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ANALYSIS OF THE SURGE CAPACITY OF A LOCAL HOSPITAL IN THE FACE OF PANDEMIC THREATS

by

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September 2021

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As technology advances and nature becomes more unpredictable, hospitals need to focus on their response to specific threats and their capacity to handle them efficiently. Many studies have shown that due to underfunding, hospitals lack the basic size required to properly service populations. The purpose of this thesis is to build and analyze a model of a local hospital's emergency room operations under typical and surge conditions in terms of resource demand and utilization. The model will analyze emergency room bed capacity based on day-to-day operations and potential threats that could impact the surrounding area, thus creating a surge in bed capacity. This study shows where local resources may be under capacity and provides ways for them to improve their operations by planning a solid budget. Local community planners must understand the challenges and current limitations for their hospitals to receive assistance from state and federal funding. If planners do not grow their hospitals to coincide with their cities' population growth, they will continue to fail and provide increasingly inadequate care.

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ANALYSIS OF THE SURGE CAPACITY OF A LOCAL HOSPITAL IN THE FACE OF PANDEMIC THREATS

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ABSTRACT

As technology advances, and nature becomes more unpredictable, hospitals need to focus on their response to specific threats and their capacity to handle them efficiently. Many studies have shown that due to underfunding, hospitals lack the basic size required to properly service populations. The purpose of this thesis is to build and analyze a model of a local hospital's emergency room operations under typical and surge conditions in terms of resource demand and utilization. The model will analyze emergency room bed capacity based on day-to-day operations and potential threats that could impact the surrounding area, thus creating a surge in bed capacity. This study shows where local resources may be under capacity and provides ways for them to improve their operations by planning a solid budget. Local community planners must understand the challenges and current limitations for their hospitals to receive assistance from state and federal funding. If planners do not grow their hospitals to coincide with their cities' population growth, they will continue to fail and provide increasingly inadequate care.

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LIST OF ACRONYMS AND ABBREVIATIONS

AHA	American Hospital Association
CDC	Centers for Disease Control and Prevention
CI	Confidence Interval
COVID-19	Coronavirus Disease 2019
ED	Emergency Department
ER	Emergency Room
FIFO	First in First out
H1N1	Hemagglutinin Type 1, and Neuraminidase Type 1
HA	Haemagglutinin
ICU	Intensive Care Unit
NA	Neuraminidase
SARS	Severe Acute Respiratory Syndrome
SIMIO	Simulation Modeling Framework Based on Intelligent Objects
SMORE	Simio Measure of Risk & Error
U.S.	United States
VHI	Virginia Health Information
WHO	World Health Organization

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EXECUTIVE SUMMARY

Historically, hospitals are known to be the first line of defense when a threat occurs. Local hospitals should be built to sustain their local community on a day-to-day basis and during a surge event. Many local hospitals struggle with normal operations, so if or when a surge happens, local hospitals can become overwhelmed with the influx of patients, and bed capacity can quickly diminish.

A model simulation was created modeling Stafford Hospital, a local suburban hospital located in Stafford, Virginia. The purpose of the model design was to incorporate the process of the hospital's Emergency Department (ED) and the age demographics of the surrounding population. The simulation will provide insight on any existing chokepoints the ED may have, analyze if the hospital is keeping pace with the surrounding population and determine if the hospital could handle a surge event.

The entity-based simulation program Simio was used to model the ED flow process. Simio was used to help determine the normal operation and surge rates for Stafford hospital based on the surrounding population. The model was designed for a 30-day snapshot using normal operational data from 2018. The annual data was analyzed and then calculated to a daily rate of 0.06 arrivals/minute. That metric was used to get the number of patient arrivals for a 30-day period. The number of patients that visited within 30 days was then multiplied by the age group demographic percentage to estimate the amount of people that visited per group. The baseline model takes this data into account and adjusts the interarrival rate, the rate that the entities arrive to the hospital, of the four age demographics, 0–24, 25–49, 50–64, and 65+, at varying interarrival times to mimic around 86 people per day. The model also accounts for five triage levels that the entities could randomly have upon arrival. Each age demographic was given probabilities of arriving at each triage level. The cumulative probability for each triage level is calculated with the likelihood of it happening. The outcomes of the triage levels are based on discrete random variables, which fall between zero and one. We calculated the probability density for each outcome by calculating the difference between the levels. Four scenarios were run and analyzed on the model.

Scenario one focused on the analysis of 2018 normal operation data and altering the amount of exam rooms and trauma rooms to see if there was a more efficient combination based on the surrounding population. The original configuration had 13 exam rooms and one trauma room. The simulation only showed a max of seven rooms being used concurrently with six rooms being empty 46% of the time. It also showed the max concurrent usage rate between three to four beds. Additional simulations were run with the combinations of 11 exam rooms and two trauma rooms, nine exam rooms and two trauma rooms, and seven exam rooms and two trauma rooms. These configurations showed that as the exam room number decreased the utilization rate increased, meaning there is less time when the rooms are not in use.

Scenario two focused on the analysis of 2018 normal operation data with changes to age demographic interarrival rates and triage level probabilities based on influenza strain, H1N1, 2009 infection rates. The highest infection rate occurred in the 0–24 age group. The simulation showed the most impact from the model design occurred at triage. The triage utilization rate increased from a mean of 89.7 to 99.4%. This increase occurred because every entity must flow through triage. The average output for trauma increased from 230 to 372, a 62% increase. Admission rates increased by 20% and all stations had a decrease in the amount of idle time.

Scenario three focused on the analysis of 2018 normal operation data with changes to age demographic interarrival rates and triage level probabilities based on influenza strain, H1N1, 1918 infection rates. This virus has a "w-shaped" pattern that significantly impacts three age demographics: individuals younger than five years old, 20–40 years old, and individuals 65 years and older. The simulation showed the most impact from the model design occurred at triage. Triage utilization in the original baseline had a mean of 89.7, the mean for the H1N1, 1918 output increased around 10% to a mean of 98.9. The average output for trauma increased from 230 to 360, a 56.5% increase. Admission rates increased by 18% and all stations had a decrease in the amount of idle time.

Scenario four was like scenario one, except the estimated 2020 population data was supplemented to see if a more efficient combination between exam rooms and trauma rooms exists. This scenario used the estimated 2020 population data to run normal operations and alter the amount of exam rooms and trauma rooms to see if there is a more efficient combination. The 2020 estimated population size of 155,940 people will be run to see how the hospital fares to the local population. The simulation showed with the original configuration of 13 exam rooms and one trauma room, the max concurrent usage rate between three to four beds with the use occasionally going as high as seven. With the increased population the exam rooms' concurrent utilization is still seven or fewer, leaving an additional six rooms unused. The simulation also showed that a decrease in the amount of exam rooms yields higher utilization rates.

The results of the simulations show that the hospital appears to be keeping pace with its population. Based on the 2018 data simulation and the estimated 2020 data simulation, there was no difference in max bed usage. This could be due to the young age of the surrounding population. Over 70% of the citizens in Stafford County are under 50 years of age. The model also showed that for each scenario where the hospital saw a surge, the triage station had the most impact. This is explained because every patient must flow through triage to determine their acuity rating. When there was an influx in patients, the resource easily became overwhelmed. Based on the scenario's analyses, it appears that the hospital has the proper bed capacity to attend to day-to-day needs and the capability to handle short-sustained surges.

The hospital should consider adding an additional triage room. The additional triage room slows down the resource from being in a continuous busy state of max capacity, slightly increased the idle time and allows more patients to flow through the system. This addition could benefit the hospital by leading to more profit and providing more efficient patient care.

As the population ages, the hospital should consider adding an additional trauma room. Currently, with a young population there is not a significant need to add an additional trauma room. The patient flow would not offset the costs and the hospital would lose money due to the rooms being idle. However, as the population ages, new simulations based on the changing age demographics may prove to be a solid investment.

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First and foremost, I would like to thank my advisor, Dr. Roberto Szechtman. When I was finally able to narrow multiple ideas down to one concept, it took several months for me to try to figure out the proper software to use to design the model. Dr. Szechtman agreed to be my advisor and really helped me to stay true to my idea and focus on how to pull it all together. His encouragement to continue with the design and guidance on how to implement my ideas within the model provided the confidence I needed to finish this thesis, and for that, I am truly grateful.

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I. INTRODUCTION

A. BACKGROUND

As technology advances, and nature becomes more unpredictable, hospitals need to focus on their response to specific threats and their capacity to handle them efficiently. Humanity has long contended with epidemics and acts of nature that challenge healthcare operations. In the fourteenth century, bubonic plague quickly spread through multiple countries within Europe, decimating populations. Local hospitals were not able to contain the spread. To combat the disease, organized institutions responded by constructing hospitals known as "lazarettos." To prevent the proliferation of the disease, it was necessary for lazarettos to be located a reasonable distance from the communities but close enough for patients to be quickly and efficiently transferred to them (Tognotti 2013, 254–259). These hospitals helped to contain the spread of the disease by keeping infected individuals away from the rest of the population. In 1918–1919, it is estimated that 50 to 100 million individuals perished because of the H1N1, "Spanish Flu." This deadly pandemic claimed millions of lives, but it also overwhelmed the world's hospital resources (Hobday and Cason 2009, S239–S242). Due to the high incidence rate of infection, hospitals quickly became inundated with patients and had to turn people away. In 2003, the Severe Acute Respiratory Syndrome (SARS) outbreak occurred in more than two dozen countries and was eventually contained. In 2005, Hurricane Katrina destroyed the southern portion of the United States and exposed the deplorable hospital facilities. These historical examples created surge conditions that devastated the hospital systems of their day.

> On September 10, 2001, the cover story of *U.S. News and World Report* described an emergency care system in critical condition as a result of demands far in excess of its capacity. While the article focused on the day-to-day problems of diversion and boarding, the events of the following day brought home a frightening realization to many: If we cannot take care of our emergency patients on a normal day, how will we manage a large-scale disaster? More than 4 years after the terrorist attacks of 2001, Hurricane Katrina revealed how far we have to go in this regard. (Institute of Medicine 2007, 8)

Now we are facing another pandemic with the capability of stalling our healthcare systems. In December 2019, China reported respiratory illness cases with unknown causes. Several deaths started to emerge within China and later spread to other parts of the world. On March 11, 2020, the World Health Organization (WHO) labeled the disease a pandemic known as Coronavirus Disease 2019 (COVID-19). As of May 31, 2021, the latest numbers of confirmed cases worldwide have surpassed over 170,000,000 people, with over 33,000,000 of them in the United States (Johns Hopkins University 2020). Several hospitals, such as those located within New Delhi, India, are reporting they are unable to meet the demand and have run out of beds for patients. Worldwide, healthcare facilities are worried that if the infection number continues to rise, they will not have the capability to treat all patients. The rise of COVID-19 cases around the globe demonstrates the modern-day threat of disease to existing hospital systems. Is enough being done for the hospitals to keep pace? Over the past decade, United States (U.S.) hospital systems have experienced an increase in spending. "The U.S., on a per capita basis, spends much more on health care than other developed countries, due to higher pricing, not better health care" (Johns Hopkins Bloomberg School of Public Health 2019, 1). The U.S. pays substantially more than other developed countries for pharmaceuticals, health services and labor prices. Even though overall spending on health care has increased, medical equipment has a small share within the budget and funding for local hospitals to keep pace with the surrounding population is lagging.

B. OBJECTIVE

The objective of this thesis is to develop a model of a local suburban hospital based on the need(s) to respond to normal operations based on the surrounding population in terms of Emergency Room (ER) bed capacity utilization. The experimental method applies stochastic simulation to collect hospital resource utilization data. The data will consist of input variables such as: number of patient arrivals and departures, number of beds available, population size, and the number of admissions and discharges relating to patient length of stay. Based on this data, the author will create the baseline model to represent the day-to-day needs, meaning no catastrophic events, to operate an ER given a specific population range. The baseline model will then be used to incorporate pandemic data from the novel H1N1 2009 influenza "Swine Flu" strain virus and the H1N1 1918 influenza strain virus. Analysis of the data will determine if the hospital has enough bed capacity to cover normal operations and surge operations for its given population. The results from this research are not intended to address current events, but the model can be used to anticipate normal and surge capabilities for hospital systems in any setting based on the given population size they service.

C. RESEARCH QUESTIONS

Current models incorporate general numbers for hospital bed capacity. If a more accurate model were constructed specifically for a hospital using its local population and broken down by age demographics, would it yield a better model for hospital organizations? When biological pandemics occur many times, specific age groups within the population are impacted. Using this information, how much bed capacity do hospitals require to meet average and surge demands for their local population? How can models of hospital demand be used to inform fiscal planning given a set of assumptions about average and surge conditions for a local population?

D. SCOPE, LIMITATIONS AND ASSUMPTIONS

The scope of this thesis was narrowed down to Stafford Hospital, a local hospital located in Stafford, Virginia. The goal of the model is to obtain specific insights pertinent to the hospital and surrounding population. Many current models base bed capacities on values as 1 bed per 1,000 individuals. That is a broad spectrum that may not fit all hospitals into the model. Depending on the population's age demographics this value could be too high or too low. For example, if the population has 40% age 65+ citizens, they may require more beds than if the population had 40% age 30 citizens. The model proposed by this research focuses on the actual surrounding population and the throughput of the hospital to determine if it is meeting the needs of local citizens on a day-to-day basis and if it could sustain the community during a pandemic threat. Using a model with a narrow scope can yield more accurate spending plans and save money. If a hospital has a lower throughput based on its population, then it may not need to adhere to a model of one bed per 1,000 individuals. A narrow scope will help to focus local planners on what is needed to service their communities and promote better advocation for funding.

Due to the current COVID-19 outbreak, several limitations occurred during this thesis. First, the data used to create this model was taken from 2018–2019. Recently published data was not available at the time of writing, and healthcare professionals were exhausted treating patients and unable to respond to calls or emails. However, a full set of hospital data was available online for the entire year of 2018. Second, a full set of population estimates were available for 2018. Currently, the 2020 census is underway, with results yet to be published.

For the purposes of this thesis, the data collected from public healthcare sites and from the local hospital site was assumed to be accurate and no effort was expended on verifying their accuracy.

E. ORGANIZATION OF STUDY

Chapter I highlights the need for enhancing hospital systems infrastructure. If the capability is barely available to execute day-to-day operations, we cannot expect the outcome to improve during surge conditions. Surge capacity is a random influx of patients based on a specific event. Surge conditions occur during an event caused from natural, man-made or terrorism activities that injure a significant amount of people at once causing the hospital system to operate above its normal capacity. Chapter II describes the methodology behind the model design. This chapter is broken into three phases. Phase one discusses the collection of the population data and hospital data. Phase two emphasizes the importance of the two diseases selected to run scenarios on the model. Phase three discusses the logic used for designing the model within Simio. It details the build of the model's baseline operations under normal conditions. Chapter III discusses four scenarios run on the model and the data outputs. Chapter IV compares the results of the scenarios run on the model and cost impacts. Chapter V concludes with recommendations for further development of the model.

F. LITERATURE REVIEW

This review describes relevant sources of work that contain elements of hospital system surge or modeling discrete events. Hospital system surge has many encompassing elements such as personnel support, equipment support, and building/infrastructure support. Many of the sources reviewed look at different angles of the overarching problem, but the main question remains, how to effectively manage hospital surges. Since September 11, 2001, more focus has been placed on how hospitals should respond to events, how the process should flow, and how the infrastructure needs to be able to meet the demand.

Santiago (2006) conducted a case study on Union County, New Jersey, to determine a proper manpower matrix during surge conditions. This study focused on manpower within healthcare in relation to homeland security strategies. Santiago included several reports from the 9/11 commission reports, Institute of Medicine and other case studies all coming to the same conclusion: that even though health care spending has increased within the U.S., there are still large disparities when it comes to health infrastructure. This case study addressed the deficit in personnel. The results of the study showed how Union County is undermanned and expected to do more with less; the county is currently staffed at 68% of where its workforce should be. The deficit for normal operations also concluded that in the case of an event occurring, the workforce shortage would prove to be a critical downfall in relation to health care. Even though this study examined the personnel aspect of hospital surges, it is relevant because the amount of assigned personnel is usually tied to a bed. The assumption would be if an institution is lacking personnel, it is lacking the proper number of beds to handle a surge effectively.

Another approach to managing hospital surge is reverse triage. Reverse triage is a technique that a hospital can use to look at patients with the least severe injuries first who can be safely discharged. This will then free up more bed capacity for patients with more serious injuries. Dunne (2018) discusses an assessment tool that can assist clinician judgment to determine which patient's care can be downgraded or which patients can receive an early discharge to make room for the hospital surge. Dunne addresses a different method to create additional beds, by freeing them up instead of adding more. Many hospitals do not have the capacity or funding to store extra gear for when an event occurs.

By using the assessment tool, along with medical knowledge, clinicians can make sound decisions on when a patient could be released early with no detriment to their well-being. In Dunne's study, the tool was more accurate at predicting patients who were safe to discharge but fell short in predicting patients unsafe to discharge. However, with an 88% reliability for the prediction tool, with further research this tool could prove to be useful in conjunction with other methods to manage hospital surge. This means that it accurately predicted those patients that were safe to discharge. Another topic Dunne discusses within this paper is funding. He states that hospitals operate on thin budgets with little capacity to handle hospital surge. This is a recurrent theme among the papers reviewed.

A similar thesis by Vranich (2020) models a discrete event simulation concept. Vranich wrote a thesis based on modeling the training pipeline of Surface Warfare Officers to measure the overall friction (amount of wait time throughout the training process) that may occur prior to fleet assignment. One of the programs used to create the model was an entity-based simulation program called Simulation Modeling Framework Based on Intelligent Objects (Simio). Simio is a modeling program that is easy to use and provides multiple functions such as: ability to import spreadsheets, perform sensitivity analysis, run experiments off a baseline and can create tally statistics. Using Simio, Vranich was able to create a model, input model logic, run 50 experiments off the model, conduct sensitivity analysis and provide meaningful data to assist with his conclusion. This review was important because this thesis will use modeling logic like Vranich's model.

II. METHODOLOGY

The focus of this thesis is to build and analyze a model of a local hospital's operations under normal and surge conditions in terms of bed capacity and utilization to determine if there is an imbalance between demand and capacity. This chapter comprises three phases used to develop the model of this thesis.

Phase one discusses the collection of the population data and hospital data. The experimental method applied stochastic simulation to hospital resource data. The data consisted of input variables such as: number of patient arrivals and departures, number of beds available, population size and age demographics, and the number of admissions and discharges and wait times throughout the process.

Phase two considers the importance of the two diseases selected to run scenarios on the model. Each disease selected targets a different age demographic within a population. This is important because most biological epidemics or pandemics target a specific age range. If a model is built where that information can be an input, it will yield better planning results for the hospital.

Phase three discusses the logic used for designing the model within Simio. Simio is a tool capable of entity-based simulation, was used to help determine the normal operation and surge rates for a hospital of a given size based on the specific event scenario and expose the gaps that exist within the hospital operational process to meet both normal and surge demands. A baseline model was created to represent the day-to-day needs, meaning no catastrophic events, to operate a hospital given a specific population range. After collecting available public data about typical utilization of resources, the model was run to verify the logic and validate its completeness for a given set of assumptions. The baseline model established a normal operational tempo. With the baseline model enacted, threat simulations were implemented on the model. The model exposed if bed capacity for any given scenario did not meet the population demand, and where additional funding could be used to fill the gaps.

A. POPULATION, AGE DEMOGRAPHICS AND HOSPITAL DATA

The model will create a narrow focus of the hospitals servicing population for more efficient planning purposes. Currently, many models focus on broad numbers to accommodate all types and sizes of hospitals. Many models researched compares U.S. hospitals and those around the world based on one bed for every 1,000 people. A more refined hospital model that could determine the number of beds needed for specific situations within a given population would yield more feasible and reliable results. In a 2007 Institute of Medicine report, it was stated that "between 1993 and 2003, the population of the United States grew by 12%, hospital admissions increased by 13%…during this same period, the United States experienced a net loss of 703 hospitals, 198,000 hospital beds, and 425 hospital EDs, mainly in response to cost-cutting measures and lower reimbursements by managed care, Medicare, and other payers. By 2001, 60% of hospitals were operating at or over capacity" (Institute of Medicine 2007, 19).

For the purposes of this thesis, the model was built based on information collected for Stafford Hospital, located in Stafford Virginia. Stafford, Virginia is a county within the Commonwealth of Virginia. It was mostly rural until the Interstate 95 was built in the late 1960s. Since then, Stafford County has experienced a population boom that is continuing. Stafford's rapid growth has earned the county recognition as part of the Northern Virginia region. Schmidt (2019) states, "it is one of the fastest growing, and highest-income counties in America ranking in the top 20" (Schmidt 2019). In 2010, the census data reported Stafford county's population at 128,961 people; the estimated number for 2019 is 152,882 (U.S. Census Bureau n.d.), an 18.5% increase in local citizens. A census was conducted in 2020 and the official results have yet to be published; however, it is estimated that Stafford County grew another 2%, as shown in Figure 1.

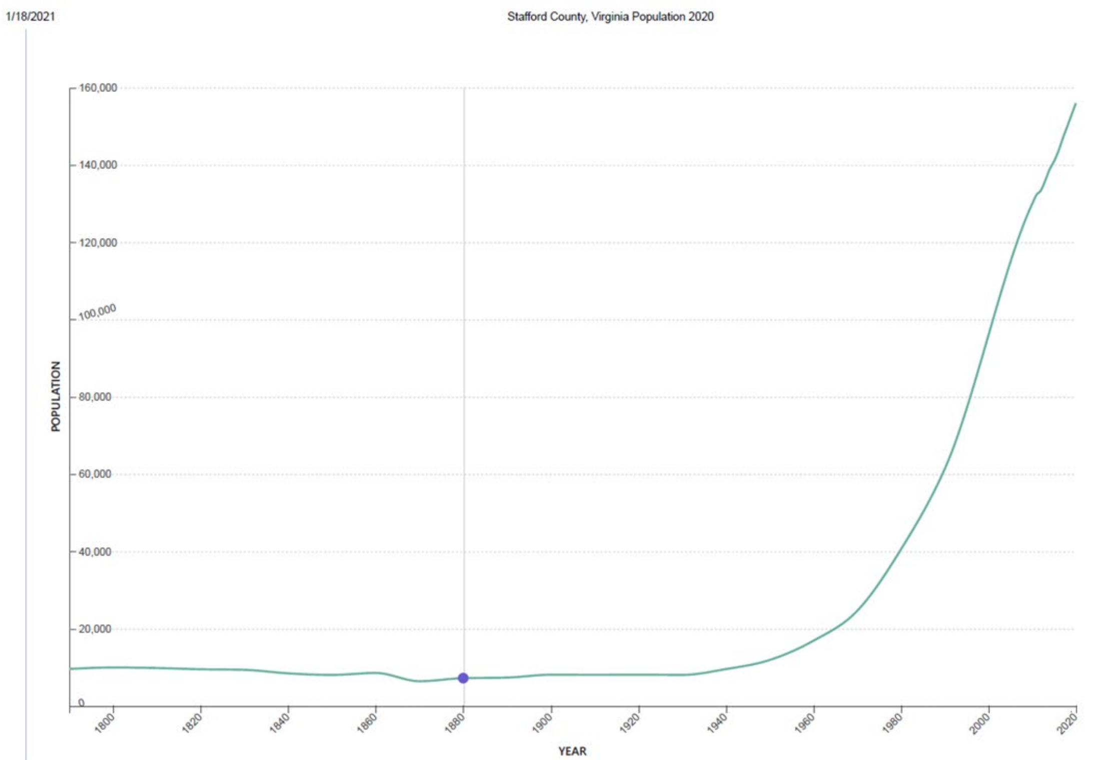
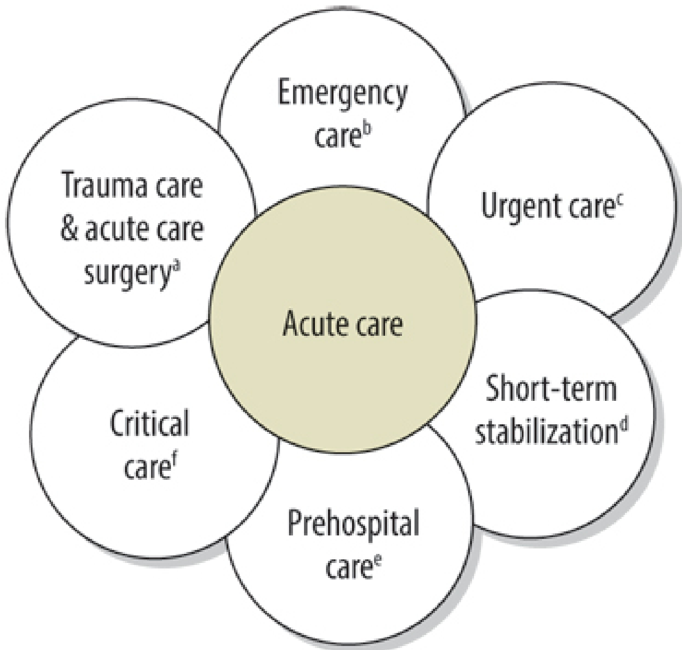


Figure 1. Stafford County population growth. Source: World Population Review (2020).

With this increase and the expected increases for years to come, it is questionable whether the hospital infrastructure has kept up with the current population.

Currently Stafford Hospital services three surrounding zip codes and is part of the Mary Washington Healthcare, not-for-profit healthcare system. The American Hospital Association (AHA) defines a system as: "a multihospital or a diversified single hospital system. A multihospital system is two or more hospitals owned, leased, sponsored, or contract managed by a central organization" (American Hospital Association 2019). Even though Stafford Hospital is part of a system, the data used to build the model was solely based on the hospital and not the system. Stafford Hospital is a short-term acute care local hospital. Acute care is defined as, "an inpatient medical facility providing therapy for severe illness or injury; average length of stay of 30 days or fewer" (Medical Dictionary for the Health Professions and Nursing 2012). Hirshon and team define acute care as, care that comprises emergency medicine, trauma care, pre-hospital emergency care, acute care surgery, critical care, urgent care, and short-term inpatient stabilization (Hirshon et al. 2013, 386–388), as shown in Figure 2.



a Treatment of individuals with acute surgical needs, such as life-threatening injuries, acute appendicitis, or strangulated hernias.

b Treatment of individuals with acute life- or limb-threatening medical and potentially surgical needs, such as acute myocardial infarctions or acute cerebrovascular accidents, or evaluation of patients with abdominal pain.

c Ambulatory care in a facility delivering medical care outside a hospital emergency department, usually on an unscheduled, walk-in basis. Examples include evaluation of an injured ankle or fever in a child.

d Treatment of individuals with acute needs before delivery of definitive treatment. Examples include administering intravenous fluids to a critically injured patient before transfer to an operating room.

e Care provided in the community until the patient arrives at a formal health-care facility capable of giving definitive care. Examples include delivery of care by ambulance personnel or evaluation of acute health problems by local health-care providers.

f The specialized care of patients whose conditions are life-threatening and who require comprehensive care and constant monitoring, usually in intensive care units. Examples are patients with severe respiratory problems requiring endotracheal intubation and patients with seizures caused by cerebral malaria.

Figure 2. Domains in acute care. Source: Hirshon et al. (2013).

Stafford Hospital is a 100-bed community hospital that offers a multitude of services to include: Emergency Services, Imaging Services, Heart Health, Laboratory Services, Orthopedics, and Surgical Services. It consists of an Emergency Department (ED) that houses 14 beds, Intensive Care Unit (ICU) rooms, Labor and Delivery rooms, Cardiac Care rooms and general surgical inpatient and outpatient rooms (Mary Washington Healthcare n.d.).

In 2018, the population of Stafford County was estimated to be 149,960 (U.S. Census Bureau n.d.). An age demographics table was modified to fit the age ranges for the model. Figure 3 shows the results from the derived data.

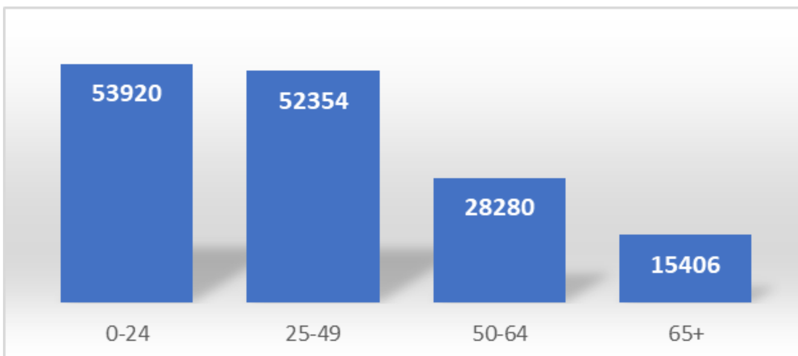


Figure 3. Stafford County age demographics Adapted from U.S. Census Bureau (n.d.).

Figure 3 shows that 36% of the population falls between ages 0 and 24, 35% falls between 25 and 49, 19% falls between 50 and 64 and only 10% falls within the 65+ range. This breakdown helps show that Stafford, Virginia is a young county, with over 70% of its citizens under 50 years of age. This data will be important when looking at different scenarios using the model.

Studies have shown when events occur within a population it usually targets an age range, excluding terrorist attacks and other attacks that target the general population. The 2009 novel H1N1 flu outbreak targeted a younger population. Figure 4 shows how the disease was mostly confirmed in the 0–24-year-old age demographic; this age demographic also resulted with higher mortality rates.

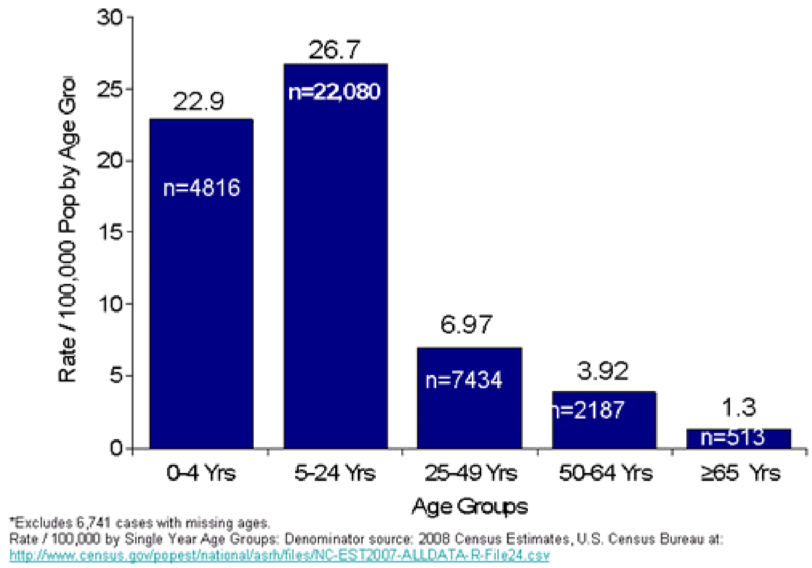
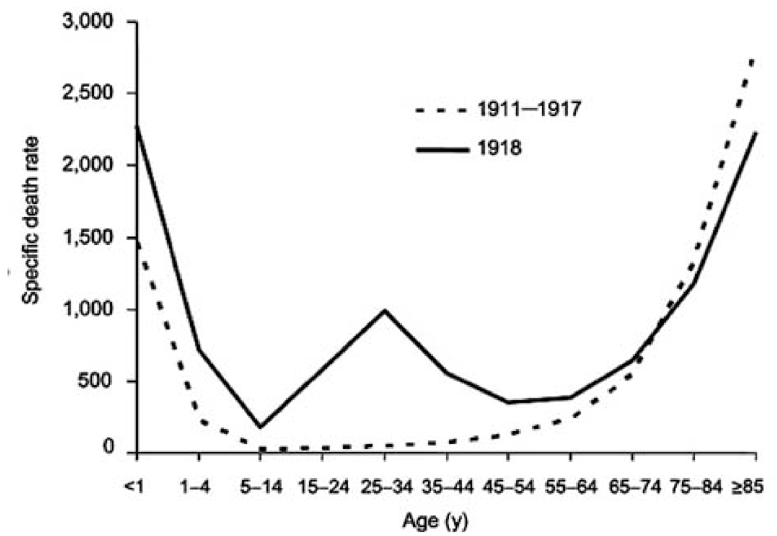


Figure 4. Novel H1N1 confirmed and probable case rate in the United States, by age group. Source: Centers for Disease Control and Prevention (2009).

The data collected on Stafford County would make H1N1 highly susceptible to 36% of its population. Looking at the 1918 influenza pandemic, it shows distinct age demographics that were targeted. To date the 1918 strain has been the only strain to show a "W-shaped" curve, instead of the common "U-shaped" curve (Taubenberger and Morens 2006, 15–22). Figure 5 shows how this strain of virus significantly impacted three age demographics: individuals younger than five years old, 20–40 years old, and individuals 65 years and older.



"U-" and "W-" shaped combined influenza and pneumonia mortality, by age at death, per 100,000 persons in each age group, United States, 1911–1918. Influenza- and pneumonias specific death rates are plotted for the interpandemic years 1911–1917 (dashed line) and for the pandemic year 1918 (solid line).

Figure 5. "U-" and "W-" shaped combined influenza. Source: Taubenberger and Morens (2006).

Applying this curve to the Stafford county population would roughly make 44% of the population more susceptible to this deadly virus.

These two events, in addition to the current event of COVID-19, does show that age demographics plays a role in viral infections. "According to data from the Centers for Disease Control and Prevention, COVID-19 is deadliest among older populations. In fact, through February 17, 2021, 93% of COVID-19 deaths nationwide have occurred among those ages 55 or older. Only 0.2% were younger than 25. This trend can also be found on state level statistics" (The Heritage Foundation 2021, 1). To date, the age demographic most impacted by COVID-19 is 55 years and older, shown in Figure 6. However, testing and retrieval of death certificates is a slow-moving process that may show different trends within other age groups in the future.

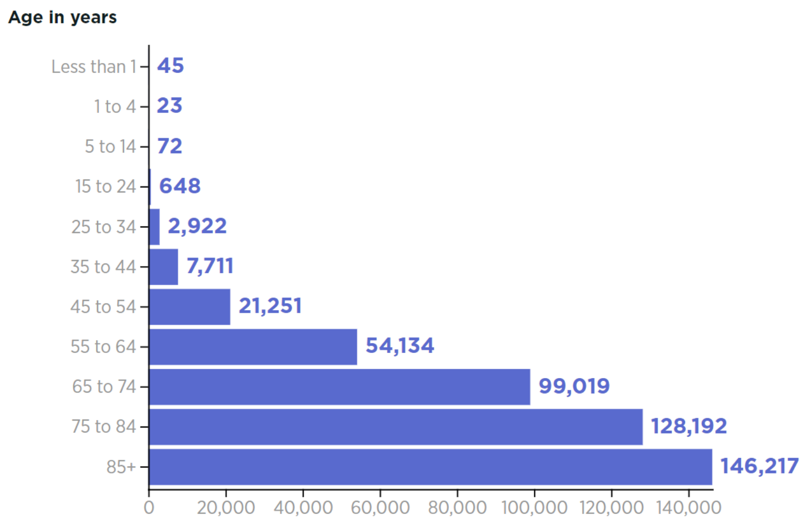


Figure 6. USA COVID-19 deaths by age as of February 2021. Source: The Heritage Foundation (2021).

B. WHY INFLUENZA

Influenza A is an ideal virus to use in the model because it is constantly changing and can become a pandemic. Many believe that some form of influenza will be the cause of the next world pandemic on the scale of the 1918 influenza outbreak. If or when this happens the new methods of transportation would cause the devastation to be much greater than the 1918 outbreak.

> Virtually every expert on influenza believes another pandemic is nearly inevitable, that it will kill millions of people, and that it could kill tens of millions—and a virus like 1918, or H5N1, might kill a hundred million or more—and that it could cause economic and social disruption on a massive scale. This disruption itself could kill as well. (Institute of Medicine 2005, 68)

Of the four types of influenza viruses, the A type is the only one that can cause a pandemic. Center for Disease Control and Prevention states, "a pandemic can occur when a new and very different influenza A virus emerges that both infects people and has the ability to spread efficiently between people" (Center for Disease Control and Prevention 2019). Influenza can change based on antigenic drift and antigenic shift shown in Figure 7.

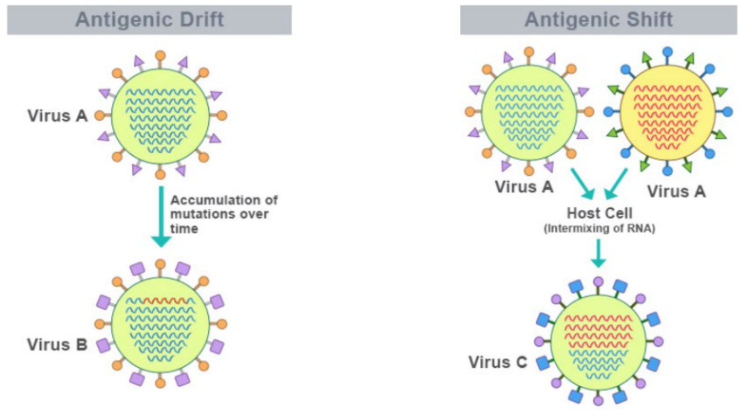


Figure 7. Antigenic drift vs. antigenic shift. Source: Teich (2017).

Antigenic drift is several minor mutations over time within genes that can lead to a change in surface proteins. The HA and NA surface proteins are antigens that the immune system acknowledges. Even with minor mutations, the virus is still closely related and can provide some immunity. An example of antigenic drift occurs during flu season, when it is possible to catch the flu twice. A host can catch flu strain A and later catch flu strain B. Due to both strains being similar, antibodies created to protect against strain A could also provide some protection against strain B. Antigenic shift is a sudden and unforeseen change in an influenza A virus, resulting in completely different surface proteins. These proteins can create a new subtype that could easily infect humans because no one will have immunity against it. Fortunately, shifts do not happen as often as drifts. Antigenic shift is what created the novel 2009 H1N1 strain shown in Figure 8. Pigs are important because they are mixing vessels capable of carrying both avian and human strains of influenza. However, there has also been some occasions of direct avian to human re-assortment within humans, such as the Avian influenza H5N1 from Hong Kong.

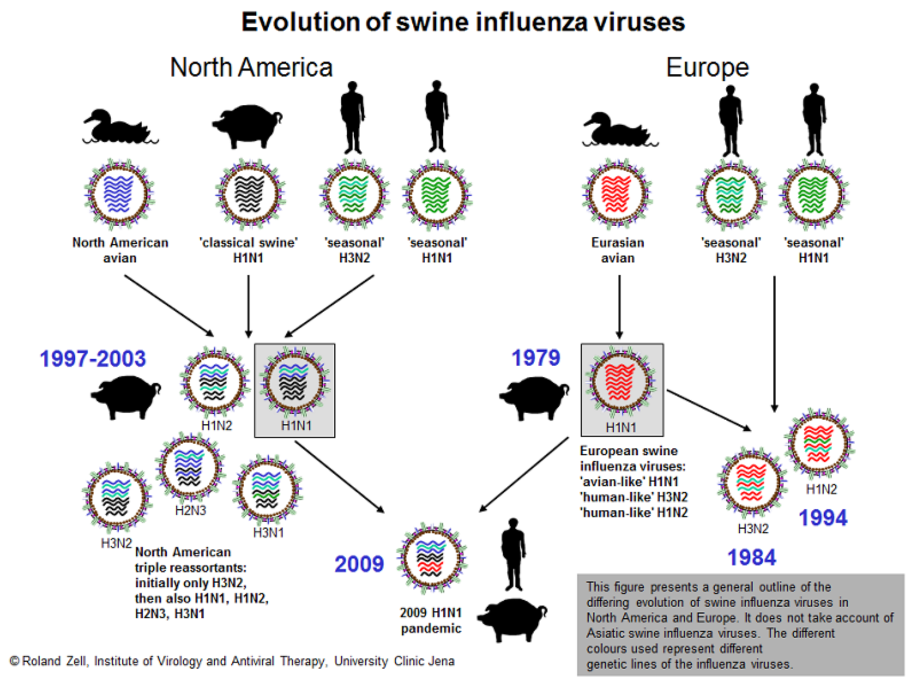


Figure 8. Evolution of swine influenza viruses. Source: IDT Biologika (n.d.).

C. MODEL DESIGN

With the data organized, we entered phase three, designing the model. The baseline model for this thesis was created within Simio. Simio is a tool capable of entity-based simulation used to help determine the normal operation and surge rates for Stafford hospital based on the surrounding population, using specific event scenarios to expose the gaps that exist within the hospital's operational process to meet normal and surge demands.

A flow process chart was created within PowerPoint to reflect the flow of patient movement within the Emergency Department (ED). Figure 9 shows the steps that the model will need to capture.

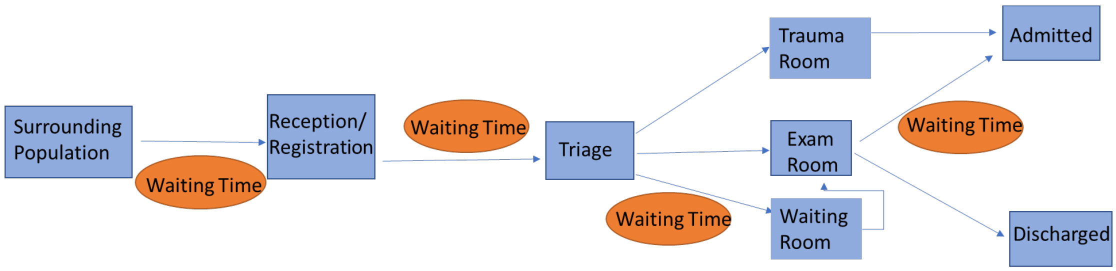


Figure 9. Emergency Department flow process

The flow chart was then created within Simio. The Simio model depicts the surrounding population being broken down into four age demographics, shown in Figure 10.

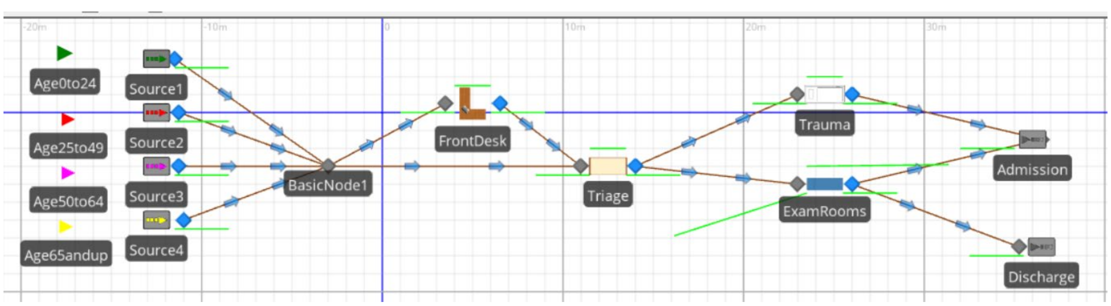


Figure 10. Simio base model design

There are basic elements used to create models within Simio based on what the model needs to capture. Model entities were used for the age demographics because the patients are the objects that will move through the system. Sources were then paired with the entities. Sources generate specific entities and determine arrival patterns. Next, the entities travel to a basic node which is a fixed object input used as an intersection to help entities transfer in or out of an object. From the basic node the entities can travel to the front desk, triage, trauma, or exam rooms, which are modeled as servers. A server model is used to signify a capacity constrained process. Last, the model entities will either go to admission or discharge, which are modeled as sinks. A sink object destroys entities that have completed the process. The sink serves two purposes: to collect data from departing entities and to release memory.

Figure 10 shows the four sources (age demographics) used to populate the model. We used data from 2018 to calculate the interarrival rate for each age demographic. This year of data was used due to completeness and best for a baseline model with no effects of the COVID-19 pandemic. The 2018 data showed the Stafford, Virginia, population to be 149,960. During that year, the ED received a total of 31,492 patients, which is 21% of the general population. The data showed that 4,724 (15%) patients were admitted to the hospital that year, which means 26,768 (85%) were discharged. These numbers were important for determining the interarrival rate for each age demographic. The total patient arrival number 31,492 was divided by 525,600 minutes in a year to determine that the arrival rate is 0.06 arrivals/minute. The model was built on a 30-day snapshot of time. The arrival rate of 0.06 arrivals/minute was multiplied by 43,200 minutes, the number of minutes in 30 days, to determine that 2,592 patients visited the ED within 30 days. The number of patients that visited within 30 days was then multiplied by the age group demographic percentage to estimate the amount of people that visited per group. The baseline model takes this data into account and adjusts the interarrival rate of the four age demographics, 0–24, 25–49, 50–64, and 65+ at varying interarrival times to mimic around 86 people per day. Since Stafford, Virginia is a younger county, the interarrival times for age demographics 0–24 and 25–49 was lower because they account for over half of the population. Figure 11 shows how the interarrival times were set within Simio.

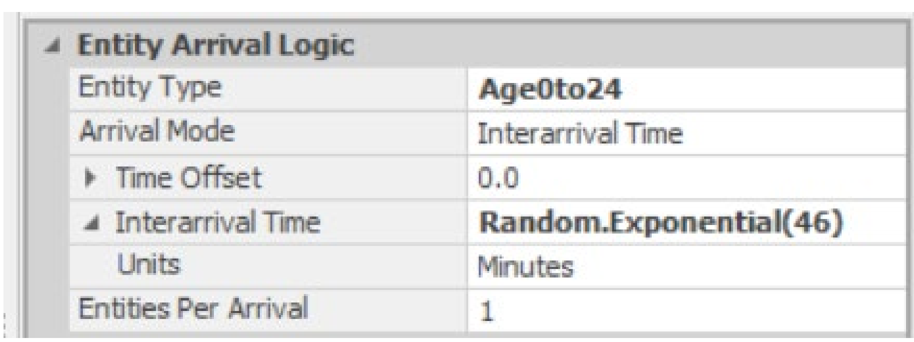


Figure 11. Interarrival time

We chose the interarrival times distribution to be exponential so that the arrival process is a Poisson process. Poisson processes are commonly employed to model customer arrival data. Age demographics 0–24 has an interarrival time of a random exponential of (46); this means on average one person from this demographic will arrive at the hospital every 46 minutes. This interarrival time was calculated by knowing the amount of people that visited per age demographic. We then used a process in which we took 1,440 minutes, the number of minutes within a day and divided that number by the minutes it would take to yield the average amount of people visited within a day for the age demographic selected. We verified the number by multiplying it by 30, to ensure the product was close to the amount for that age demographic for the 30-day period. We applied this method to each age demographic with the results shown in Table 1.

Table 1. Interarrival time exponential values

Age Demographic (years)	Interarrival time exponential values (minutes)
0-24	46
25-49	48
50-65	88
65+	167

Age demographic 25–49 has an interarrival time of a random exponential of (48), age demographic 50–64 has an interarrival time of a random exponential of (88), and age demographic 65+ has an interarrival time of a random exponential of (167). When setting up the interarrival rates two assumptions were made. First, that the total amount of patients per 30 days was broken down based on the percentage within the population. Second, the model only accounts for surrounding population and excludes travelers in and out of the area.

Next, the flow model showed all age demographics flowing into a basic node that leads to the front desk or directly to triage. With the rate of arrival determined we now must adjust the model to account for critical patients. Whether the arrival was a walk-in or via an ambulance was irrelevant for this model because all patients must pass through triage. There is a general misnomer that ambulance arrivals are seen first; however, with a triage system in place, all patients must flow through triage first, resulting in cases where ambulance patients must wait if they are not at a critical triage level. "The purpose of triage in the ED is to prioritize incoming patients and to identify those who cannot wait to be seen. The triage nurse performs a brief, focused assessment and assigns the patient a triage acuity level, which is a proxy measure of how long an individual patient can safely wait for a medical screening examination and treatment" (Key Medical Resources n.d., 3). Stafford Hospital's ED is based on the level of patient acuity without regard to wait times. Patient acuity is the level of care that a patient may require based on the manpower required of the hospital staff to address the patient's needs. Figure 12 shows an example of a chart with triage levels up to five. Many ED's operate with some variation of a triage scale, as of now there is no national standardization among the scales.

Level I	Resuscitation	see patient immediately
Level II	Emergency	within 15 minutes
Level III	Urgency	within 30 minutes
Level IV	Less Urgency	within 60 minutes
Level V	Non Urgency	within 120 minutes

Figure 12. Example triage scale

Triage levels were introduced into the model to meet this requirement. For the purposes of this thesis the model incorporates a five-level scale into the design as shown in Table 2.

Table 2. Triage level probabilities based on age demographics

	Level 1	Level 2	Level 3	Level 4	Level 5
0-24					
X	1	2	3	4	5
P	0.1	0.2	0.35	0.55	1
%	10	10	15	20	45
25-49					
X	1	2	3	4	5
P	0.05	0.15	0.4	0.7	1
%	5	10	25	30	30
50-64					
X	1	2	3	4	5
P	0.08	0.28	0.48	0.78	1
%	8	20	20	30	22
65+					
X	1	2	3	4	5
P	0.2	0.45	0.7	0.9	1
%	20	25	25	20	10

Based on the scale each age demographic was given probabilities of arriving at each triage level. The probability for each triage level is calculated with the likelihood of it happening. For age demographic 0–24, there is a 10% or 0.1 probability that someone will show up as a level one. The outcomes of the triage levels are based on discrete random variables, which fall between zero and one. We calculated the probability density for each outcome by calculating the difference between the levels. The P value shown in the table is the cumulative probability that any of the triage levels will happen. The sum of all the probabilities equal one or 100%.

Levels one and two on the triage scale skips to the head of the line; this is known as a priority queue. The model was designed to recognize levels one and two as severe and when those patients randomly entered, they were moved immediately to triage, bypassing the front desk, while levels three–five had to go through the process. Within Simio, determining where the patient's movement will be from the node to the next destination is accomplished by setting an Outbound Link Rule to use link weights, shown in Figure 13.

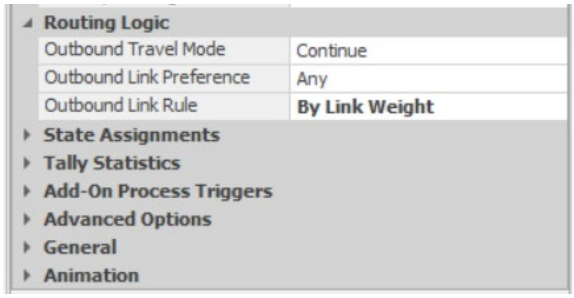


Figure 13. Link weight

Link weights can be customized according to the model design and capture the relative probability of each link. For this thesis, the link weights were customized based on priority triage levels one–five. This weighting system is used for front desk or triage decisions and for trauma room or exam room decisions. A weighting system based on percentage is used from the exam rooms to either admission (15%) or discharge (85%) based on the research data.

The ranking for the model was First-In, First-Out (FIFO) and the bed capacity was based on the number of beds within the ED, for Stafford Hospital that is one trauma room and 13 exam rooms. The model was designed to send level one patients after triage straight to the trauma room. Levels two–five go directly to an exam room based on patient acuity and a FIFO ranking. In the case when the trauma room was occupied all other trauma patients, triage level one, are routed to another facility and levels two–five are placed in a waiting queue and route through the exam rooms according to triage level priority. This is accomplished by changing the Dynamic Selection Rule to smallest value first, shown in Figure 14.

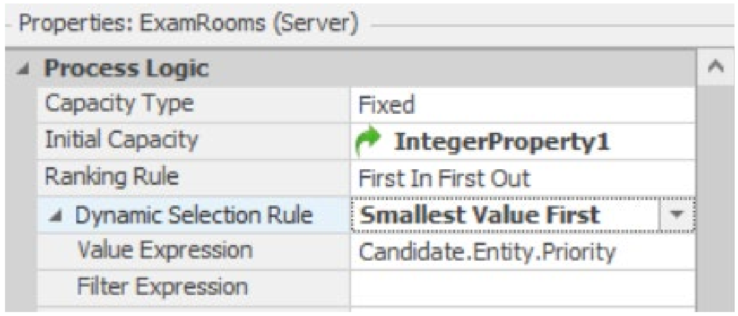


Figure 14. Dynamic selection rule

The Dynamic Selection Rule indicates how a resource is to proceed once it becomes available. Setting the value expression to operate against the triage priority level will make the model allow the most critical patients to enter the exam rooms first. The final step of the model automatically admits trauma room patients to the hospital and some exam room patients are admitted to a max of 15%. The remaining patients (85%) are sent through discharge.

With the general mechanics incorporated within the model, we further defined the model by adding in additional processes. The first add-on process was for exam rooms. The model needed to capture the percentage of occurrence when a patient gets in the line to wait but ends up leaving if the wait is too long. To capture this a reneging trigger was added to the model. The wait time was set to 300 minutes or five hours and the probability of occurrence was set to 1%. Adding this process meant that the model would capture the 1% of patients that chose not to wait more than five hours to be seen. The second add-on process was for the trauma room. The model needed to account for the level one patients that may show up as walk-ins and needed to be redirected due to the room being occupied. It will not consider level one arrivals by ambulance because they would be diverted prior to arrival. To capture this process a balking (abandonment) trigger was added to the model with a decision type to block. A balking decision is used by an entity to decide rather to balk at entering a buffer. Making the decision type blocked means that the entity would abandon the line if the buffer were full. Adding this process meant that the model would capture the number of patients that left because the trauma room was full.

Last, the model is designed to capture the total wait time for two intervals. The first interval is the wait time from the front desk to admission. This wait time is expected to be longer because it is calculating the usage times for the exam rooms and the trauma room. The second interval is the wait time from the front desk to discharge. This wait time is expected to be shorter because it does not incorporate the trauma room. These calculated wait times help to determine the efficiency of the ED. The wait times are captured within Simio by setting expressions and tally statistics. The model captures the time that the entities enter the front desk. Once the entities flow through the model and upon exiting the model the entity is captured as a tally statistic. Figure 15 shows how the calculation is setup within Simio. When the entity enters at the front desk the time is captured. To determine the difference between the arrival and departure you must subtract the TimeNow, that the entity arrives from when the entity departs. This calculation was setup at the input node for admission and the input node for discharge.

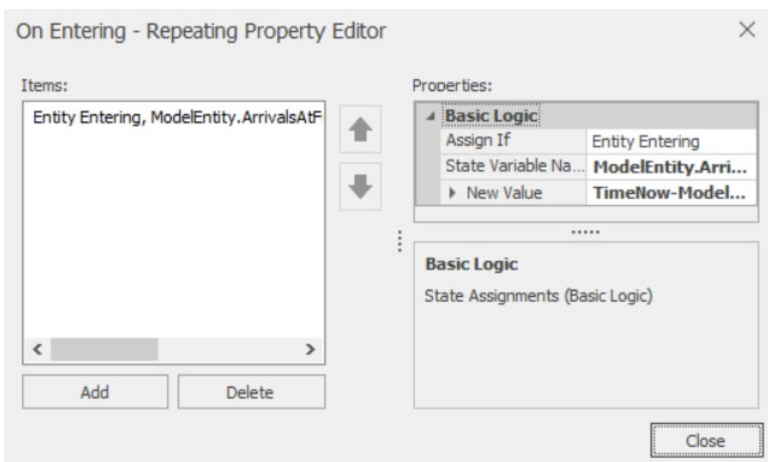


Figure 15. Wait time setup

The model design outlined within this section was meant to simulate a basic 30-day period within the ED department of Stafford Hospital. All data inputs were based on 2018 data collected. Chapter III presents the analysis of the model and the analysis of the different scenarios run on the model.

D. VALIDATION/VERIFICATION METHOD

Verification of the model was done by running a simplified version of the model at each interval and several iterations once all the pieces were in place to ensure the model returned the expected results. Once the model produced the output expected, it was then populated with the derived data to see if the output would match the real-world data collected.

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III. DATA ANALYSIS

This chapter discusses how the number of replications was determined for the scenarios on the model and how to interpret a SMORE plot. The focus of this chapter is the analysis output for each scenario.

Scenario one focuses on the analysis of normal operation data and altering the amount of exam rooms and trauma rooms to see if there is a more efficient combination based on the surrounding population.

Scenario two focuses on the analysis of normal operation data with changes to age demographic interarrival rates and triage level probabilities based on influenza strain, H1N1, 2009.

Scenario three focuses on the analysis of normal operation data with changes to age demographic interarrival rates and triage level probabilities based on influenza strain, H1N1, 1918.

Scenario four is like scenario one, except the estimated 2020 population data is supplemented to see if a more efficient combination between exam rooms and trauma rooms exists.

A. REPLICATIONS

With the normal operation data implemented within the model, the next issue is how to determine the right number of replications to perform for the data sets. Using experiments within Simio the normal operation data was run with 10, 30 and 50 replications to see which amount provides the most statistical value. The larger the number of replications the smaller the resulting confidence intervals, which narrows at rate one over the square root of the number of replications. Hence, increasing replications becomes increasingly less efficient in relation to the computational cost. This issue is important when running simulation experiments over several parameter configurations. The model is comparing the sample mean of the data, so more replications will decrease the margin of error, but at some point, the return will be minimal.

B. DATA VISUALIZATION

Simio includes SMORE plots for analysis of data. A SMORE plot provides a lot of data for analysis and comparison between scenarios. Figure 16 shows an example SMORE plot.

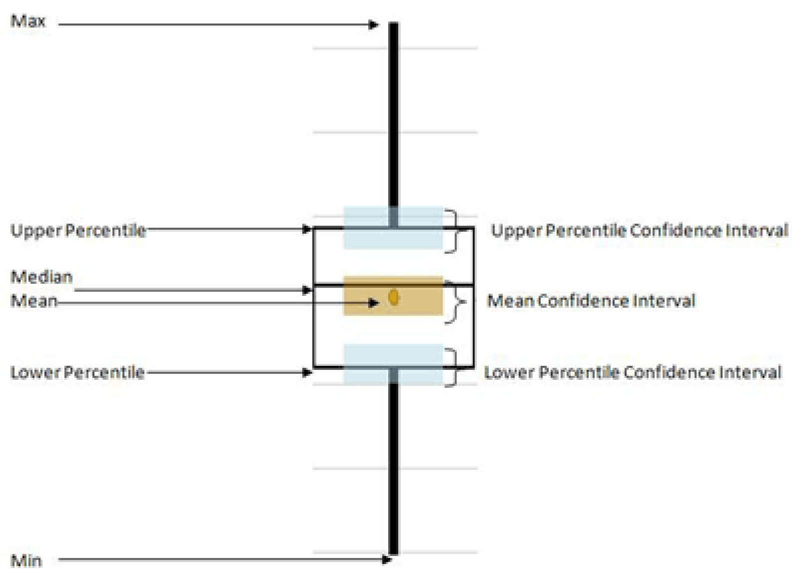

Figure 16. SMORE plot. Source: Simio (2020).

A SMORE plot provides the range of the sample size, mean and median of sample data, upper and lower CI intervals and the mean CI interval. A Confidence Interval (CI) is the probability that a sample size parameter will fall between a set of numbers. CI's measure the degree of certainty or uncertainty for a sampling method. For this thesis, the CI is 95% and n – 1 degrees of freedom. The n is the number of replications for the results, n = 50.

C. SCENARIO ONE

The first scenario is using the normal operation data and altering the amount of exam rooms and trauma rooms to see if there is a more efficient combination based on the surrounding population. The current configuration has 13 exam rooms and one trauma room. With the current configuration the max number of exam rooms used at once is seven, meaning six rooms are left unused. Figure 17 shows a plot of exam room utilization within a 30-day timeframe.

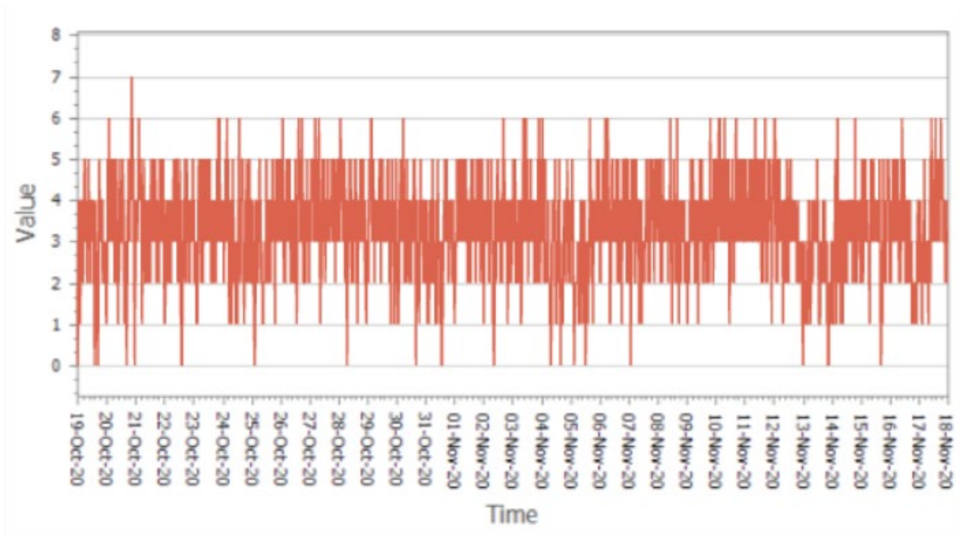

Figure 17. Exam room utilization

Within the 30-day timeframe there is only one spike at seven rooms being used. This means the six additional rooms remain empty 46% of the time. Figure 17 also shows that the most concurrent room usage occurs between three to four beds, due to the thickness of the line on the plot, which is a 23–31% usage rate. This is the normal input of the hospital based on its surrounding population. We ran an experiment where the exam room number was decreased, and the trauma room number was increased. Figure 18 shows the results of the exam room utilization rates.

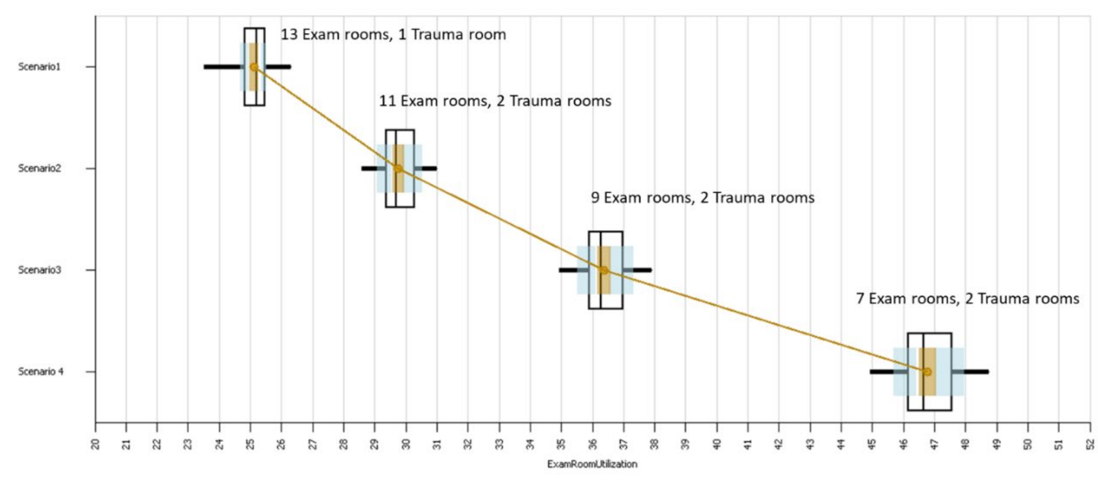

Figure 18. Exam room utilization results

Figure 18 shows that as we decrease the amount of exam rooms, the utilization rate increases. This means there is less time when the rooms are not in use. A reduction of six rooms gets the exam room utilization rate almost to 50%. These results can also be shown in Table 3.

Table 3. Exam room utilization. Adapted from Simio (2021).

Scenario	Configuration	Average Utilization (%)
Scenario 1	13 Exam Rooms 1 Trauma Room	25.1
Scenario 2	11 Exam Rooms 2 Trauma Room	29.8
Scenario 3	9 Exam Rooms 2 Trauma Room	36.4
Scenario 4	7 Exam Rooms 2 Trauma Room	46.8

Table 3 shows the average, minimum and maximum utilization for each exam room configuration. Between scenario one and scenario four there is an 86.3% increase in room utilization.

D. SCENARIO TWO

The second scenario uses the normal operational data with a few changes. The first change is that the interarrival rates for each age group changes. This change occurs because from looking at the pattern of H1N1, 2009 infection rates, the data shows that the highest infection rate occurred in the 0–24 age group. Baseline numbers were recalculated to include the increases. These results can be seen in Table 4.

Table 4. H1N1, 2009 interarrival rates

Age Group	Baseline Rates	H1N1, 2009 Rates	Percentage Increase	Old Interarrival Rate (mins)	New Interarrival Rate (mins)
0-24	933	1166	25%	46	36
25-49	907	971	7%	48	44
50-64	494	514	4%	88	84
65+	260	263	1%	167	164

Table 4 shows the baseline rates used for a normal operational day. If an outbreak of H1N1, 2009 were to occur, it shows the percentage increase per age group and how that increase will impact the interarrival rates. A higher infection rate means an increase in ED visits. The second change that occurred within the data was to update the triage level probabilities to account for the outbreak. Table 5 shows the triage levels used for this scenario.

Table 5. H1N1, 2009 triage level probabilities

	Level 1	Level 2	Level 3	Level 4	Level 5
0-24					
X	1	2	3	4	5
P	0.2	0.45	0.7	0.9	1
%	20	25	25	20	10
25-49					
X	1	2	3	4	5
P	0.05	0.15	0.5	0.8	1
%	5	10	35	30	20
50-64					
X	1	2	3	4	5
P	0.08	0.28	0.58	0.88	1
%	8	20	30	30	12
65+					
X	1	2	3	4	5
P	0.2	0.45	0.72	0.92	1
%	20	25	27	20	8

Table 5 shows that the 0–24 age demographic probabilities increased the most compared to the other age demographics. This increase is to simulate that this age group will have a higher probability to treat compared to the other age groups. The model was then run with these changes incorporated. Figure 19 shows a significant increase in the triage station.

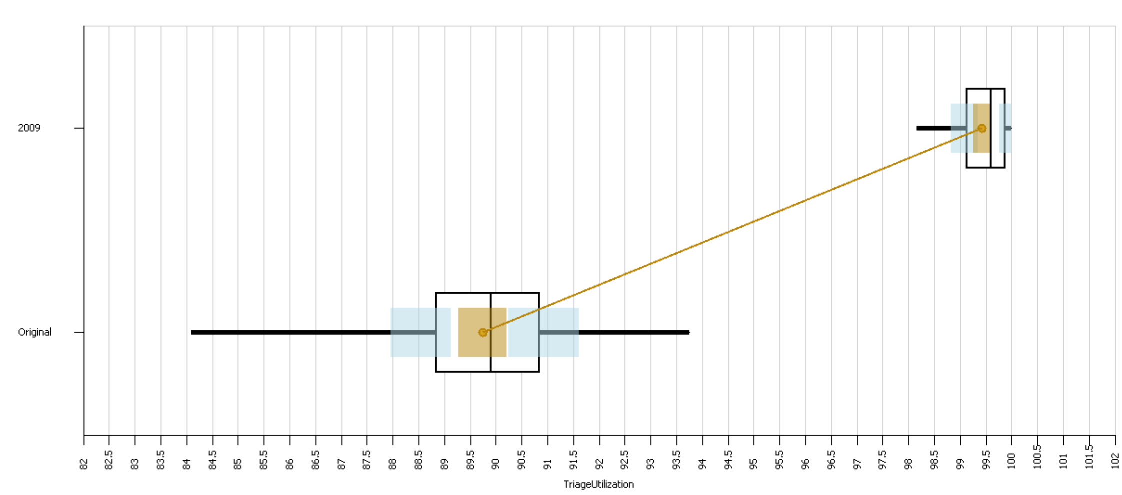

Figure 19. H1N1, 2009 triage utilization

The triage station is the one station that every patient must flow through prior to leaving the model. The utilization rate increased from a mean of 89.7 to 99.4%. There was also a noticeable increase with the trauma output. Figure 20 shows the trauma output increase based on the average value.

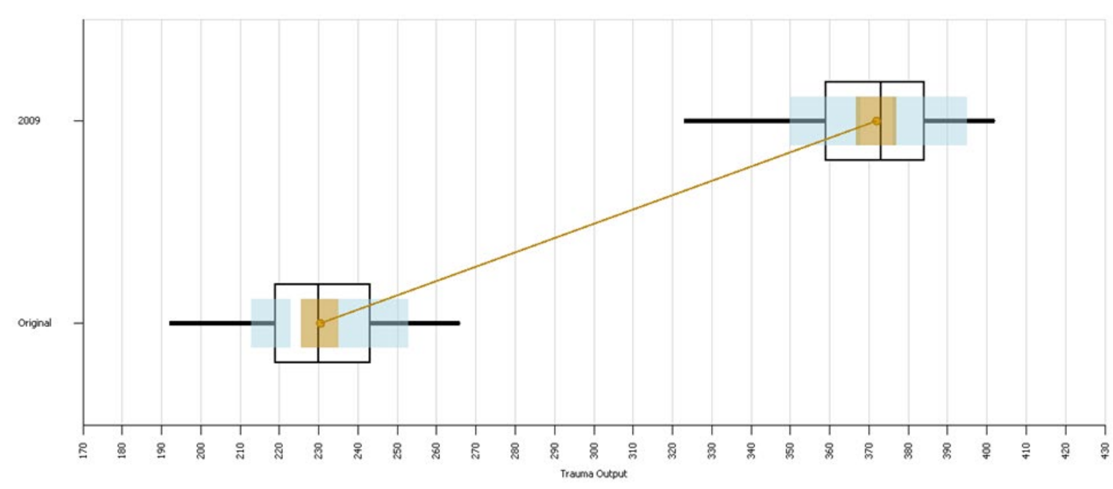

Figure 20. H1N1, 2009 trauma output

The average output for trauma increased from 230 to 372, a 62% increase. Admission rates increased by 20% and all stations had a decrease in the amount of idle time, meaning there was less time that the station was not utilized, producing higher utilization rates. The exam room capacity stayed at the original number of 13 rooms. The maximum usage of the rooms at one time was seven and the average room usage was between three to five rooms.

E. SCENARIO THREE

Scenario three uses the normal operational data with changes to the interarrival rates and triage level probabilities. These changes occur because, from looking at the pattern of H1N1, 1918 infection rates, the data shows that this strain of virus is the only one with a "w-shaped" pattern that significantly impacts three age demographics: individuals younger than five years old, 20–40 years old, and individuals 65 years and older. To simulate this situation, Table 6 shows the recalculated interarrival rates.

Table 6. H1N1, 1918 interarrival rates

Age Group	Baseline Rates	H1N1, 1918 Rates	Percentage Increase	Old Interarrival Rate (mins)	New Interarrival Rate (mins)
0-24	933	1073	15%	46	40
25-49	907	1043	15%	48	41
50-64	494	494	0%	88	88
65+	260	273	5%	167	158

Table 6 shows the percentage increase of the age groups based on the virus strain. Age group 50–64 had no changes because there was no increase for that age group. Next the triage level probabilities for each age group were recalculated to account for the increase in patient severity levels shown in Table 7.

Table 7. H1N1, 1918 triage level probabilities

	Level 1	Level 2	Level 3	Level 4	Level 5
0-24					
X	1	2	3	4	5
P	0.15	0.35	0.55	0.85	1
%	15	20	20	30	15
25-49					
X	1	2	3	4	5
P	0.1	0.3	0.6	0.8	1
%	10	20	30	20	20
50-64					
X	1	2	3	4	5
P	0.08	0.28	0.48	0.78	1
%	8	20	20	30	22
65+					
X	1	2	3	4	5
P	0.22	0.5	0.8	0.9	1
%	22	28	30	10	10

Table 7 shows increases to each age demographic except for age group 50–64. The model was then run with these changes incorporated. Figure 21 shows that the triage station showed a significant increase.

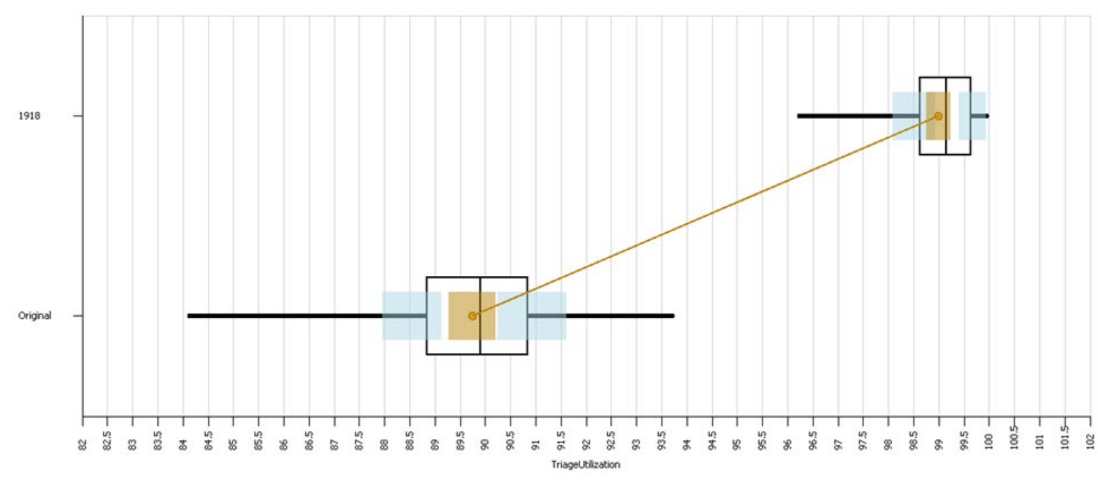

Figure 21. H1N1, 1918 triage utilization

Triage utilization in the original baseline had a mean of 89.7; the mean for the H1N1, 1918 output increased around 10% to a mean of 98.9. Figure 22 compares the trauma output from the original baseline to the H1N1, 1918 variant.

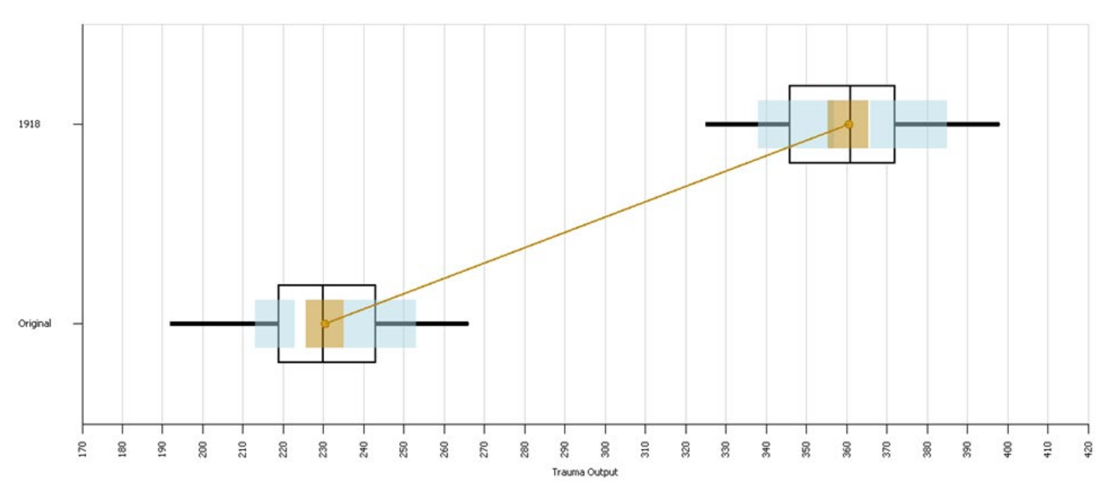

Figure 22. H1N1, 1918 trauma output

The average output for trauma increased from 230 to 360, a 56.5% increase. Admission rates increased by 18% and all stations had a decrease in the amount of time starved, yielding higher utilization rates.

F. SCENARIO FOUR

Scenario four was the final scenario run on the model. This scenario is set up much like scenario one. This scenario uses the estimated 2020 population data to run normal operations and alter the amount of exam rooms and trauma rooms to see if there is a more efficient combination. The 2020 estimated population size of 155,940 people, is run to see how the hospital fares compared to the local population. Table 8 shows the new interarrival times based on the 2020 estimated population.

Table 8. Estimated 2020 interarrival rates

Age Group	Baseline Rates	2020 Est. Rates	Old Interarrival Rate (mins)	New Interarrival Rate (mins)
0-24	933	969	46	45
25-49	907	942	48	46
50-64	494	512	88	85
65+	260	296	167	147

Table 8 shows the slight increase in each age group and how it impacts the interarrival rates. The percentage for age group 65+ increased causing the interarrival rate to have a more significant increase. Figure 23 shows a plot of exam room utilization within a 30-day timeframe.

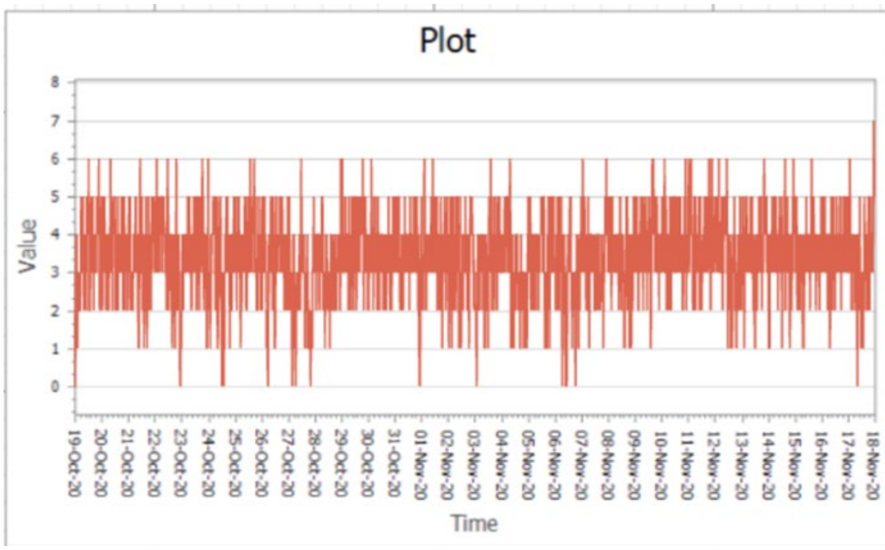

Figure 23. Exam room utilization

This plot shows solid use of three to four rooms being used concurrently, with the use occasionally going as high as seven. With the increased population the exam rooms' concurrent utilization is still seven or fewer, leaving an additional six rooms unused. Figure 24 shows the same inverse trend as scenario one, that as we decrease the amount of exam rooms, we can increase the utilization rate.

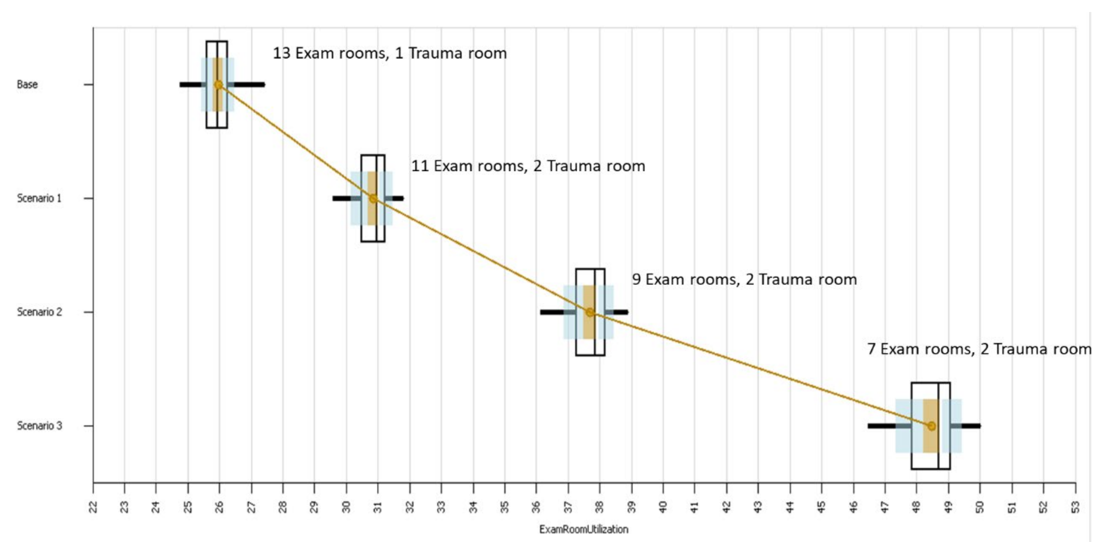

Figure 24. Exam room utilization

Table 9 shows the information from Figure 24 in a table format.

Table 9. Exam room utilization. Adapted from Simio (2021).

Scenario	**Configuration**	**Average Utilization %**
Base	13 Exam Rooms 1 Trauma Room	26.2
Scenario 1	11 Exam Rooms 2 Trauma Room	31.5
Scenario 2	9 Exam Rooms 2 Trauma Room	38.5
Scenario 3	7 Exam Rooms 2 Trauma Room	49.9

Table 9 shows that utilization increases from each scenario, when the exam rooms decrease. The base scenario to scenario one shows a 19.9% increase; the base to scenario two shows a 46.6% increase and the base to scenario three shows a 90.3% increase. A decrease in the amount of exam rooms yields higher utilization rates.

IV. RESULTS AND COST ANALYSIS

This chapter discusses the results from the scenarios analyzed in Chapter III and compares them against one another. This chapter also examines ways for optimal use of the hospital's Emergency Department (ED) while still allowing for surge contingencies.

A. COMPARING SCENARIO ONE AND SCENARIO FOUR

Comparing scenario one, populated with 2018 data, and scenario four, populated with the estimated 2020 data, illustrates the effects of the upward trend within population demographics. Figure 25 shows an increasing trend in all age groups.

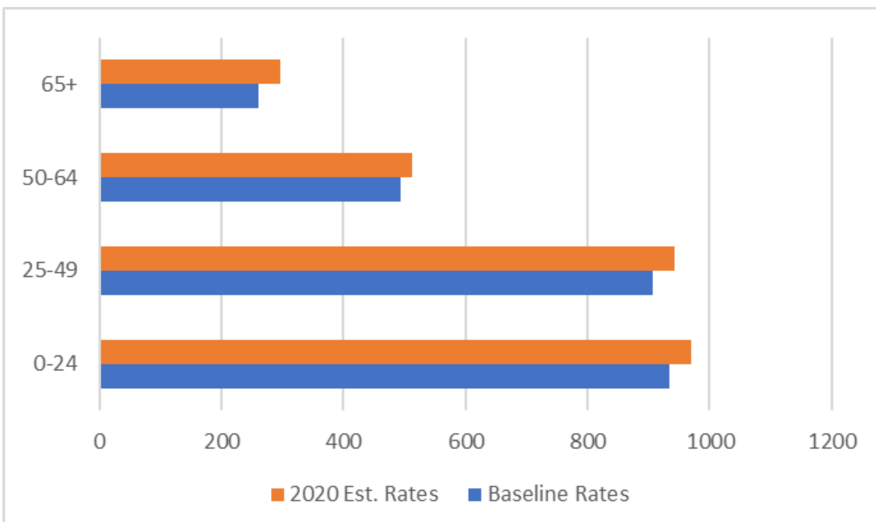

Figure 25. Comparison of age demographics

In the 65+ age group there is a 14% increase. The other three age groups show a steady 4% increase. When running the model with 13 exam beds and one trauma room, the highest concurrent bed usage for the exam rooms for both sets of data was seven beds. Based on the model, the hospital tends to be keeping pace with the surrounding population. However, as the population slowly continues to increase and the current citizens' ages increase, the hospital may see a shift in populations needs that will need to be addressed.

Next, we compared the utilization rates of both sets of data with the current configuration of 13 exam rooms and one trauma room. The utilization rates pertain to the entire resource state and not per entity. A resource is considered busy if any unit of that resource is occupied and idle if no unit within the resource is occupied. Table 10 shows the busy and idle rates for each resource within the model.

Table 10. Busy and idle rates

	Baseline Rates		2020 Est. Rates	
	% Busy	% Idle	% Busy	% Idle
Exam Rooms	99.0%	1.0%	99.3%	0.7%
Front Desk	46.5%	53.5%	48.1%	51.9%
Trauma	33.4%	66.6%	33.8%	66.2%
Triage	96.4%	3.6%	97.0%	3.0%

The exam rooms are busy 99% of the time within a 30-day period with very little idle time. This means that at least one room is occupied 99% of the time, so the resource stays busy. The front desk shows a 3.4% utilization increase based on the population increase. With the estimated 2020 rates, it still shows 51.9% idle time. This resource is manned by one person so there is no current need to increase staffing. The trauma room shows a slight busy increase with idle time over 66%. The hospital is not rated as a trauma center but has the capability to handle the few cases that it receives. For other scenarios that had two trauma rooms instead of one, the trauma room idle time increased to 72%. This happens because the hospital does not receive enough trauma cases within a 30-day period for the resource to hit 50% utilization. The additional trauma room increased idle time due to not having enough patients to care for on a consistent basis. The triage resource only shows a slight increase. However, the model shows that a point for concern for the hospital would be the triage station. There are only two rooms for triage and every patient must flow through triage to receive their acuity rating. This table shows that the resource is busy 97% of the time. Exam rooms show a higher busy rate, but the model showed that the most rooms used at one time is 7 out of 13 or 53.8%, whereas with the triage station there are only two rooms, so that resource has a higher chance of becoming the chokepoint within the model.

When comparing the two scenarios we examined the wait times for exam rooms. Since the exam room resource was close to 100%, we wanted to see how the wait times would impact quality of care. When looking at the exam room average wait times over the 30-day period, we see that most patients waited around 60 minutes and 10 seconds in scenario one, shown in Figure 26.

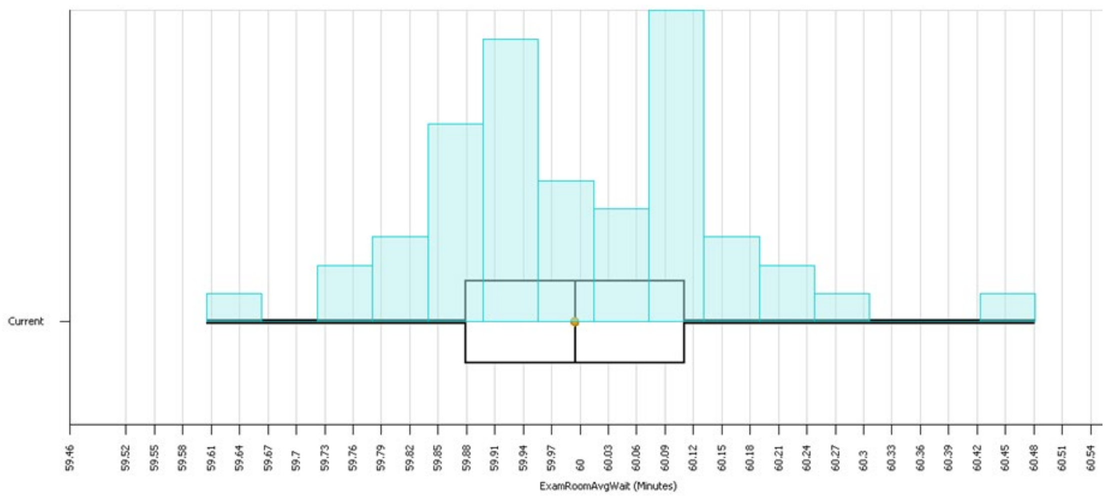

Figure 26. Exam room wait times, scenario one

When we look at the exam room average wait times for scenario four, we see a different numerical distribution based on the data, shown in Figure 27.

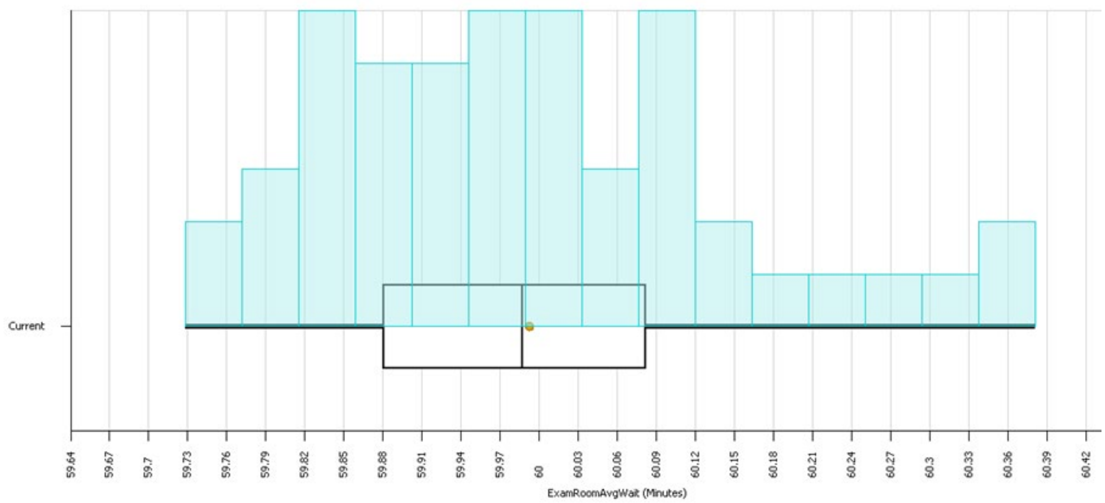

Figure 27. Exam room wait times, scenario four

Scenario four shows more people waiting for longer periods of time, with most people waiting between 59.82 minutes to 60.12 minutes. The wait time for exam rooms is increased in scenario four but does not have a significant impact on quality of care. This is due to more concurrent bed usage in scenario four to keep pace with the inpatient flow. The wait times did not fluctuate too drastically for the exam rooms because the resource has up to 13 units that can be utilized.

Comparing all scenario data simultaneously helps to show the throughput of the model. Figure 28 shows how the interarrival rate changes impacted the total throughput within the 30-day period.

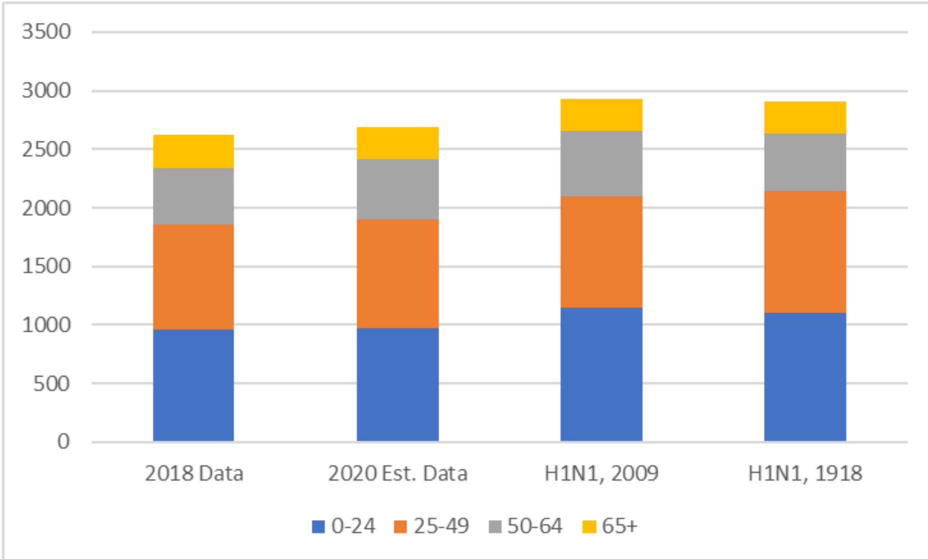

Figure 28. Scenario throughput values

Figure 28 shows the total throughput per each scenario and how many entities went through per each age group. The figure illustrates how more entities went through with the estimated 2020 data due to an increase in the population. Looking at the H1N1, 2009 scenario it shows a significant increase in the 0–24 age group, because that was the group most impacted by that strain of virus. The total throughput for that scenario is highest out of all four scenarios. Compared to the 2018 and estimated 2020 data we can see the influx of patients with the H1N1, 1918 scenario mostly impacting the 0–24 and 25–49 age groups. Comparing the utilization rates of the four resources across each scenario shows the areas to address should an event occur over a sustained amount of time. Figure 29 shows a line graph of the four scenarios and the resource utilization rates.

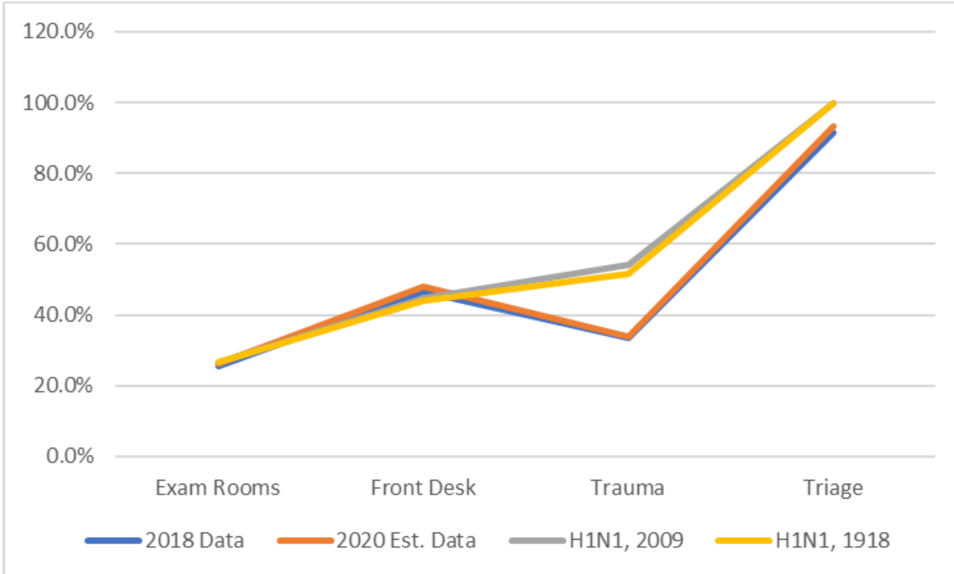

Figure 29. Scenario resource utilization

This graph shows the percentage of the resource utilized. The 2018 and estimated 2020 data show the same trend when it comes to resource utilization. Except for the slight increase due to population increase, both lines show the highest utilization within triage. When looking at the two surge lines H1N1, 2009 and H1N1, 1918, we notice an increase in the trauma room compared to normal utilization rates and almost a 100% utilization rate for triage. Notice during surge events that the front desk decreases in utilization compared to normal utilization. This is explained because during a surge event more entities are considered level one or two triage, which means more entities will bypass the front desk and go straight to triage. During a sustained surge event it would be critical to increase the triage resource to prevent a chokepoint and keep the entities flowing.

B. ADDITIONAL TRIAGE ROOM

When looking at resource utilization rates compared to all scenarios it appears that focusing additional resources on the triage station would be beneficial. The most exam rooms used within any scenario was seven, leaving six rooms not utilized. We assumed that an exam room could be converted to a triage room. We ran the H1N1, 2009 model with this assumption, using 12 exam rooms and three triage rooms to see the impact. This scenario was chosen because it had the highest triage utilization resource rate at 99.9%.

When we ran this simulation, we noticed that the max concurrent exam room usage went from seven rooms to nine rooms. We also saw significant changes within the resource utilization rates. Table 11 shows the changes between the current configuration and the new configuration.

Table 11. Resource utilization rates

	Current Configuration	New Configuration
Exam Room	26.7%	29.1%
Front Desk	44.8%	45.2%
Trauma	54.0%	50.9%
Triage	99.9%	66.8%

The results of Table 11 show significant improvements to the triage utilization rates. Adding an additional triage room and decreasing the exam rooms by one, shows a decrease of 33.1% in triage. This decrease will help this area avoid being a chokepoint and reduce delays in the flow rate. Also, notice that the exam room utilization rate slightly increased. This is caused by more entities flowing through triage and more exam rooms being utilized. The maximum exam room usage with this simulation was nine rooms, leaving three unused rooms for additional surge requirements.

The additional triage room also helped to increase throughput rates from 2863.56 patients to 2972.30 patients. This accounts for an 3.8% increase in patients flowing through triage. Even with an increase of patient flow the additional room helped to decrease the resource processing time from an average 13,682 minutes to an average 151 minutes. This means that the average time triage was in a constant busy state dropped significantly. Due to the inverse relationship, this also means that the triage resource idle time increased from 0.2% to 8.9%. The data shows that the additional triage room slows down the resource from being in a continuous busy state of max capacity, slightly increased the idle time and allows more patients to flow through the system at a steady average wait time of 29.9 minutes.

C. COST ANALYSIS

The model was set up to account for entities that left due to the trauma room being occupied and entities that left due to the wait being too long. We decided to look at how much money the hospital was missing out on due to these two factors. Due to varying conditions and health plans, we assumed that each entity pays $5,000. When looking at the four scenarios we compared the two factors to see how much revenue the hospital gains per entity. Table 12 shows the admission, discharge, left without being seen and the trauma entities that left due to the trauma room being occupied.

Table 12. Entity end destination behavior

	2018	Est. 2020	H1N1, 2009	H1N1, 1918
Admission	450	508	569	581
Discharge	2021	2023	2113	2088
Leave-Not Seen	24	33	19	24
Trauma Occupied	129	113	183	168

Table 12 accounts for the entity's behavior for each scenario. The hospital charged the $5,000 rate for the admission and discharge entities. Looking at the 2018 scenario, the hospital charged 2,471 entities and made $12,355,000. They lost a total of 153 entities, at a cost of $765,000. When the 2018 data was run with the option of 11 exam rooms and two trauma rooms, the leave without being seen entities decreased to 23 and the trauma room occupied entities decreased to 115. We assumed that the cost to convert an exam room to a trauma room would be $100,000. The difference between 129 and 115 is 14. With the rate of $5,000 per entity the hospital could make an additional $70,000 by adding a trauma room. This would leave the hospital in a deficit by $30,000. From previous simulations run we also saw where an additional trauma room would significantly decrease the utilization rate of the resource. This would not be an effective cost option for the hospital at this time. However, this configuration would help to decrease the number of patients that have to leave due to the trauma room being occupied by 10.9%, which over time could produce additional revenue and improve quality of service for the surrounding population.

V. CONCLUSIONS

This thesis shows the usefulness of a local suburban hospital model based on the surrounding population. The model simulation of Stafford Hospital located in Stafford, Virginia, demonstrates that the hospital appears to be keeping pace with the current surrounding population and has the capability to handle a community surge. The current number of exam rooms and the one trauma room appear to be sufficient for the current population. The hospital is functioning to meet normal operational tempo in terms of ED bed capacity utilization.

The model demonstrates that designing around the surrounding population age demographics does prove useful when determining normal operation and surge capacity. The model can ensure the hospital keeps pace with the surrounding population by running different scenarios to analyze the output. The output can help the hospital to adjust its process or determine if more beds are required. Placing monetary values within the model can help to budget for future designs, such as an additional triage room.

A. RECOMMENDATIONS

The hospital should consider adding an additional triage room. The model simulation showed an additional triage room helped to increase throughput rates of patients by 3.8%. The model showed a significant decrease in resource processing time from an average 13,682 minutes to an average 151 minutes. The additional triage room slows down the resource from being in a continuous busy state of max capacity, slightly increased the idle time and allows more patients to flow through the system. This addition could benefit the hospital by leading to more profit and providing more efficient patient care.

B. FUTURE WORK

The model could be expanded to account for all beds throughout the hospital. This is a critical step because the availability of those beds determines the throughput of the ED. When the hospital has no beds available to move an ED patient, that patient must stay in the ED, thus decreasing a bed for new patients to use. When EDs must board patients until a room becomes available, they can quickly become overcrowded.

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