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OPTIMIZING EMERGENCY DEPARTMENT THROUGHPUT: A DISCRETE EVENT SIMULATION STUDY TO MITIGATE THE IMPACT OF IMMINENT PATIENT VOLUME INCREASES AT STANDALONE EMERGENCY DEPARTMENT

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ABSTRACT

This study optimized resource allocation in a standalone Emergency Department projected to experience a 10-30% patient volume increase. Combining data analysis, interviews, and process mapping, a Discrete Event Simulation model was created in Simio, replicating patient flow. The model revealed the ED could manage a 20% volume surge with minor staffing adjustments while maintaining current resources. At 20% increased volume, key metrics such as door-to-provider and treat-and-release times increased to 18 and 200 minutes, surpassing 2023 results by 38% and 12%, respectively. However, exceeding 20% led to an 87% utilization rate for nighttime nurses, creating a potential bottleneck. Minor staffing adjustments mitigated increased treat-and-release times under moderate volume surges, and the site used simulation optimization results to add an 8-hour shift of provider support in the Sunday nighttime hours. This framework offers valuable insights for other EDs anticipating similar challenges, enabling proactive resource management and process optimization.

1 INTRODUCTION

Due to changing factors in the surrounding healthcare landscape, a standalone Emergency Department (ED) in Lower Manhattan anticipates a substantial increase in patient volume. To prepare for the anticipated 10-30% volume increase relative to 2023, we employed discrete event simulation (DES) to model the ED's operational response to various patient volume scenarios. The purpose of this study is to optimize resource allocation to enhance (or at least maintain) high-quality care and efficient patient flow during times of increased demand.

Combining patient-level data analysis and statistical distributions with qualitative information gathered through in-depth interviews, along with process mapping techniques, the team modeled the operational impacts of increased patient volume due to changing community resources. This comprehensive approach was applied to model the ED patient flow under various volume scenarios in a DES model using Simio software. The simulation's baseline results replicated the patient journey and were statistically validated, enabling an analysis of staff utilization and patient wait times for both baseline and alternative scenarios.

The framework developed in this study offers a novel DES approach that specifically addresses an anticipated volume surge driven by changing environmental factors, focusing on proactive, cost-effective, resource-based strategies rather than testing reactive crowding solutions, conducting general sensitivity analyses, or exploring process changes. This model offers staff-centric analysis, linking operational metrics to workforce sustainability. It also supports time-varying optimization and granular adjustments, where smaller, low budget shifts lead to statistically significant improvements. Additionally, it provides greater hour-by-hour precision compared to similar studies. Hybrid validation, combining quantitative statistical validation with qualitative staff feedback, ensures sustainable improvements and effective Change

Management. Overall, these innovations offer a replicable framework for EDs anticipating demographic or structural changes, balancing quantitative rigor with operational feasibility.

Section 2 of this paper reviews the relevant literature on ED process improvement methodologies, focusing on strategies employed to address increasing patient volumes. Section 3 details the methodology of this study, including process mapping, data collection and analysis, model development, and validation. Section 4 presents the results of the simulation experiments, including the baseline scenario, sensitivity analysis, and optimization experiments. Section 5 discusses the key findings, their implications for the studied ED and other similar facilities, and limitations of the study. Finally, Section 6 concludes the paper by summarizing the key contributions and highlighting areas for future research.

2 LITERATURE REVIEW

EDs face significant challenges in delivering high-quality care amid increasing patient volumes and limited resources. This review examines process improvement methodologies applied in EDs experiencing volume increases and compares them with the current study's approach.

Several studies highlight the role of system-wide surge planning and coordinated protocols in managing unexpected volume spikes. Massey (2023) implemented hospital-wide surge plans activating early discharges, reviewing elective surgeries, and utilizing overflow areas during capacity crises, cutting ED boarding times by 50%. Anarki et al. (2022) strengthened this by integrating real-time occupancy tracking and tiered response protocols, enabling dynamic resource reallocation and faster door-to-provider times during high volumes. Such systems align with Mostafa and El-Atawi (2024), which linked ED occupancy above 85-90% to delays and safety risks, emphasizing the need for predefined escalation. Michael et al. (2019) found that physician-led intake models reduced door-to-provider times by 25 minutes and ED Length of Stay (LOS) by 36 minutes, showcasing operational tweaks that absorb surges without adding physical capacity. These studies show that multidisciplinary surge protocols and real-time coordination can mitigate crowding effects.

Lean methods have been used to effectively streamline ED workflows and eliminate waste during demand surges. Kenny et al. (2004) implemented a Lean intervention post-pandemic that cut ED LOS by 9% and reduced the rate of patients leaving before complete treatment by almost 30%. A study from Massachusetts General Hospital (White et al., 2014) used Fast Track to shorten ED LOS by 15 minutes and increased the rate of discharge in under one hour by 2.8%. Fuerter (2018) cited a 30% drop in ED LOS and slashed patient "left without being seen" rates from 6.5% to 0.3%. These results demonstrate Len's strength in improving flow without major resource increases.

Lean Six Sigma applications combine waste reduction with defect and variation control to boost ED efficiency and efficacy. Daly et. al (2001) introduced real-time dashboards, cutting data access time from 9 minutes per case to immediate availability, supporting faster decisions during peaks. Chmielewski et al. (2021) standardized front-end triage across six hospitals, improving door-to-triage, door-to-provider, and ED LOS across the system with varying results by site. The American Hospital Association (2008) cited St. Vincent's Hospital in Florida reducing LOS from 413 to 286 minutes in two years after a Six Sigma project tackling ED wait times.

Simulation has a long history in ED research, modeling patient flow and resource allocation to test improvements before implementation. Early foundational work by Sinreich and Marmor (2004) established adaptable ED simulation tools, emphasizing the development of flexible frameworks applicable across multiple hospital settings with default parameter values to reduce implementation complexity. Their analysis highlighted that patients are better characterized by patient type (Internal, Surgical, Orthopedic) rather than by other hospital characteristics, enabling broad applicability of simulation models. Komashie and Mousavi (2005) demonstrated how Discrete Event Simulation via Arena could highlight bottlenecks, proving that resource reallocation rather than adding beds could cut waiting times by 20% at a major metropolitan ED. Ahmed and Alkhamis (2009) further integrated simulation with formal optimization techniques, boosting throughput by 28% and cutting wait time by 40% via systematic resource allocation optimization at a Kuwaiti federal hospital.

Integrated care models extend DES applications by combining traditional ED service with alternative care models. Mes and Bruens (2012) uses DES to validate a model of ED treatment to test the usage of an "Integrated Emergency Post" (IEP) system, which combines the classic ED with a General Practitioner's Post. Mes et al. (2021) further uses DES to test the usage of the IEP, concluding that IEP reduces overcrowding in the ED only when paired with capacitive changes such as triage nursing and ED physician staffing modifications. Borgman et al. (2014) focused on process changes within an IEP system as well as staffing considerations, calculating the correlation of various resource and process interventions and their interactions with each other to reduction in ED LOS, highlighting the optimal combinations of interventions to reduce ED LOS. The three studies have similarities with this paper in that DES is used to test the impact of staffing modifications to improve ED operations. However, the approach and results diverge in that this study focuses on modeling for a proposed future state scenario with higher patient volume and no process changes, maintaining the current state due to quickly changing environmental factors. Alternatively, these three studies test the impact of an implemented system in the IEP, distinguishing various degrees of success corresponding to not only the staffing model, but also ED design/process changes.

Staffing adjustments specifically tailored to volume increases can significantly alleviate congestion without expanding facilities. Khare et al. (2008) employed simulation to model staffing, identifying a 7-minute increase in ED LOS when the census increases 15%. Like the current study, Khare validated models against historical data, ensuring predictive accuracy for key metrics like door-to-provider and ED LOS or Treat-and-Release (T&R). Both studies emphasize targeting staffing adjustments over physical expansion to mitigate ED LOS increases. The current study builds on this by incorporating multi-modal data integration, combining analysis from 35,000 patient records with staff interviews to model time-varying arrival patterns and triage-specific pathways. This study also extends beyond physician staffing to nurses and patient care technicians, capturing utilization peaks and optimal shift additions for the anticipated 10-30% increased patient volume.

Algorithmic tools represent another advancement in ED optimization and help refine prioritization and triage for busy EDs. Ashour and Okudan Kremer (2013) developed a Fuzzy Analytic Hierarchy Process with Multi-Attribute Utility Theory (FAHP-MAUT) that incorporates multiple patient factors to generate quantitative rankings that reduces bias and outperforms the classic Emergency Severity Index (ESI) for less acute patients in terms of timely treatment. While different in focus, this study shares the method of using a validated simulation to guide proactive staffing decision, contributing to a shift towards predictive capacity planning in emergency care.

3 METHODS

Our methodology combined quantitative data analysis with qualitative insights to build a comprehensive and validated DES model.

3.1 Process Mapping

We initiated the project by developing a comprehensive Swimlane process map. This involved a series of meetings with staff representing all roles impacting patient flow, including physicians, nurses, patient care technicians (PCTs), and registration staff. The collaborative nature of this process ensured that the map accurately captured the nuances of patient journeys through the ED, including key decision points, handoffs between staff, and potential challenges and delays. The full map consists of more than fifty process steps, fifteen decision points, ten rows or "swim lanes" representing the unique staff groups, and up to thirty different handoffs of the patient or patient information. These process steps and decision points informed the build of the simulation model logic and identified measurement points for data collection, analysis, and statistical distribution for model customization.

3.2 Data Collection and Analysis

We obtained detailed patient-level data for the full year of 2023, encompassing approximately 35,000 patient encounters. This data included timestamps for critical process steps, arrival modes Emergency

Medical Services (EMS) or Walk-ins (presenting into the Emergency Room), triage level (also known as Emergency Severity Index or ESI), tests performed, and locations occupied for each patient. To understand patient flow dynamics, identify patterns, and derive realistic distributions for patient interarrival times, patient volume was analyzed as depicted in Figure 1. Although the turnaround time (TAT) or ED LOS each ESI level is different the pattern remains similar between days of the week as shown in Figure 2 There was also a significant difference between the TAT for EMS vs. Walk-in patients, including within each ESI level (p=0.000). Based on these initial data analysis, 10 distinct patient types are identified, two arrival modes with the five ESI levels, with varying arrival rate per hour of the day. The same logic is applied for service time distributions of each process.

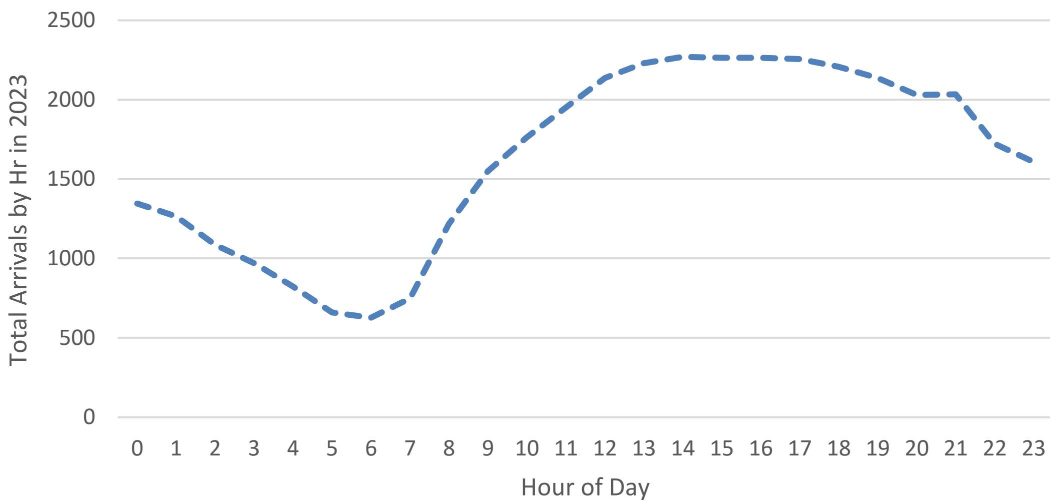

Figure 1: Patient arrival volume in 2023 by hour of arrival in a day.

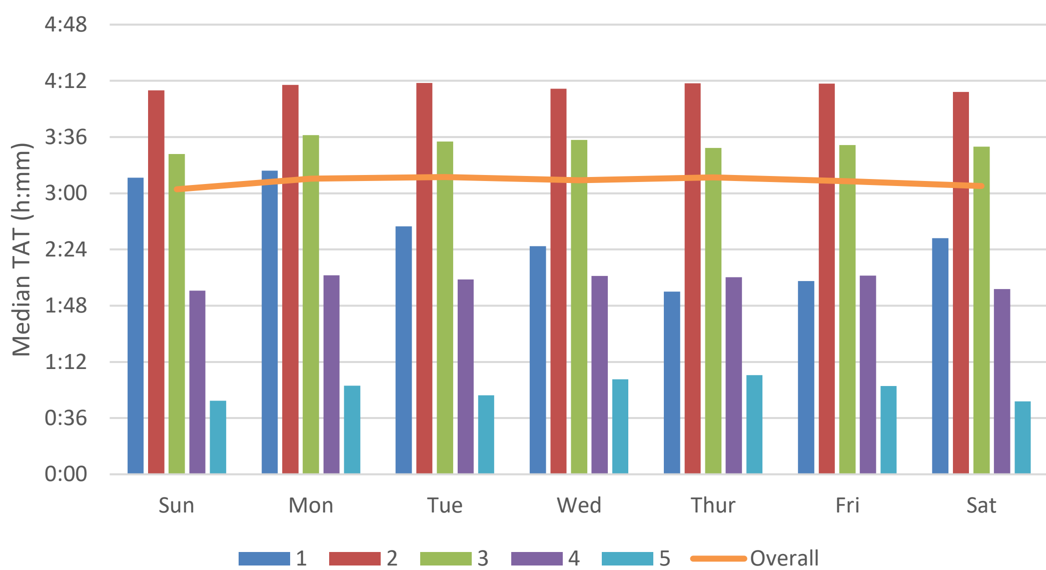

Figure 2: Median turnaround time (TAT) by ESI (colored) and day of week (labeled on X-axis).

3.3 Model Development in Simio

Using the logic defined in our process mapping sessions, as well as the analysis available from the 2023 data pull, we used Simio simulation software to build a DES model that replicated the ED's operations.

Distinct patient entity types flow through various process steps based on their arrival mode and triage level. The volume of Walk-in triage level 1 was too low for significant customization, totaling .02% of all patients, those patients' data was included with the EMS triage level 1 patients. EMS triage levels 1-5 and Walk-in triage levels 2-5 were used to build and run the model. The model included:

- Time-varying patient arrival rates by hour of day and patient type.
- Service time distributions for each process step of patient care as examples as shown in Figure 3.
    - Top 5% of each distribution trimmed due to potential documentation error.
- Routing logic and probabilities as shown in Table 1 consistent with our data analysis.
- Potential outputs such as T&R, patients left without being seen, admit, or transfers.
- Scheduling logic for ED staff and clinicians including weekly rotations and breaks

Pt Type	Distribution	Parameters
EMSt1	Log-Logistic	3.11, 3.78
EMSt2	Pearson VI	14.2, 8.88, 2.27
EMSt3	Pearson VI	17.2, 7.54, 1.57
EMSt4	Pearson VI	14.3, 9.69, 2.19
EMSt5	Triangular	1.00, 1.87, 7.34
WALKt2	Pearson VI	18.6, 6.88, 1.27
WALKt3	Lognormal	1.24, .407
WALKt4	Pearson VI	20.5, 7.53, 1.05
WALKt5	Johnson SB	3.94, 1.83, 0, 20.0

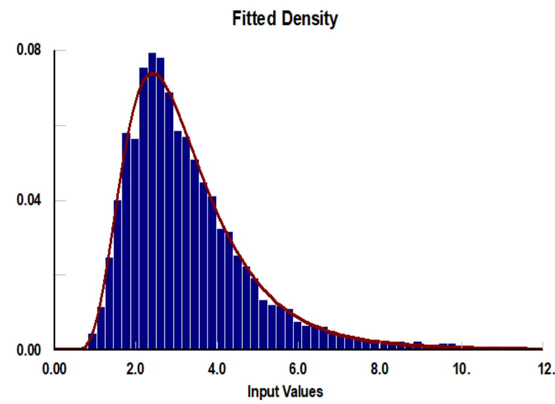

Figure 3: Includes both the table on the left and corresponding example of a distribution curve on the right. The table shown in the Figure contains processing time distributions for EMS Triage.

Table 1: Table containing probabilities for patient routing including patient bed locations.

Patient Type	EMS Triage	Walk-in Triage	Chair	Exam Room	Hallway	Elope	Resus	Triage Reg
EMSt1	100%	0%	0.0%	9.6%	0.0%	0.0%	90.4%	36.4%
EMSt2	100%	0%	4.6%	52.2%	41.8%	0.8%	0.5%	17.0%
WALKt2	0%	100%	12.9%	53.7%	32.2%	0.8%	0.4%	21.4%
EMSt3	100%	0%	21.5%	42.4%	35.3%	0.8%	0.0%	20.0%
WALKt3	0%	100%	37.7%	35.8%	25.6%	0.9%	0.0%	28.4%
EMSt4	100%	0%	71.5%	12.0%	13.6%	2.9%	0.0%	23.8%
WALKt4	0%	100%	81.7%	8.2%	5.3%	4.7%	0.0%	29.8%
EMSt5	100%	0%	48.3%	5.4%	6.1%	40.1%	0.0%	33.1%
WALKt5	0%	100%	58.9%	3.0%	2.5%	35.6%	0.0%	32.1%

The customizations result in each patient type having distinct probabilities for corresponding processing tasks and pathways, distinct processing times per task, appropriate staff processing each patient step. Figure 4 shows an example of a patient in an Exam Room "server" receiving an EKG. Each patient has a probability of an EKG being performed defined by type, and the processing time is selected from a fitted distribution on the row data as seen in Figure 4. An available PCT processes the patient, moving to the Exam Room to process. After the EKG is performed, or if a patient does not receive an EKG, the sequence would proceed with the first RN visit and subsequent tasks asigned for the patients in that path.

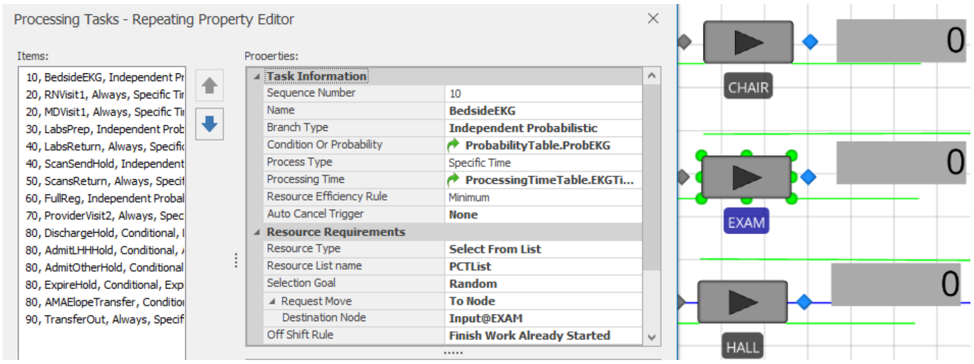

Figure 4: Exam room task processing logic and sequence.

3.4 Model Validation

To ensure the accuracy and reliability of our model, we rigorously validated it against the 2023 input data. Performing fifty replications of one-year (365 day) simulations, we compared key performance indicators of treat-and-release/patient TAT time and patient throughput against the observed values using moods median tests. The simulation did not incorporate any warm-up, since the first day accounts for just 0.27% of the simulation period, which is well within the 95% confidence interval under which the validation is performed. Additionally, the relatively quick TAT of entities (<4 hours) and very low arrival volumes during the 12am-7am hours result in very minimal queues during those off-peak times, which implies even less statistical impact. As shown in Table 2, all P-values, except for the P-value from the TAT moods median test for EMSt1 (EMS arrival, triage level 1), are greater than 0.05, indicating no statistically significant difference between the simulation output and the actual data. Although a statistical difference was observed for EMSt1, this can be attributed to the small sample size, high variability in processing times, and the conservative nature of the simulation results, which allocated more time than necessary for these more acute patients. Despite this difference, the variation was practically acceptable and does not impact the validity of the conclusions drawn. This high level of agreement gave us confidence in the model's ability to accurately represent the ED's operations and predict the impact of potential changes.

Table 2: Model validation for Patient TAT / treat-and-release time.

Patient Type	2023 Avg TAT (Hrs)	50 one-yr Sim Avg (Hrs)	Percent Difference	Minutes Difference	P-Value
EMSt1	2.169	2.673	23.26%	*30.3*	*0.000*
EMSt2	3.558	3.554	-0.12%	-0.3	0.292
EMSt3	2.968	2.964	-0.14%	-0.2	0.338
EMSt4	1.885	1.889	0.23%	0.3	0.336
EMSt5	0.814	0.810	-0.53%	-0.3	0.657
WALKt2	3.123	3.120	-0.10%	-0.2	0.333
WALKt3	2.968	2.962	-0.12%	-0.2	0.184
WALKt4	2.009	2.009	-0.02%	0.0	0.881
WALKt5	0.939	0.939	0.01%	0.0	0.986

4 RESULTS

Given the validation of the model, the simulated model was used to measure baseline statistics such as process time, queue length and time, staff and resource utilization, overall patient TAT/T&R time, and patient throughput. Further, additional patients were added to the model to predict constraint points in preparation for an impending volume increase. Each experiment run contained ten replications of 365-day simulations.

Model optimization statistics were selected based on patient experience, site operational value, staff engagement, and capability of measurement. Thus, the following metrics were prioritized: door to doctor assigned, door to doctor seen, T&R by patient outcome, and staff utilization broken by shift. Variation in staff schedule per shift was significantly changing bedside nurse (RN), PCT, and provider (combining MD and ACP roles) utilization in the baseline.

4.1 Baseline Scenario

The baseline simulation, representing the 2023 operational performance, showed an average D2D (in this model defined as time of Registration to time of Provider Assignment) of 14.9 minutes and an average treat-and-release time of 173.5 minutes, compared to goal times of 14 minutes and 180 minutes and 2023 results of 13 minutes and 179 minutes, respectively. Staff utilization is within acceptable ranges, below the recommended safe utilization threshold of 80%.

4.2 Sensitivity Analysis: Impact of Increased Patient Volume

There was an estimate for a potential 10-30% increase in patient volume relative to 2023, so the model was run with various experiments testing the additional percentages of patients in 5% increasing intervals. As patient volume increased in the simulation experiments, we observed a corresponding increase in utilization of the clinical staff, notably the PM shift bedside nurses (RN pm) and the PM shift ACPs and MDs (Prov PM) reached critical levels at around a 20% volume increase as seen in Figure 5, indicating potential staffing shortages and burnout if the patient influx materializes to this level.

10 Sim Avg	**Utilization**										
Patient Increase	RN am	**RN pm**	RN Mid	Prov PM	**Prov PM**	Prov Swing	MD Swing	PCT AM	PCT AM	Triage AM	Triage PM
Baseline	60%	71%	55%	64%	64%	62%	62%	58%	44%	41%	26%
10%	65%	79%	60%	69%	72%	68%	68%	63%	49%	45%	29%
15%	67%	*82%*	63%	72%	*75%*	71%	71%	65%	51%	47%	30%
20%	70%	**87%**	65%	*75%*	*79%*	74%	74%	68%	54%	49%	31%
25%	74%	**91%**	68%	*78%*	**82%**	*77%*	*77%*	70%	56%	51%	33%
30%	*76%*	**95%**	71%	**81%**	**86%**	**80%**	**80%**	73%	59%	53%	34%

Figure 5: Heat map displaying simulated staff utilization rates by incremental volume increases.

At a 20% volume increase, the average D2D time reached 18.6 minutes, and the T&R time increased to 200.3 minutes (Figure 6). These findings confirmed our initial concerns that the increased patient load would significantly impact throughput times, exceeding the ED's target goals of 14 minutes for D2D and 180 minutes for T&R at all patient volume increases. Note that there is an additional statistic of "Door to Doc Seen", distinct from the goal D2D that measures the time to Provider assignment, which the simulation can measure but is not used by the site due to documentation limitations in the electronic medical record.

10 Sim Avg	**Goal Times (minutes)**			**Patient Outcomes**		
Patient Increase	**Door to Doc Assign (D2D)**	*Door to Doc Seen**	**Treat & Release (T&R)**	Admissions to Partner Hospital	Discharges	Other Admissions
Baseline	14.9	27.5	173.5	3170	31943	768
10%	*16.5*	33.4	*183.6*	3487	35033	849
15%	*17.5*	37.4	*190.2*	3674	36620	867
20%	*18.6*	43.2	*200.3*	3832	38255	901
25%	*19.8*	50.5	*211.8*	3951	39840	960
30%	*21.4*	60.5	*226.3*	4126	41417	995

Figure 6: Heat Map displaying simulated goal times and patient transfers by volume increases.

4.3 Optimization Experiments and Results

To identify effective strategies for mitigating the impact of the patient surge, we conducted a series of optimization experiments within the Simio model. These experiments focused on adjusting staffing levels and shift times without major changes requiring minimum additional budgets for both bedside RNs and providers with a maximum 20% increase in patient volume to maintain acceptable staff utilization, throughput, and turnaround times.

4.3.1 Bedside RN Optimization

We tested various combinations of additional RN shifts, focusing on peak hours. Our findings indicated that the addition of a 10am-10pm RN shift had the most significant impact, reducing the average T&R time by approximately 3 minutes. Combining this with an additional 2pm-2am shift yielded further improvement, with a total T&R reduction of 5 minutes. Adding shifts during other times had less pronounced effects.

Table 3: Table showing results of simulation for additional 12-hour nursing shifts.

Scenario	10-10 RN	12-12 RN	2-2 RN	4-4 RN	AM RN (8a-8p)	PM RN (8p-8a)	Avg T&R (min)	P-Value
No Change	-	-	-	-	-	-	200.27	-
1 (add 2)	-	1	-	-	1	-	195.61	.006
2 (add 2)	1	-	1	-	-	-	195.85	.002
3 (add 1)	1	-	-	-	-	-	197.19	.016

4.3.2 Sunday Provider Optimization (12-hour shifts)

We explored adding 12-hour provider shifts on Sundays, given the greater patient volume to staff ratio that day. The most effective addition was a 2pm-2am provider, with an average T&R reduction of over four minutes. Adding 12pm-12am provider also improved results, especially when paired with other staff adds.

Table 4: Table showing results of simulation for additional 12-hour Sunday provider shifts.

Scenario	10-10 Pr	12-12 Pr	2-2 Pr	4-4 Pr	Avg T&R (min)	P-Value
No Change	-	-	-	-	200.27	-
A (add 2)	-	1	1	-	194.76	.000
B (add 2)	1	1	-	-	195.51	.001
C (add 1)	-	-	1	-	196.10	.003

4.3.3 Sunday Provider Optimization (8-hour shifts)

Recognizing that 8-hour provider shifts might be more feasible to implement, we ran experiments with various 8-hour provider shift additions on Sundays. A 6pm-2am shift consistently emerged as the most effective single 8-hour addition, aligning with our observations from the 12-hour shift experiments and indicating a critical need for provider coverage during these hours. The 4pm-12pm Provider (*as eventually piloted by the site) makes improvement, but not as strong as the 6pm-2am Provider.

Table 5: Table showing results of simulation for additional 8-hour Sunday provider shifts.

Scenario	10-6 Pr	12-8 Pr	2-10 Pr	4-12 Pr	6-2 Pr	Avg T&R (min)	P-Value
No Change	-	-	-	-	-	200.27	-
D (add 2)	1	-	-	-	1	194.30	.000
E (add 2)	-	-	1	-	1	196.86	.009
F (add 1)	-	-	-	-	1	197.38	.048
F.1 (add 1) *	-	-	-	1	-	198.20	.066

4.3.4 Expanding 6pm-2am Evening Provider Coverage

Based on the consistent identification of the 6pm-2am period as a critical need, we tested adding 6pm-2am provider coverage to other days of the week. Thursday followed by Tuesday emerged as the most beneficial days for this additional coverage. These results reinforced the importance of aligning staffing resources with patient volume fluctuations throughout the week.

Table 6: Table showing results of simulation for addition of 6pm-2am provider shifts by day of week.

Scenario	Su	M	Tu	W	Th	F	Sa	Avg T&R (min)	P-Value
No Change	-	-	-	-	-	-	-	200.27	-
G (add 2)	-	-	1	-	1	-	-	193.81	.000
H (add 2)	1	-	1	-	-	-	-	195.08	.000
J (add 1)	-	-	-	-	1	-	-	197.23	.041

4.3.5 Combined Optimization Strategies

Finally, we evaluated the combined impact of RN and provider additions. Combining the most impactful individual additions (10am-10pm RN, 2pm-2am RN, and 6pm-2am providers on Sunday, Tuesday, and Thursday) produced the largest reductions in T&R, closer to the ED target goal of 180 minutes.

Table 7: Table with combined staffing optimization strategies.

Scenario	Avg T&R (min)	P-Value
No Change	200.27	-
G3 (Tuesday and Thursday 6pm Provider, 10am RN)	195.62	.064
H2 (Sunday and Tuesday 6pm Provider, 10am and 2pm RN)	*188.16*	**.000**
H3 (Sunday and Tuesday 6pm Provider, 10am RN)	191.41	.000

5 DISCUSSION

Our findings demonstrated the value of DES in proactively addressing ED capacity challenges. The Simio model provided a robust platform for replicating existing operations, predicting the impact of increased patient volume, and evaluating the effectiveness of various staffing interventions. The model's validation against historical data further strengthens the reliability of our findings and buy-in from stakeholders. The optimization experiments revealed that targeted staffing adjustments during peak hours can significantly mitigate increases in patient turnaround times and surge events, ultimately helping the ED maintain a higher quality of service during this anticipated period of higher volume. While adjustments to bed allocation did not significantly impact throughput times, the results support minor staffing additions as being impactful and effective improvements to be made.

In conjunction with the model results and identified constraint of Sunday night provider shifts, the site decided to implement an additional 8-hour shift from 4pm-12am on Sundays. Though only the second most optimal Sunday coverage option, the site found that the 4-12 coverage was a more appealing and practical shift time range for staff to fulfill and still provides support for the most constrained time range on Sundays between late night and early morning. The site also factored the potential constraint on Tuesdays and Thursdays into their support and surge coverage planning. No additional consistent nursing shifts were planned, but the site used the simulation results to monitor the realized patient influx.

For this model, we did not test any process changes to remedy the bottlenecks inherent to the baseline process. There may be opportunities for further improvement with a shift of the baseline structure, but this model focuses on maintaining baseline operations under higher patient demand and cannot quantify baseline improvement opportunities. An example of DES methods testing process flow changes can be seen in a study from Norouzzadeh et al. (2014), where a focus on flow changes can help identify streamline opportunities for admitted patient flow.

Opportunities for model improvements exist in future replications of similar applications. During subsequent DES model development for alternative projects, a feature within Simio software called “Input Parameters” was discovered, which would have greatly streamlined the process of distribution fitting for variable processing times during the model build. Instead of copying the 2023 data from our data source, transferring to a distribution fitting software, and manually programming the distribution into the Simio tables, the Input Parameter feature allows direct pasting into Simio data tables, in which Simio can read, develop, and output an even more precise distribution for the input data. Additional lessons learned about defining and capturing key ED metrics in the simulation have been leveraged to streamline model build and project delivery time for future ED simulations with varying scopes.

6 CONCLUSION

This study leveraged discrete event simulation (DES) to model the operational impact of a projected 10-30% patient volume increase at a standalone Emergency Department (ED) necessitated by shifts in the surrounding healthcare landscape. The validated Simio model, informed by a rich dataset of 35,000 patient encounters, various staff interviews, and detailed process mapping, provided a robust platform for replicating and analyzing patient flow. The model revealed that the ED could accommodate up to a 20% surge in patient volume with minor staffing adjustments while maintaining existing physical resources. However, exceeding this threshold resulted in an 87% utilization rate for nighttime (8pm-8am) nurses, highlighting a critical bottleneck and the potential for negative impacts on staff well-being. Further, key performance indicators, such as door-to-provider (D2D) and treat-and-release (T&R) times, decreased under increased patient loads, exceeding the ED’s targets of 14 and 180 minutes and 2023 performance of 13 minutes and 179 minutes.

The simulation experiments demonstrated that strategically targeted staffing adjustments, particularly during peak hours and on Sundays, could effectively mitigate the negative impact of moderate volume surges on T&R times. Optimization experiments revealed that the addition of specific RN and provider shifts, especially during evening and overnight hours, yielded the most significant improvements of 4-6% reduction in T&R/ED LOS. Informed by these findings, the ED implemented an additional 8-hour provider shift from 4pm to 12am on Sundays, reducing full week T&R by 2 minutes and alleviating the Sunday night strain. While not the single most optimal solution identified by the model, this shift addressed the most critical constraint period while also considering staff preferences and operational feasibility. The insights from the simulation also informed surge planning for Tuesdays and Thursdays, allowing the ED to prepare for potential bottlenecks on those days.

This study contributes a practical and replicable framework for other EDs anticipating similar capacity challenges. The integrated approach, combining quantitative data analysis with qualitative insights, provides a holistic understanding of ED operations and enables the development of tailored staffing solutions. The model's focus on granular, time-varying adjustments allows for cost-effective interventions that can significantly improve patient flow and staff utilization without requiring substantial capital investments. Furthermore, the proactive nature of the study, addressing anticipated volume increases rather than reacting to existing overcrowding, empowers EDs to implement preemptive strategies to maintain quality of care and staff well-being amidst changing demands. Future research could explore the integration of process improvement initiatives within the DES framework to identify further opportunities for optimizing ED throughput and enhancing patient care.

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