9	1.2	275
10	1.8	247.9
11	5	283.6
12	0	228.9
13	9	257.1
14	5.5	291
15	2.1	245
16	4.4	225.7
17	11.2	236.9
18	3.3	256.3
19	8.6	251.5
20	14.3	276.1
Average	**7.745**	**269.325**

Data Source: Bellevue Hospital

M/M/3 QUEUE SIMULATION FOR Bellevue Hospital
First available teller

	Random Number for arrival	Interarrival time	Clock (Arrival time)	Random Number for service	Service time	Teller 1		Teller 2		Teller 3		Waiting Time	Time in System	Which server				
						TS	TF	TS	TF	TS	TF	Wq	Ws	↓	Min work	Work 1	Work 2	Work 3
1	0.3848813	108.3085318	108.30853	0.5005885	233.0327	108.3	341.3					0.0	233.0	1				
2	0.1384779	33.22194896	141.53048	0.3888527	191.5727			141.5	333.1			0.0	191.6	2	0.0	341.3	0.0	0.0
3	0.7551205	313.5961565	455.12664	0.6587521	299.6788					455.1	754.8	0.0	299.7	3	0.0	341.3	333.1	0.0
4	0.0297293	6.726689398	461.85333	0.1953323	119.8872			461.9	581.7			0.0	119.9	2	333.1	341.3	333.1	754.8
5	0.5322049	169.330939	631.18427	0.4471924	212.916	631.2	844.1					0.0	212.9	1	341.3	341.3	581.7	754.8
6	0.9113055	539.9506452	1171.1349	0.5405597	248.6676			1171.1	1419.8			0.0	248.7	2	581.7	844.1	581.7	754.8
7	0.1647192	40.11639971	1211.2513	0.9511286	555.5256					1211.3	1766.8	0.0	555.5	3	754.8	844.1	1419.8	754.8
8	0.1612715	39.19831852	1250.4496	0.3573687	180.188	1250.4	1430.6					0.0	180.2	1	844.1	844.1	1419.8	1766.8
9	0.1620156	39.39612456	1289.8458	0.6503087	295.7114			1419.8	1715.5			130.0	425.7	2	1419.8	1430.6	1419.8	1766.8
10	0.2690112	69.84245825	1359.6882	0.3708045	185.0415	1430.6	1615.7					70.9	256.0	1	1430.6	1430.6	1715.5	1766.8
11	0.7960848	354.3977905	1714.086	0.1396237	96.56938	1714.1	1810.7					0.0	96.6	1	1615.7	1615.7	1715.5	1766.8
12	0.1986373	49.35590719	1763.4419	0.8201058	394.2052			1763.4	2157.6			0.0	394.2	2	1715.5	1810.7	1715.5	1766.8
13	0.2059998	51.4131183	1814.855	0.5284396	243.8635					1814.9	2058.7	0.0	243.9	3	1766.8	1810.7	2157.6	1766.8
14	0.0058847	1.315480385	1816.1705	0.1513694	101.71	1816.2	1917.9					0.0	101.7	1	1810.7	1810.7	2157.6	2058.7
15	0.988628	997.7655029	2813.936	0.6106189	277.826	2813.9	3091.8					0.0	277.8	1	1917.9	1917.9	2157.6	2058.7
16	0.5948854	201.395225	3015.3312	0.8112512	387.6054					3015.3	3402.9	0.0	387.6	3	2058.7	3091.8	2157.6	2058.7
17	0.5068991	157.5886341	3172.9199	0.3560059	179.6959			3172.9	3352.6			0.0	179.7	2	2157.6	3091.8	2157.6	3402.9
18	0.3287523	88.84557102	3261.7654	0.6971695	318.601	3261.8	3580.4					0.0	318.6	1	3091.8	3091.8	3352.6	3402.9
19	0.1969906	48.89837944	3310.6638	0.472422	222.3304			3352.6	3574.9			42.0	264.3	2	3352.6	3580.4	3352.6	3402.9
20	0.6418514	228.8595084	3539.5233	0.2778483	151.2987					3539.5	3690.8	0.0	151.3	3	3402.9	3580.4	3574.9	3402.9
21	0.1203797	28.58827726	3568.1116	0.6373975	289.7613			3574.9	3864.7			6.8	296.6	2	3574.9	3580.4	3574.9	3690.8
22	0.0609225	14.00991701	3582.1215	0.7262434	334.0531	3582.1	3916.2					0.0	334.1	1	3580.4	3580.4	3864.7	3690.8
23	0.2859917	75.08103437	3657.2026	0.1933059	119.079					3690.8	3809.9	33.6	152.7	3	3690.8	3916.2	3864.7	3690.8
24	0.5295283	168.0592966	3825.2619	0.417839	202.1191					3825.3	4027.4	0.0	202.1	3	3809.9	3916.2	3864.7	3809.9
25	0.4546539	135.1426157	3960.4045	0.2304584	133.5647			3960.4	4094.0			0.0	133.6	2	3864.7	3916.2	3864.7	4027.4

Works Cited

"About NYC Health Hospitals/Bellevue - Facts." *About NYC Health Hospitals/Bellevue - Facts*. Web. 29 Apr. 2016.

"A New Look at Leaving Without Being Seen in EDs." *Physicians Weekly for Medical News Journals Articles*. 2012. Web. 11 Apr. 2016.

Bellevue Hospital Emergency Department Corporate Dashboard November 2013-June 2015. Raw data. Bellevue Hospital, New York City.

Gilman, Kurt, Matthew Pereira, Americo Pietropaolo, Susan Schiffler, and Amit Sharma. Optimizing the Emergency Department Triage Process: Developing an Analytic Approach to Assign Patients to Work Groups in Bellevue Hospital's Emergency Department. 2014. The Capstone Project Team in Partial Fulfillment of the Requirements for the Degree of Master's of Science in Business Analytics.

Johns Hopkins Medicine. *Hospital Patient Loads Often at Unsafe Levels, Physician Survey Says*. *Http://www.hopkinsmedicine.org/*. 28 Jan. 2013. Web.

Melo, Teresa. "A Note on Challenges and Opportunities for Operations Research in Hospital Logistics." *Saarland University of Applied Sciences (htw Saar), Saarland Business School* (2012). Web. <http://econstor.eu/bitstream/10419/98155/1/722231369.pdf>.

"NYC Health and Hospitals' Operating Loss Soars." *Modern Healthcare*. Web. 23 Apr. 2016.

Saghafian, Soroush, Garrett Austin, and Stephen Traub. "Operations Research Contributions to Emergency Department Patient Flow Optimization: Review and Research Prospects." *SSRN Electronic Journal SSRN Journal*. Web.

"Timely and Effective Care." *Timely and Effective Care*. Web. 20 Apr. 2016.