UVA Emergency Department Patient Flow Simulation and Analysis

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Abstract - **One of the most pressing issues facing the American healthcare system is an inability to meet the ever-increasing demand for emergency department (ED) care. EDs across the country are experiencing overcrowding that exhausts resources, creates unacceptable waiting times, diminishes the quality of patient care, and increases financial costs for both the patients and medical departments. The ED at the University of Virginia (UVA) Medical Center is no exception. From 2014 to 2015, the number of patients seen at the UVA ED grew by 4%, which is expected to continue to increase annually. In response, the UVA Medical Center will construct a new "ED Tower" that will double the department's bed capacity, improving departmental efficiency and providing better patient care. This paper reports on a simulation study of patient flows in the UVA ED under alternative demand scenarios, staffing levels, and operating practices. Key performance measures include overall patient length of stay and arrival to provider time. A trace simulation of the current ED was conducted using data from 2014 to validate the model and this model was updated with new logic for the future ED. Our results suggest that the additional space, coupled with staffing schedule changes, will help alleviate the overcrowding problem at the UVA ED for the foreseeable future. For example, the future ED with the current staffing schedule would reduce the average arrival to provider time by 29.5% and overall average length of stay by 3.7%. By incorporating the results of our analysis with our research into best practices of process flow within EDs, we expect our recommendations to improve patient flow efficiency of the future ED and help maximize the quality of care that is delivered to patients.**

Index Terms - Discrete Event Simulation Modeling, Emergency Department, Overcrowding, Resource Utilization

INTRODUCTION

According to a survey of 2,099 member physicians of the American College of Emergency Physicians, 75% of those surveyed claimed that their emergency departments (EDs) had experienced an increase in patient volume since the passage of the Affordable Care Act in 2010 [1]. A hospital's ED often provides the first and only point of contact between patients and health providers, and as such, it is crucial that the ED's patients receive optimal care at all times.

At the University of Virginia (UVA) Medical Center, the ED provides medical treatment to almost 60,000 patients every year. The number of patients who visit the UVA ED has been steadily rising every year. For example, from 2014 to 2015, the UVA ED experienced a 4% annual increase in demand. The increase in patient volume has led the ED to experience frequent overcrowding. Patients who visit the UVA ED have a length of stay that is approximately 1.25 hours longer than the national average [2]. Not only can such high demand on hospital resources lead to long wait times for patients, but it can lead to lower quality of care and worse patient outcomes.

In order to alleviate these problems, UVA has begun plans to build a future ED, with increased size and capacity to deal with high levels of demand. Although this new "ED Tower" will help to reduce some of the overcrowding problems, it may not necessarily lead to better patient care. Other studies have shown that expanding ED capacity without simultaneously improving processes may not lead to a more efficient emergency department [3].

Our team was asked to examine whether the future ED facility would be able to handle the upcoming yearly demand and how different resource schedules would affect the average length of stay and average arrival to provider times. Using a discrete event simulation (DES) approach, we first constructed a model of the current ED and validated it using data analyzed from an external source. Assuming that ED procedures would remain the same between the current and future EDs, we modified the logic of the current ED model with updated logic of the future ED. Based on this assumption we were able to estimate the performance of the future ED, and to recommend an optimal staffing schedule to improve ED efficiency in the future.

LITERATURE REVIEW

One of the primary methods used to study and improve the effectiveness and function of emergency departments is DES. A DES is a simulation that models the functioning of a complex system as a series of discrete "events," an event in this case being a change in the state of the system at a specific point in time. Hamrock et al. studied the applicability of DES in ED modeling and concluded it was an effective tool for "improving patient flow, managing bed capacity, scheduling staff, managing patient admission and scheduling procedures, and using ancillary resources" [4]. Their research concluded that DES provides a low-cost, low risk method to help prevent costly inefficient decisions because of DES's ability to show how a change in one part of the system will affect the functioning of the ED as a whole.

There is a vast amount of literature about DES techniques successfully applied to healthcare settings [5]. For example, Al-Araidah et al. used DES to model an outpatient clinic in Jordan [6], and Gul and Guneri performed a similar analysis at an ED in Turkey [7]. Both studies used time spent in wait rooms and total patient length of stay as their key metrics. Both studies were able to reduce average length of stay by about 20-30% and wait room time by 10-20%. Additionally, Joshi and Rys studied the operational effectiveness of an ED in Kansas during simulated emergency scenarios, with the objective of determining how many additional staff would be required to reduce the key metric of patients left without being seen and number of patients diverted down to zero [8]. Their simulation was able to produce estimates of the number of additional resources required to handle the disaster, as well as the optimal allocation of those resources.

Our team's work with patient flow and ED efficiency is different because we had a single end goal in mind: to improve patient flow in the future ED. In 1999, Rosetti et al. used a DES model to study the current UVA ED and determine optimal attending physician staffing schedules [9]; however, our methods will be unique in that we will be using an empirically verified model of the existing UVA ED to model the future ED still in planning. Our team uses DES to determine whether key performance metrics are superior in the new hypothetical ED compared to the existing ED. In a sense, the current ED serves as a benchmark to which our team will compare the strengths and weaknesses of the future ED.

Approach

Our approach to modeling the future ED was first to develop a model of the current ED. Using Arena Simulation Software (Rockwell Automation, Austin, TX), a DES package, we developed a model of the current ED reading in actual patient arrivals, demographics and processing times provided by the Huron Healthcare Consulting Group. We verified the logic of the model with UVA ED physicians and the results were compared to those published in UVA Epic Healthcare Reports. With this verification, we were confident that our logic for how the ED operated was reasonably accurate. Out of this model we replaced reading in data with distributions formed from 2014 UVA ED data to allow us to transition into incorporating uncertainty in a model of the future ED. We confirmed our distribution model remained accurate and began working on the model of the future ED. In order to test whether the future UVA ED would be able to handle the anticipated demand in the future, we assumed that the procedures in the future ED would be similar to those in the current ED, except for the cases where the future ED offered different capabilities. Using the current ED model as a backbone, we worked alongside our clients to make some changes that will occur in the future ED, such as room resource differences, and an addition of a behavioral health ward. We changed resource capacities, made adjustments to the overall model where the future ED's innovative design would affect patient flow, and ran analyses to see how the future ED would be able to handle future increasing demand and how different staffing models would affect patient flow.

Metrics

The two main metrics we used to evaluate our model were overall patient length of stay (LOS) and average arrival to provider time. We chose overall patient LOS because it was a metric that encompassed the entire ED process from start to finish. We chose the arrival to provider time because it captured the time the patient waited for treatment before all the appropriate resources were available, such as a nurse, attending, resident and bed.

Current ED Model

I. Overview

The current UVA ED has 54 beds spread across four different zones, referred to as pods: orange, blue, pediatrics, and express. The orange and blue pods are general adult acute treatment pods. Both pods have trauma rooms and resuscitation rooms to treat the seriously ill and injured. For our purposes, there is no difference between the two pods other than the number of beds: orange has 22 beds (5 hallway beds and 17 in-room beds) and blue has 17 beds (4 hallway beds and 13 in-room beds). The pediatric pod treats any patient who is 18 years or younger, and it has 10 beds, 3 of which are hallway beds. The final pod in the ED is the express pod, which treats low acuity patients which have minor illnesses and injuries. Express care runs between 11am and 11pm each day to alleviate the burden of allowing low acuity patients to clog up the patient flow process through the rest of the ED. The express pod has 5 beds, 1 of which is a hallway bed. Patients flow through each pod in the same fashion.

II. Model Assumptions

The team made several key assumptions when creating our simulation of the current ED, assumptions are listed below:

- While patients can have total LOS greater than 72 hours due to waiting, the total treatment time in our model is capped at 72 hours.
- Once a patient seizes a bed they keep the bed for the rest of the time they are in the ED. Patients may switch rooms, which works in our logic, but our model does not allow patients to be released back into the waiting room.
- Patients seize the same number of physician and nurse resource throughout the time they are in the room.

- Our model demonstrates the overall average patient-provider level of interaction, but does not capture the specific instances of interactions during the stay.
- Every room in the ED remains open throughout the day, with exception to the express care pod which is closed between 11pm and 11am.
- When deciding which patients should be seen first, our model allows patients with the highest acuity, one with the most serious conditions, to go back to a room and seize resources first.

III. Process Flow

The patient registration process, which normally takes less than 5 minutes, is a procedure by which patients are entered into the ED's cataloging system. At registration, patients provide basic information about themselves and what symptoms they are experiencing. If the symptoms they present appear serious, triage nurses will either immediately triage the patient or escort the patient back to the room for attention. Patients who are transported to the ED via ambulance or helicopter usually have their registration completed in their room rather than at the registration desk near the entrance of the ED. Patients who do not have severe symptoms are sent to the waiting room to wait for a spot in the triage bay, where they will receive a first medical screening. At the triage bay, the nurse checks the patient's vitals and determines an Emergency Severity Index (ESI) that represents patient acuity and resource needs. The ESI ranges from 1 (immediate attention required) to 5 (non-emergent care) and plays a role in determining the urgency of the care needed for a patient. This process takes five minutes or less, and can be performed back in the patient's room if necessary. When there is not a treatment room available for the recently triaged patient, they will be sent to the waiting room until a treatment room opens up. Once the patient is roomed, they sit in their room until a doctor comes and sees them. The time for this process is recorded and referred to as "roomed to MD seen time." Once the patient sees a doctor their treatment begins. The doctor will evaluate the patient's condition and decide which labs and tests need to be performed to determine what is causing that patient's condition. The time from a patient's first interaction with the doctor up until to the point when the doctor has determined a disposition decision (e.g., discharge to home, admit to hospital) is referred to "MD seen to disposition decision time." Once the doctor has assigned the patient a disposition, the patient leaves the ED when they are either discharged or transported to an inpatient ward in the hospital. Occasionally, however, patients stop treatment and opt out of the system at any stage of the process and leave the ED.

IV. Arrival Schedule

We analyzed the schedule of arrivals by looking for nonstationary behavior over days, weeks, months, and years. As demonstrated in Figure I, we used weekly nonstationarity to best represent ED traffic.

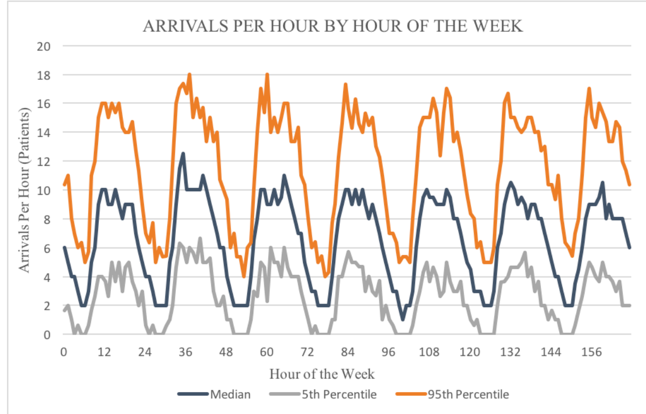

FIGURE I
ARRIVALS TO UVA ED PER HOUR BY HOUR OF THE WEEK

Figure I demonstrates variable demand in two key ways. First, Monday and Tuesdays have the highest level of arrivals, and that decreases throughout the rest of the week. Secondly, there is daily variation incorporated into the week such that overnight through the early morning have the lowest arrival rates. We used this clear trend to fit distributions to all 168 hours of the week for our model.

V. Patient Demographics, Process Times, and Resources

For each patient we assigned acuity based on the demographics of the population contained in the 2014 data set. Using acuity as a basis, we then assigned patients an age and disposition based on breakdown in the data for each acuity level. For the registration process, our team visited the UVA ED to record patient registration times. After collecting a limited number of observations, we bootstrapped the data to determine the distribution for registration times. For the triage time and MD seen to disposition decision time, we fit distributions for each patient acuity. For the disposition decision to departure time, we created distributions conditioned on the particular disposition. Resources were allocated on a patient to resource ratio based on acuity. A patient of a higher acuity may seize several resources strictly for herself, whereas a patient of lower acuity may be able to share resources with other patients. The ratios, representing the *average* of resources seized by a patient, were acquired through interviews with nurses, residents, and attending physicians in the ED. It is important to note that this is a key simplification of our model. As we focus primarily on the relationship between staffing and treatment rooms from the current ED to the future ED, we did not examine changes in patient care over time.

FUTURE ED MODEL

I. Updated Room Resources

We assumed that patient flow in the future ED follows a similar process as the current ED with some changes as outlined below. The future ED will have significantly greater capacity with 74 treatment rooms, each with its own bed.

Should the future ED meet its treatment capacity and the need should arise for extra beds, hallway beds could be added to supplement the 74 treatment rooms. Similar to the current ED, the future ED will be broken up into pods where certain types of treatment will occur. The future ED will have 38 rooms for acute adult care. Of these 38 rooms, 12 are specifically designated as trauma or resuscitation rooms, where patients with serious immediate medical conditions will be treated. The other 26 rooms will be dedicated to an emergent area, which will treat the bulk of incoming patients (acuity 3). In addition, the future ED will contain a pediatrics pod which will treat patients aged 18 or younger. The future ED's pediatrics pod will have 9 rooms with one room dedicated to treating trauma pediatrics patients. The future ED will also have rapid medical evaluation (RME) pod which will treat patients types similar to that of express care in the current ED. Just like express care, the RME will treat patients with minor conditions from 11am to 11pm. The RME pod will have 9 rooms.

II. Behavioral Health Pod

The future ED will have a behavioral health area set aside for the purpose of treating behavioral health patients. In the current ED, these patients are treated like any other patient and can be sent back to any room. The behavioral health area in the future ED will be built to handle the specific needs of behavioral health patients and will improve both the level of care and efficiency of treatment. It will contain 8 rooms.

III. Clinical Decision Unit

The clinical decision unit (CDU), is a new space in the future ED. This unit houses patients who are stable and awaiting lab results, as well as stable patients awaiting a decision on whether or not they should be discharged or admitted to the hospital. The purpose of the CDU is to keep these types of patients from taking up space in treatment rooms and will allow the future ED to function more efficiently. Though the CDU will exist in the future ED, the team did not incorporate it in our simulation model of the future ED. The ED staff themselves are still uncertain about specifically which types of patients will be sent to the CDU, and this uncertainty made it impossible to accurately model the CDU.

TESTING AND EVALUATION

We tested our model over a series of demand levels and staffing schedules to measure the effectiveness of the ED in terms of average LOS and time from patient arrival to seeing an MD. We ran the model for a full year after a one-week warm-up period. The warm-up period is required to represent a steady-state system like an ED and ensure that performance measures are not biased. For each scenario, we ran the model with five replications to measure the variability of the results.

Initially, we tested both the current ED and the future ED with the level of demand for the year 2014 using the current level of staffing. This test served as a control to give us a baseline against which we could compare our other results. After establishing the control, we manipulated the staffing levels to simulate the ED staffed at 100%, 110%, 125%, and 150% of the current level. For example, if the ED currently has 10 doctors and 20 nurses, the 150% staffing simulation would have 15 doctors and 30 nurses.

Our data suggested that the number of patients who visit the ED annually increases at a rate of about 4% every year. Therefore, we decreased the inter-arrival time of patients by 4% for each year into the future we needed to predict. We also ran analyses for 2% and 6% increases in demand, in order to account for deviation in this growth rate. Using this analysis, we were able to examine combinations of staff and resources that optimize the efficiency of the ED.

RESULTS OF ANALYSIS

First, we found that for all staffing levels the future ED heavily outperformed the current ED. Specifically, the results from our DES demonstrated that if the patient flow volume of 2014 occurred in the future ED there would be a 29.5% decrease in arrival to provider time down from 32.0 minutes [28.3, 35.7, 95% C-I] in the current ED to 22.6 minutes [19.0, 26.2, 95% C-I] in the future ED model. Overall, such a decrease in time from arrival to seeing a provider would decrease overall LOS by 3.7%.

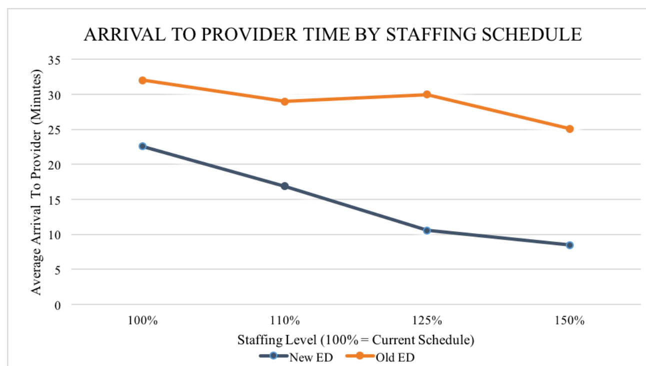

FIGURE II
ARRIVAL TO PROVIDER TIME BY STAFFING SCHEDULE

This outperformance of the current ED by the future ED is further demonstrated with an increase in staff, suggesting the future ED will enable an increase in staff to be more effective. For example, if staff is increased by 25%, we could expect the arrival to provider time to be 67% less in the future ED than in the current ED. An increase in staff by 25% combined with the opening of the future ED is expected to decrease overall LOS by 8.1%.

It is important to recognize that the results are based on the base resources of the future ED, meaning the addition of hallway beds or the CDU will only exaggerate the outperformance of the current ED (see *Limitations* section).

While these results are seemingly conclusive for 2014, we used past trends to predict increases in demand through 2018 (when the future ED is scheduled to open). We used these predictions to scale our exponential forecasts of patient inter-arrivals, and thus measure new lengths of stay. Naturally, the increase in patient flow increased the LOS of individuals. We ran this analysis with five replications for each year through 2018, and then used a linear model to predict the overall trend. We found that each year, the expected increase in patients of approximately 4% increased LOS by 6.73 minutes.

It follows that the future ED will need to increase productivity in order to maintain (or improve) the current LOS for patients. We ran analysis for predicted LOS in the future ED if it were to operate in the next five years across five different staff levels. We found that a staff schedule with 110% of the current resources would be sufficient to maintain operation in 2015, but not 2016 (note: this is not depicted in Figure III for graphical clarity). However, we found that 125% and 150% staff would keep LOS below the current expectation through the future ED's opening in 2018. In fact, staffing resources at 150% keeps LOS very close to the value added time through 2018, which is the optimal solution.

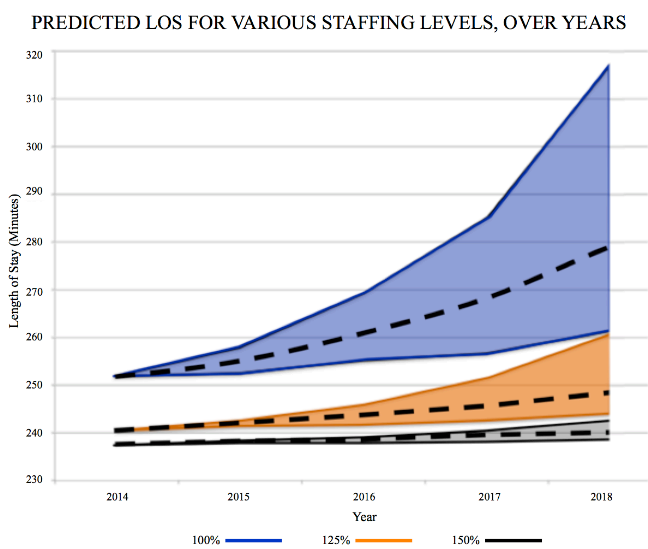

FIGURE III
PREDICTED LOS FOR VARIOUS STAFFING LEVELS OVER YEARS

We ran this analysis for our expected increase in patient demand, of an aforementioned 4% per year. However, as patient demand is difficult to predict, we ran a sensitivity analysis for demand from 2% (the current growth rate of Charlottesville), to 6% which is depicted as variable error in Figure III. Additional sources of error from multiple runs were included, but did not exceed a deviation of one minute.

LIMITATIONS

Because our model of the future ED does not include the CDU, we anticipate the average length of stay and arrival to provider seen to be smaller than what we forecasted in our results. We anticipate this result because patients who are clogging up the system waiting for lab and imaging results will be able to wait in the CDU which will free up bed, nurse and doctor resources in the regular part of the ED. Additionally, with the behavioral health pod being new in the future ED, no procedures or staffing schedules were available for us to use, so we assumed that once a patient was sent to the behavioral health pod they will have one nurse and one bed all to themselves. Our analysis also does not include the use of hallway beds in the future ED, however, if hallway beds are used in the future ED, we expect both the overall length of stay and the arrival to provider times to further decrease. Finally, our model does not capture any efficiency improvements that will take place as a function of the increased space and resources that will be available in the future ED. Given the update on the technology used and more efficient design of the future ED, it can be expected that individual process times will decrease throughout and will further decrease both arrival to provider times and overall length of stay times.

FUTURE WORK

To improve upon our simulation model, future work could incorporate a greater volume of data to make certain portions of our simulation more specific and more accurate. For example, our model uses a very basic distribution to simulate the process of a patient waiting for results from the lab. By expanding upon the model to include the specific type of lab test a patient requires, and creating different distributions for each test, future scholars could model the patient flow process within the ED in greater detail. Another example would be acquiring more information about how the CDU will operate.

Future work could focus on ways to reduce ED overcrowding on days of the year that the hospital knows will be particularly busy. For example, holidays and UVA football game days are known to be especially difficult on the hospital's resources. Future scholars could use our simulation to determine what staffing positions could be bolstered with extra personnel to most effectively handle the increase in ED demand.

One of the biggest concerns that lead to the need for constructing a future ED was overcrowding of the current ED. Our model accounts for an increase in demand on ED resources year-over-year, but does so by simply incrementing the number of patients seen by about 4% every year. In order to get a more accurate idea of the actual future demand, a more in-depth of analysis of future demand on the ED could be performed, incorporating factors such as increase in the size of the UVA student body, increase in Charlottesville's population, and the effect of transfer patients from other local hospitals. Such an analysis could help determine how long the future ED would be effective and when or if the future ED would need to be expanded or replaced.

Furthermore, future work should try to model the interactions between patients and providers. There is limited data about how often and how long a doctor or nurse interacts with a patient. While the number and length of these interactions vary based on the patient's overall condition and the specific ways individual doctors and nurses work, it would be interesting to see if the results would look different based on that type of analysis.

CONCLUSIONS

In conclusion, we recommend (a) continuing with the future ED opening as planned and (b) increasing staff by 25% of the current schedule. The opening of the future ED will decrease length of stay at all staffing levels. Continuing with the current staffing path, even with the future ED, could result in increases in length of stay by upwards of 25 minutes in the next four years. Within the new environment, a staff level of 125% the current level demonstrates the largest decrease in length of stay per additional resource, and enables length of stay to be relatively constant and predictable through 2018.

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