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PHYSICIAN SHIFT SCHEDULING TO IMPROVE PATIENT SAFETY AND PATIENT FLOW IN THE EMERGENCY DEPARTMENT

Vishnunarayan Girishan Prabhu
Kevin Taaffe

Department of Industrial Engineering
Clemson University
100 Freeman Hall
Clemson, SC 29631, USA

Ronald Pirrallo
William Jackson
Michael Ramsay

Department of Emergency Medicine
PRISMA Health - Upstate
701 Grove Road
Greenville, SC 29605, USA

ABSTRACT

Emergency Departments (ED) act as the healthcare safety net for millions of people seeking medical care. To ensure smooth patient flow and efficient ED operations, it is crucial to maintain appropriate staffing levels and resource allocation. Although a well-recognized problem, ED crowding and patient safety concerns are still prevalent, with recent studies identifying ED as one of the leading departments prone to medical errors. This research focused on developing an optimization model to identify optimal physician staffing levels to minimize the combined cost of patient wait times, handoffs and physician shifts in the ED and testing in the simulation model. By generating two new shift schedules and testing them in the validated simulation model for a three-week period, we observed that patient time in the ED and handoffs can be reduced by as much as 27% and 26%, with a 1.4% increase in full-time equivalents compared to the current practices.

1 INTRODUCTION

According to the 2017 Centers for Disease Control and Prevention (CDC) reports, approximately 145 million visits are made to Emergency Departments (EDs) in the US annually (Centers for Disease Control and Prevention 2016). These numbers are expected to increase based on the current trends where ED patient arrivals have seen a 24.7% increase over the last ten years. While the Affordable Care Act has slightly helped reduce ED visits by uninsured patients, ED access by the underserved population has increased significantly. Moreover, the federal mandate, Emergency Medical Treatment and Active Labor Act (EMTLA), which requires an ED physician to provide stabilizing care to a patient irrespective of their ability to pay, makes ED the healthcare safety net (Centers for Medicare and Medicaid Services 1986). According to the latest reports, approximately 70% of inpatient hospital admission occurs through the ED and an additional 3% transferred to a different hospital for inpatient admission.

The overwhelming patient volumes and their diverse medical conditions make ED one of the most complex healthcare environments predisposed to crowding. The American College of Emergency Physicians defines crowding as a situation in which the identified need for emergency services exceeds available resources for patient care in the emergency department, hospital, or both (American College of Emergency Physicians 2019). ED crowding is a patient safety issue as well as a public health problem. Crowding disrupts the ED patient care processes, negatively impacts patient safety, and increases the health system costs (Derlet and Richards 2000; Kane 2019; Morley et al. 2018; Trzeciak and Rivers 2003). Crowding is a result of multiple factors, including high patient volumes, inadequate staffing, and bed shortages resulting in a longer patient length of stays and slower discharge rates (Hoot and Aronsky 2008; Schneider et al. 2003; Trzeciak and Rivers 2003). Additionally, the reduced availability of ED beds due to

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admitted patients awaiting transfer into an in-hospital bed restricts an ED's capacity to accept new patients, resulting in higher patient boarding time and delays in providing patient care (George and Evridiki 2015).

It is imperative that the resource allocation, which includes healthcare provider staffing, number of beds, and ancillary units, is well planned to improve the patient flow within the healthcare system and avoid ED crowding. As the most intuitive solution to address crowding is by adding extra resources, including beds, staff, and ancillary units, adding a new ED resource could be very expensive. Moreover, among these different resources, rather than adding physical resources (e.g., beds and equipment), temporarily adding or changing staff schedules are comparatively cheaper options. However, the schedules should be carefully planned to ensure that the EDs are not overstaffed or understaffed and ultimately improve the patient flow and patient safety within the staffing budget of the health system.

Operations research models and methodologies have had a significant impact on improving EDs throughout the world. A variety of approaches, including mathematical and optimization models, queuing theory, simulation modeling and probabilistic models, have been used to address a variety of ED issues, including resource allocation, patient streaming, fast-track ED, patient safety, staffing and scheduling etc. A majority of the studies have used simulation models, specifically discrete event simulation (DES), because of their capability to represent various ED processes, patient flow and test "what-if" to investigate resource allocation, staffing and scheduling, patient flow and overall process improvement. One of the earliest studies that utilized DES for bed allocation was half a century ago (Goldman et al. 1968). It investigated various scenarios that compared the effect of the grouping of patients and its impact on bed utilization. Additionally, the DES approach has been used extensively to identify bottlenecks in the ED and take corrective actions by allocating resources to reduce the patient length of stay (Elbeyli and Krishnan 2000; Harper and Shahani 2002). Further, studies have used simulation models to test the impact of various ED resources on the performance metrics to identify the importance of each resource. Specifically, one study observed that adding a single physician and nurse during the peak ED hours would have the highest impact on the patient waiting times (Duguay and Chetouane 2007). Similarly, researchers have used the DES modeling approach to identify the number of various resources it would require, including beds, staff, equipment etc., to meet specific key performance thresholds such that the desired patient flow is achieved (Oh et al. 2016). Although simulation models can be used for various purposes as discussed for testing different scenarios, one of the main drawbacks is that they cannot find an optimal solution.

A mathematical model can address this issue by formulating the problem with a specific objective, constraints, and parameters representing the system to generate an optimal solution. Over the last few years, various studies have used mathematical models to identify optimal staffing levels, generate schedules, optimal bed and other resource requirements etc. A recent study used a mixed-integer linear programming (MILP) model to minimize understaffing with respect to patient volumes and resulted in significant improvements in different ED performance metrics, including median length of stay, door-to-provider time and door-to-bed time (Sir et al. 2017). Further, researchers have used a combination of simulation-optimization models to identify optimal solutions and test them in the simulation model for validating the optimal solutions (Ghanes et al. 2015; Ghanes et al. 2015). However, all these studies have focused on identifying solutions that can improve patient flow or improve ED performance by reducing the waiting time, length of stay, or improving the ED throughput. To our knowledge, none of the studies using mathematical or simulation model approaches have used patient safety as an ED performance metric except for our prior research, which aimed to identify physician shifts that can minimize patient handoffs during the end of the shift using a simulation model (Prabhu et al. 2019).

Patient safety is a crucial part of the ED as continuous patient flow, interactions with multiple departments and providers make it prone to errors. Additionally, researchers have observed ED as one of the hospital departments with high error rates. Among different issues that lead to medical errors, studies have identified handoffs, transfer of a patient's care and responsibility from one physician to another as a major patient safety issue (Maughan et al. 2011; Venkatesh et al. 2015). Specifically, studies that investigated ED shift-change handoffs observed that for approximately 75% of the patients, the vital signs were not communicated, and errors were observed in about 60% of cases. Further, insurance claims involving missed ED diagnosis that harmed patients reported that 24% of the cases involved inadequate handoffs. However, handoffs are unavoidable in EDs as they operate throughout the day, and a physician ending their shift is required to transfer their current patients to the newly arriving physician.

Hence, while developing the ED physician shift schedule, it is crucial to consider handoffs as a performance metric and along with others. To our knowledge, none of the prior studies have utilized an ED patient safety metric along with other patient flow metrics in a mathematical model to generate staffing schedules. Our research developed a MILP model for identifying optimal shift schedules that minimize the combined cost of patient wait times, handoffs, and physician shifts, thus considering the patient flow, patient safety, and staffing budget to generate schedules. Further, to ensure the generated schedule improves the ED performance, we tested it in our validated simulation model (Girishan Prabhu et al. 2020).

2 DATA

Input data for the model, including the number of beds, allowable physician shifts, patient arrivals, ESI level of the patients, patient time in the ED, and the number of interactions between physicians and patients, were gathered from the PRISMA Health Greenville Memorial Hospital (GMH), Greenville, SC. Additionally, observations were conducted in the GMH ED, and the research team included ED physicians working in GMH, SC for guidance and addressing any other physician-dependent activities in the ED to be included in the model. PRISMA Health is the largest healthcare provider in South Carolina and serves as a tertiary referral center for the entire Upstate region, and the flagship GMH academic Department of Emergency Medicine is an Adult Level 1 Trauma Center seeing over 106,000 patients annually.

We first introduce Figure 1, which represents the patient arrivals to the GMH ED utilized in our model. As seen in the image, the patient arrivals are low during the early hours and slowly start picking up from 7:00 am until 12:00 pm when they reach the maximum and stay the same until 7:00 pm. This patient arrival trend is universal, and prior studies have reported the same (Alvarez et al. 2009; Whitt and Zhang 2019). Moreover, it can be noted from Figure 1 that weekdays have higher patient arrivals compared to the weekends and Mondays have the highest patient arrivals. Rather than using an entire year's of patient arrival and using it for physician scheduling, we created clusters of 3 months and used the cluster with the highest patient arrivals for this research (July 2019 – September 2019). Additionally, based on expert opinions from the ED physicians, we wanted to use the pre-COVID-19 data as the patient arrivals varied significantly. Another reason for using this specific time period was to test the optimal schedule in our validated simulation model that used the same patient arrivals. However, the model was developed such that any patient arrivals can be used to generate a weekly schedule.

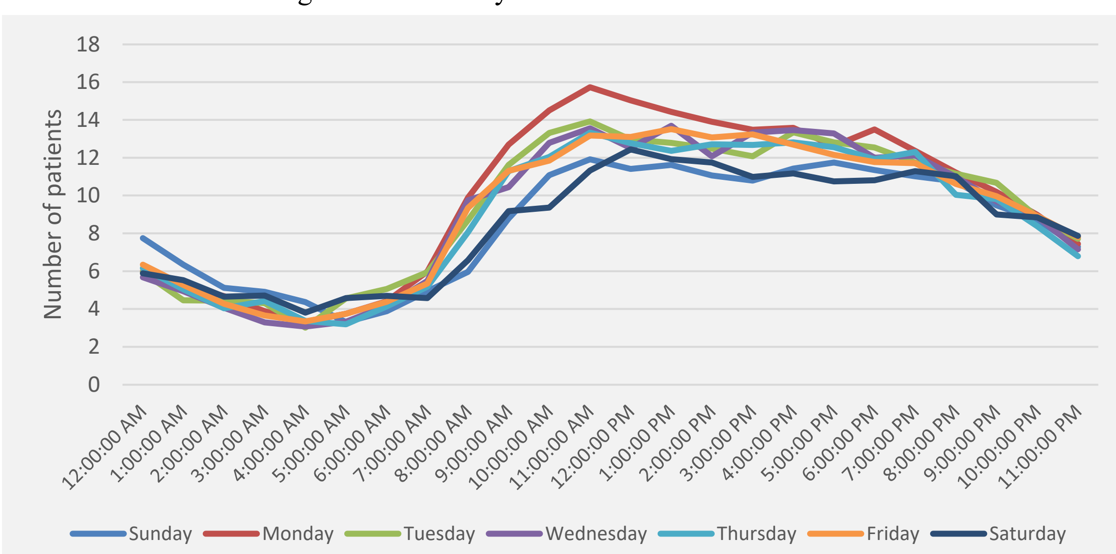

Figure 1: Patient arrivals to the GMH ED.

Next, we introduce Figure 2, which represents the time a patient spends in the ED based on their ESI levels. As seen below, we split the data into two parts: "Bed to Disposition" and "Disposition to ED Departure". Bed to disposition represents the time a patient occupies an ED bed and is provided care by physicians and other medical providers, including performing tests, providing medicines, blood draws, etc. Although patients will be waiting in their beds during this period without receiving direct care, all these delays are due to waiting for their test results, medicines, etc. In general, this represents the period a patient first occupies a bed in the ED until the physicians make a disposition decision (admit, discharge or transfer). The second part, "Disposition to Departure," is the period for which a patient occupies the ED bed from the time the physician makes a disposition decision until they are physically moved from the ED (discharged, admitted or transferred). Hence, these are logistical delays where a patient can be either waiting until a bed is available in the hospital (admission) or waiting for transportation (discharged or transfer). As seen in the figure, the disposition to discharge time for ESI-1 patients, which represents the most urgent patients, is the highest and the higher than their bed to disposition time because most ESI-1 patients are admitted to the hospital. Hence, they have to wait in the ED until a bed is available. However, as the severity reduces, the disposition to departure time also reduces as most of the low-severity patients are discharged, and the delay we observe here is usually a result of patients waiting for transportation from ED.

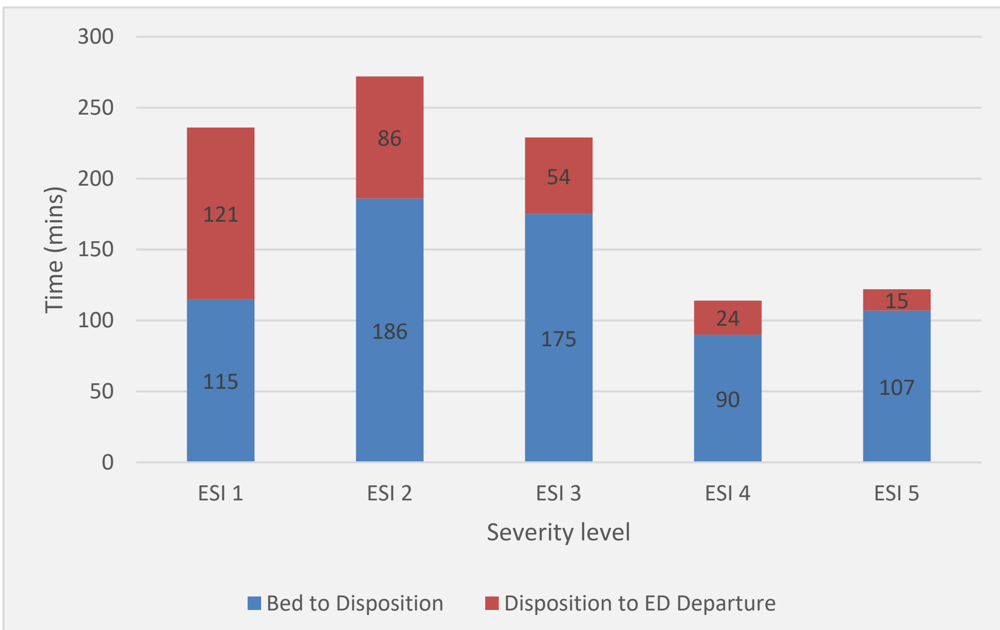

Figure 2: Patient time in the ED.

As mentioned earlier, the entire bed to disposition time of a patient is not spent with a physician as it includes other activities. Based on literature and discussions with ED physicians, we used between 15-30% of total time as the care time where a patient would be cared for by a physician (Füchtbauer et al. 2013). The percentages were assigned based on severity such that the total time spent with an ESI-1 patient was the highest and that with an ESI-5 patient was the lowest. This approach was used mainly used because of the lack of detailed visit-by-visit data available to support detailed modeling.

Further, to build a model representative of ED operations where a physician visits patients multiple times based on their severity (ESI- level), we split the care time into multiple smaller windows. Based on our past observational studies and discussion with ED faculties and physicians, on average, an ES1-1 patient was visited four times by a physician, ESI-2 and 3 were visited three times, and ES1-4 and 5 were visited two times (Girishan Prabhu et al. 2020). The physician's time with a patient for each visit was a constant time block of 15 minutes as the MILP modeling approach considers time as a discrete block of events.

3 MATHEMATICAL MODEL

In this research, we formulate the ED physician shift scheduling problem as a MILP problem. The primary goal is to identify the optimal staffing levels of ED physicians such that the patient onboarding time, waiting time after ED admit and patient handoffs are minimized while considering the physician staffing cost to avoid overstaffing. Hence the first step was to identify a common scale such as the dollar amount for each term. Based on the literature and expert opinions, different cost factors were included. Next, we define the notation we used, followed by the MILP model.

3.1 Notations

We first introduce the sets and indices considers in this optimization model. The model included four sets and corresponding indices as follows:

- I represents the set of patient arrivals to the GMH ED indexed by i.
- K represents the set of possible physicians that can be staffed for a day indexed by k.
- T represents the set of time slots considered for staff scheduling indexed by t.
- M represents the set of physician visits required by a patient indexed by m.

Here, set I include all the unique patient arrivals to the GMH ED for a week, which totals more than 1500. Set K consists of the unique physician identification number that can start an ED shift for a day with an upper threshold of 25 physicians per day. Further, we consider 24 timeslots to represent a day, meaning there would be 168-time slots for an entire week, each representing a specific hour of the day in set T. Finally, the set M includes values from 1 through 4, representing the patient interaction with a physician. Next, we introduce the parameters considered in the model. Most of the parameters represent various patient characteristics, including severity, arrival time, physician visits, time slots that should be avoided for calculating patient wait time as these delays are inherent and one parameter defining the ED bed capacity.

- α_i represents the time slot of arrival for patient i.
- β_i represents the severity level of patient i.
- γ_i represents the total number of visits required by patient i.
- w_i represents the total time slots for patient i that should not be considered for waiting cost.
- C represents the total bed capacity of the GMH ED.

Finally, we introduce the decision variables in the model:

- U_{ik} $\begin{Bmatrix} 1, \text{ If patient i served by physician k} \\ 0, \text{ otherwise} \end{Bmatrix}$
- $Ystart_{kt}$ $\begin{Bmatrix} 1, \text{ If physician k starts their shift at time slot t} \\ 0, \text{ otherwise} \end{Bmatrix}$
- Y_{kt} $\begin{Bmatrix} 1, \text{ If physician k is available for service at time slot t} \\ 0, \text{ otherwise} \end{Bmatrix}$
- X_{iktm} $\begin{Bmatrix} 1, \text{ If patient i is served by physician k at time slot t for their visit m} \\ 0, \text{ otherwise} \end{Bmatrix}$

In the formulation represented on the next page, the objective function (1) minimizes the cost of staffing the ED physicians, handoffs, patient onboarding and patient waiting time in the ED. The cost of staffing an ED physician (SC) was based using the national average rate for ED physicians, and the onboarding cost

(*OC*) for patients based on their ESI level was derived from the literature (Salary.com 2021; Woodworth and Holmes 2020). However, because of the lack of data on the cost of patient waiting once admitted, we used a factor value (*F*) between 0 and 1 and multiplied it by the *OC* to calculate the waiting cost. Finally, for the handoff cost (*HC*), we used high values to avoid any possible handoffs.

Minimize:

$$\mathrm{SC}^* \sum_{kt} \mathrm{Ystart}_{kt} + \mathrm{OC}^* \sum_{ikt} t^*\mathrm{X}_{ikt1} - \alpha_i + \mathrm{OC}^*\mathrm{F}^* \sum_{ikt} (t^*\mathrm{X}_{ikt\gamma i} - t^*\mathrm{X}_{ikt1}) - w_i + \mathrm{HC}^* \sum_{ik} \mathrm{U}_{ik} - \mathrm{I} \quad (1)$$

Subject to:

$$\sum_{kt} t^*\mathrm{X}_{ikt1} \geq \alpha_i \qquad \forall i \in I$$

$$\sum_{ktm} \mathrm{X}_{iktm} = \gamma_i \qquad \forall i \in I$$

$$\sum_{km} \mathrm{X}_{iktm} \leq 2 \quad \forall i \in I, \forall t \in T$$

$$\sum_{kt} \mathrm{X}_{iktm} \leq 1 \quad \forall i \in I, \forall m \in M$$

$$\sum_{ikm} \mathrm{X}_{iktm} \leq C \qquad \forall t \in T$$

$$\sum_{kt} t^*\mathrm{X}_{iktm} \leq \sum_{kt} t^*\mathrm{X}_{iktm+1} \qquad \forall i \in I$$

$$\sum_{mt} \mathrm{X}_{iktm} \leq 4^*\mathrm{U}_{ik} \qquad \forall i \in I, \forall k \in K$$

$$\sum_{im} \mathrm{X}_{iktm} \leq 4^*\mathrm{Y}_{kt} \qquad \forall k \in K, \forall t \in T$$

$$\sum_{kt} \mathrm{Ystrt}_{kt} \leq 1 \qquad \forall k \in K$$

$$\sum_{kt} \mathrm{Ystrt}_{kt} \leq K$$

$$8^*\mathrm{Ystart}_{kt} \leq \sum_{q=t}^{\mathrm{Min}(168,\, t+7)} \mathrm{Y}_{kq} \quad \forall k \in K, \forall q \in T$$

$$\mathrm{U}_{ik}, \mathrm{Ystart}_{kt}, \mathrm{Y}_{kt}, \mathrm{X}_{iktm} \in \{0, 1\}$$

In the formulation, the first constraint ensures that a patient is served their first visit only after their arrival to the ED. The second constraint ensures that the patient is provided all their required visits before discharging. As mentioned earlier, each hour represents a time slot, but from observations and discussions with physicians, we assume that a physician can visit four patients in an hour. However, the same patient cannot be visited four times during an hour as that not realistic as patients wait to get their tests, imaging, radiology etc., completed. The third constrain ensures that at maximum, a patient can be visited only twice by a physician in an hour. The fourth constraint assures that each visit m for a patient cannot exceed 1, making sure that each visit is completed fully during a physician visit. The next constraint ensures that at any given time t the patients served cannot exceed the ED bed capacity. As patients have multiple interactions with physicians during an ED stay, these visits must be ordered such that a later visit follows the prior visit in terms of time slot, and our sixth constraint ensures the visits are ordered. The next two constraints assure that a patient can be visited a maximum of four times by a physician, and a physician can visit up to four patients during any given time slot (1-hour block). The next two constraints ensure that a physician starts their shift only once a day, and the total number of physicians staffed per day does not exceed the maximum possible physicians that can work for a day based on health system budget constraints. To ensure that a physician shift, once started lasts for eight hours, we use the second to the last constraint. Finally, the last constraint defines the variable types, which are all binary in this case.

Formulating the problem as discussed above allowed us to replicate an actual emergency department scenario where patients interact with physicians multiple times, wait for tests between visits, and, more importantly, account for patient care handoffs that impact patient safety.

4 SIMULATION MODEL

After developing the mathematical model to generate staffing schedules, the next step was to develop and validate a simulation model representative of the PRISMA Health ED. We utilized a novel hybrid modeling approach to develop the discrete event simulation where both patients and physicians are represented as agents with unique attributes. This approach allowed us to simulate the actual patient arrivals to the PRISMA health ED with specific features, including severity level, arrival time, etc. Moreover, the main reason to adopt this modeling methodology was to replicate the physician activities in the ED in a realistic manner, including starting a shift at a particular time, spending time in their work station ordering tests, updating a patient record, visiting patients multiple times, and finally handing off a patient to the next physician when their shift ends. These activities would have been challenging to include if we followed a traditional modeling approach where physicians are denoted simply as resources.

Figure 3 below provides a high-level overview of patient flow and physician activities in the ED for a single pod. The patient arriving in the ED based on the historical data first goes through the triage process where they are assigned an ESI level as observed in the ED. We utilized historical data to assign the severity levels, and in case no ED beds are available, the patient waits in the waiting room, where the patients are prioritized based on the assigned severity level. The second block of arrivals represents physicians arriving at a specific pod in the ED at their assigned shift starting time. A physician, upon arrival, goes to the physician station, and in case another physician is leaving the ED at the same time, the patients from the leaving physician are transferred to the arriving physician representing the handoffs as observed in the ED. After patient handoffs, the physician spends time in the station going through the patient charts and starts visiting the patients in their bed, as necessary.

Further, whenever there are free beds in the ED, a physician, based on their workload, will sign up a patient from the waiting room and meet them in their bed (or room). Further, whenever there are free beds in the ED, a physician, based on their workload, will sign up a patient from the waiting room and meet them in their bed (or room). Further, to replicate the actual assignment process followed at PRISMA Health ED, physicians working in certain pods were restricted from taking high severity patients as few pods do not have the equipment required to provide care for high severity patients. After visiting a patient for the first time, a physician always returns to the station to update charts and order tests. The patient will have subsequent visits by the same physician based on ESI level, as observed in the ED. If the particular physician is ending their shift, the patient is handed off to another active physician. Further, it can be noted from the figure that after a subsequent visit, there is a 40% chance that a physician visits another patient before returning to the station. Where historical data did not exist, expert opinions from ED physicians were used for modeling.

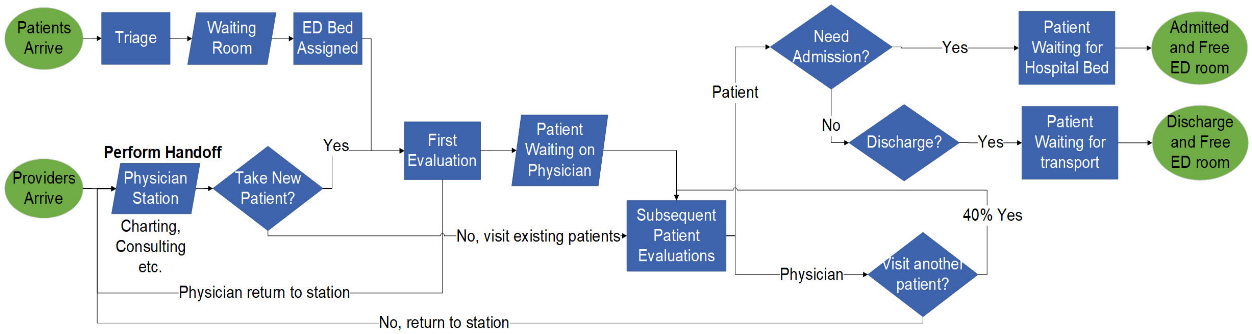

Figure 3: A high level overview of patient and physician activities in a single ED pod.

After developing the simulation model representative of PRISMA health ED, the next step was validating the model against the actual data. For this, we utilized the patient time in the ED for ESI level as the validation metric to ensure that patient time spent in the simulation model did not vary significantly from the actual data for each ESI level. The model was simulated for a three-week schedule with an additional two-day warm-up period for the model to attain equilibrium. A total of 60 replications were performed, such that the margin of error on time in the ED metric was ± 10 minutes (at α=0.05). Table 1 below represents the simulated data, and actual data for each ESI level and the difference between these was less than 7% for each ESI level. Further, on conducting an independent t-test, there was no significant difference (p-value > 0.05) between the simulated data and actual data.

Table 1: Simulation model validation.

Severity	Actual Time in ED (mins)	Simulated Time in ED (mins)	Percent Difference
ESI 1	236	218	-7.6%
ESI 2	272	281	3.3%
ESI 3	229	216	-5.7%
ESI 4	114	121	6.1%
ESI 5	122	122	0%

5 RESULTS

To comprehend staffing schedules that can minimize patient handoffs, physician shifts and patient wait times while considering the staffing budget, we specifically generated two policies.

- Policy 1: This policy aims to minimize the combined costs of handoff, patient waiting, and physician staffing using the MILP model based on the costs discussed in section 3.
- Policy 2: This policy also aims to minimize the combined costs of handoff, patient waiting, and physician staffing using the MILP model. However, here the handoffs costs are penalized with a significantly higher dollar value with the central focus of eliminating handoffs as much as possible.

In the case of policy 2, handoff reduction might come at the cost of additional staffing; however, we utilized an upper threshold on the number of physicians that can be staffed in the ED for a day. Weekly physician staffing schedules for both policies were generated such that a MipGap of < 3% was attained. Figure 4 below represents the average hourly patient arrivals and physician availability for the week under the two generated schedules and the baseline policy.

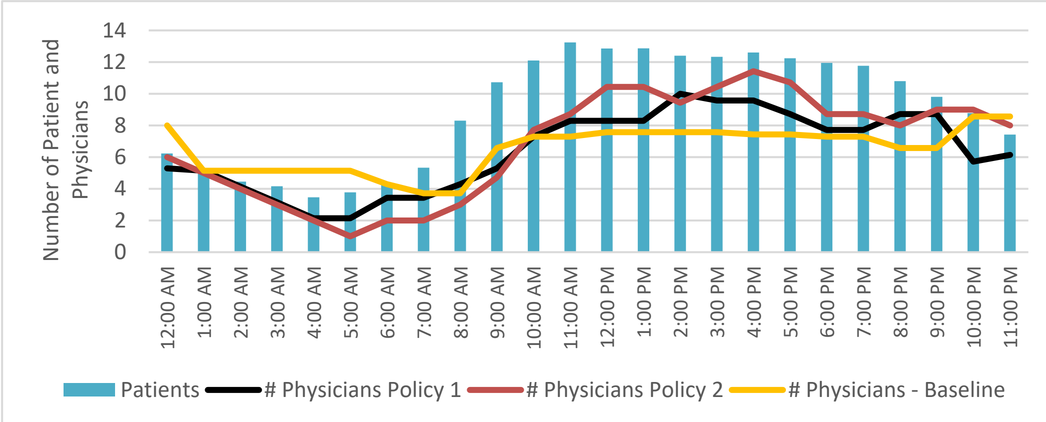

Figure 4: Hourly patient and physician availability in the ED.

From Figure 4 above, it can be clearly identified how the schedules generated using the MILP model staffs the ED compared to the baseline policy. The baseline policy aims to maintain a steady physician availability throughout the day with more physicians during the peak hours (8:00 am - 9:00 pm) and fewer physicians during the non-peak hours. However, both MILP models staff the ED in a dynamic manner considering the patient arrivals with a comparatively higher physician availability during the peak hours and lesser physicians during the non-peak hours.

Table 2: Weekly physician shift start times.

Time	Baseline	Policy 1	Policy 2
12:00 AM	0	8	7
1:00 AM	0	0	0
2:00 AM	0	0	0
3:00 AM	0	0	0
4:00 AM	0	0	0
5:00 AM	0	0	0
6:00 AM	0	9	7
7:00 AM	22	7	0
8:00 AM	4	14	14
9:00 AM	20	7	12
10:00 AM	5	14	21
11:00 AM	0	7	7
12:00 PM	2	0	12
1:00 PM	0	0	0
2:00 PM	0	21	0
3:00 PM	21	4	7
4:00 PM	4	14	21
5:00 PM	20	1	7
6:00 PM	0	7	7
7:00 PM	0	7	7
8:00 PM	0	7	7
9:00 PM	0	0	7
10:00 PM	15	0	0
11:00 PM	21	7	0
Total Shifts	134	134	143

Additionally, from Table 2 above, which represents the physician shift start times for the week, it can be noted that compared to the baseline policy, the other two policies staff more physicians during the peak hours. Further, it can be observed that the two new policies use an overlapping approach to start shifts rather than starting most of the shifts at the same time. For example, in the baseline policy, most physicians start their shift at 7:00 am, 9:00 am, 5:00 pm, and 11:00 pm, whereas the shifts are staggered for the other two policies. Further, it can be observed that policy 2 staffs more physicians as here handoffs are penalized significantly higher than the first policy. However, considering only the total number of shifts does not capture staffing cost, as some shifts are longer than 8 hours in the baseline policy. To ensure that handoffs are not minimized by overstaffing the ED, we compared the full-time equivalents (FTEs) under two new policies to the baseline policy. Although policy 1 reduced the FTE requirements by 5.2%, the FTE requirements increased by 1.4% under policy 2.

After generating the schedules, the next step was to test the two new policies along with the baseline policy in the validated simulation model. We used three ED performance metrics to compare the model performance: throughput, patient time in the ED, and the number of handoffs. The first two metrics evaluate the patient flow, and the third metric evaluates patient safety. All the three policies were simulated in the model for a three-week schedule and replicated until the margin of error on time in the ED metric was ± 10 minutes (at $\alpha=0.05$). From Table 3 below, it can be observed that both the new policies outperform the baseline policies. To comprehend if these differences were statistically significant, we conducted an independent ANOVA and observed that weekly throughput did not vary significantly among the three policies (p-value >0.05). It is imperative that the throughput will not vary significantly as the simulation model uses historical data and with a limited patient arrival. However, both handoffs per day and patient time in the ED were not the same (p-value = .01) for the three policies, suggesting a significant difference among at least one of the policies. To identify which groups varied significantly, we performed a Tukey post-hoc test and observed that both handoffs and patient time in the ED varied significantly (p-value < 0.05) for the two policies compared to the baseline policy. Compared to the baseline policy, policy 1 reduced the patient time in the ED by 10.2% and handoffs by 14.0% at a 5.2% reduction of FTE. Further, policy 2 reduced the patient time in the ED by 27.0% and handoffs by 25.9% at a 1.4% increase of FTE compared to the baseline policy.

Table 3: Simulation model results.

Policy	Weekly Throughput	# handoffs per day	Time in the ED (mins)
Baseline	1496	93	216
Policy 1	1504	80	194
Policy 2	1509	69	158

Finally, comparing policies 1 and 2, we observed that each performance metric varied significantly (p-vale < 0.05) among these two policies suggesting that policy 2 improves the patient safety and patient flow the best. However, it should be noted that the 17.5% reduction in patient time in the ED and 13.8% decrease in handoffs comes at the cost of a 6.7% increase in FTE requirements.

6 CONCLUSIONS

Emergency Department crowding is a public health issue as well as a patient safety issue, and optimal staffing of an ED is a crucial factor in ensuring smooth patient flow and improving patient safety. Prior studies have made significant contributions to improve patient flow; however, very few studies have accounted for patient safety as a performance metric to evaluate the ED. Although transfer of patient care from one physician to another is unavoidable in some instances, it is crucial to minimize these handoffs in the ED to improve patient safety.

On comparing two optimal policies to the current practices, we observed that patient time in the ED and handoffs can be potentially reduced by 27.0% and 25.9% with minimal increase in FTEs. We also generated another policy that can reduce patient time in the ED and handoffs by 14.0% and 5.2% with fewer FTE requirements. This study addresses the concerns of ED crowding and patient safety by introducing new staffing policies in the ED and reducing the patient wait times and handoffs. However, implementing these policies at other EDs would depend on their patient arrivals and the cost of staffing physicians, as these are critical factors that affect the schedule. Currently, we are performing additional cost-benefit analyses to comprehend which policy can best improve the ED performance considering the staffing budget. Additionally, we are working on improving the MILP formulation using a rolling-horizon approach to generate schedules for a longer time period to better prepare the ED.

One of the limitations in the current model is that we are not representing ancillary resources to the ED, including labs, radiology, consults, etc., as individual resources. However, the model still accounts for these delays. Additionally, we do not consider the provider's insurance, which could impact handoffs. In future work, we plan to include the impact of these ancillary resources and processes.

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AUTHOR BIOGRAPHIES

VISHNUNARAYAN GIRISHAN PRABHU is a PhD student in the Dept. of Industrial Engineering at Clemson University. His research interests include developing simulation models, mathematical models and utilizing predictive analytics techniques to improve healthcare operations. His email address is vgirish@clemson.edu.

KEVIN TAAFFE is the Harriet and Jerry Professor and Chair of the Dept. of Industrial Engineering at Clemson University. His teaching and research interests include the application of simulation and optimization in healthcare, production, and transportation logistics. Dr. Taaffe focuses on healthcare logistics problems that range from patient flow to operating room scheduling. He enjoys working on projects that bridge the gap between theoretical research and application. His email address is taaffe@clemson.edu.

RONALD G PIRRALLO is an emergency physician and the Vice-Chair for Academic Affairs for the Upstate Prisma Health Department of Emergency Medicine. He also holds an appointment as a Professor of Emergency Medicine at the University of South Caroline School of Medicine – Greenville. His email address is Ronald.Pirrallo@prismahealth.org.

WILLIAM JACKSON is an emergency physician and the Vice-Chair of Clinical Operations and Clinical Affairs for the Upstate Prisma Health Department of Emergency Medicine where he holds an appointment as an Assistant Professor of Emergency Medicine at the University of South Carolina, School of Medicine Greenville. His experience includes managing clinical operations, disaster preparedness, healthcare systems quality programming, managing large group practice risk, creating, and implementing ED design, and developing innovations in patient care delivery. His email address is William.Jackson@prismahealth.org.

MICHAEL RAMSAY is an emergency physician in the Department of Emergency Medicine at PRISMA Health Greenville Memorial Hospital. His email address is Michael.Ramsay@prismahealth.org.