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MEASURING EMERGENCY DEPARTMENT RESILIENCE TO DEMAND SURGE: A DISCRETE-EVENT SIMULATION FRAMEWORK

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ABSTRACT

This research explores the resilience components in emergency departments (EDs) during surges through discrete-event simulation (DES). By focusing on the resistance and recoverability components, the resilience of the ED is analyzed, as well as the flow of the patient and the resources required at each step. A simulation is developed to model an ED in the UAE and validated through collected timestamps. The results demonstrate the ordinary conditions of the ED and its calculated resilience, recoverability, and resistance, as well as its strength under conditions of surge demand. To investigate the impact of resources on the ED's resilience, the resilience triangle is analyzed, and different interventions are applied by adding physicians, nurses, and beds and their effects. The methodology and simulation model provide significant insights to ED managers to evaluate and improve their department's resilience during surges and emergencies.

1 INTRODUCTION

Emergency departments (EDs) around the world face the problem of overcrowding, causing delays in patient care (McKenna et al. 2019). Research on overcrowding in EDs is widespread and earlier studies identified various factors such as poor department design, capacity issues, staffing, ancillary service performance, and flow processes (Uriarte et al. 2017).

In general, overcrowding is summarized as an imbalance between supply and demand (Sartini et al. 2022). This can result in longer wait times for physicians, consultations, diagnosis, treatment, transfer or discharge, delays in patient care (sick patients), boarding (Salway et al. 2017), extended hospital stays (longer length of stay (LOS)), increased morbidity and mortality (Savioli et al. 2022), reduced quality of care and medical errors, patients leaving without being seen, and decreased overall patient satisfaction (Sartini et al. 2022). Therefore, overcrowding can have negative consequences on the overall emergency healthcare system.

In hospitals, resilience is critical to managing peak capacity and large amounts of demand during times of crisis or disaster. The strength of an ED is determined by its ability to anticipate, prepare for, and respond to these situations. The surge capacity of an ED is its ability to handle an increase in patient volume beyond its typical operating capacity. This requires planning to quickly mobilize additional resources, including staff, equipment, and supplies, to meet the increase in demand. To build resilience in the face of increased capacity and high demand, hospitals should focus on several key areas, including planning and preparation, resource management, and communication and coordination. By focusing on these areas, EDs can build resilience to handle large demand during emergencies and disasters.

This study aims to develop a simulation model for an ED in the UAE and to use it to analyze the resilience of the ED to the surge in demand. The study aims to understand the different factors that affect the strength of the ED, such as the availability of resources and the functionality of the components, and to identify potential interventions to improve the resilience of the ED.

The remainder of the paper is organized as follows. Section 2 overviews how demand surge (overcrowding) problems have been approached in the literature, and the contribution is defined. Then, Section 3 presents the conceptual model and simulation models of the ED. Section 4 discusses the experimental results. Finally, Section 5 summarizes the managerial implications, limitations, and future work.

2 BACKGROUND AND LITERATURE REVIEW

The issue of overcrowding has been widely discussed in the literature, and various definitions and perspectives have been proposed to describe this phenomenon. Different institutes define the definitions of crowding in the ED (Savioli et al. 2022). The American College of Emergency Physicians defines overcrowding as: “A situation that occurs when the identified need for emergency services exceeds available resources for patient care in ED, hospital, or both” (American College of Emergency Physicians 2013). An updated iteration of this definition was also subsequently published online in 2019. In general, the definitions indicate a state where the resources are inadequate to cater to the needs of all patients. In other words, when demand (patients) exceeds supply (resources), the ED is overcrowded. Moreover, ED crowding is a hospital-wide problem; other departments must cooperate to avoid it.

Another problem hospitals face is surge capacity, which can be defined as the point at which patient volumes or clinical needs exceed hospital services capacity (Hasan et al. 2022; Farahmandnia et al. 2017). This can happen anytime due to various hazards, from infectious disease outbreaks to mass casualty incidents (MCIs). Surge events can last from days to weeks, or even months. The ability of hospitals to provide medical care during sudden increases in patient volumes or disasters is crucial.

The variety of crowding measures cause a problem in research, and merging more than one factor measured in the ED converges into a crowding score. Equation (1) represents the National emergency department overcrowding study (NEDOCS), which is a tool developed in 2004 in the USA (Weiss et al. 2004; Ahalt et al. 2018; Davis et al. 2020). Different ED factors are considered in the regression model to measure crowding. The dependent variable is the score, which is calculated between 0 and 200. If the score is between 101 and 140, the ED is considered overcrowded; between 141 and 180 severely overcrowded; and > 180 dangerously crowded. The advantage of NEDOCS over other scores is that it does not include physician data that is not easily saved or accounted for.

$$NEDOCS = 85.8 * \frac{M}{B_T} + 600 * \frac{B_A}{B_h} + 5.64 * W + 0.93 * A_{time} + R_h * \beta \tag{1}$$

- M - Number of ED patients (Occupied beds)
- B_T - Number of ED Beds
- B_A - Number of ED admits
- B_h - Number of inpatient beds
- W - Last triage-to-bed time
- A_{time} - Longest admit time
- R_h - Number of critical care patients
- β - Value set between 13.4 and 20

Davis et al. (2020) utilized NEDOCS to investigate the resilience of disasters at the component level. The study commenced by incorporating the concept of the resilience triangle, which was initially introduced in a study conducted in 2003 (Bruneau et al. 2003). In their research, the authors defined “robustness” as the ability of the system to resist initial loss caused by disruption and “rapidity” as the speed at which the system can recover. Davis et al. (2020) adopted this perspective of different resilience dimensions, but slightly adjusted the terminology to clarify the current context. "Resistance" was defined as the ability to withstand loss of system functionality, and "recoverability" represents the time required to return to normal system functionality. Regarding the resilience triangle depicted in Figure 1, a more resistant system results in a smaller decline in the vertical dimension (Davis et al. 2020). Similarly, a system with enhanced recoverability leads to a reduced recovery time in the horizontal dimension. The forecasted level of resilience is determined by computing the normalized area under the quality curve for a standardized time interval of $T*$. This measure considers that a system with more excellent resistance or recoverability will result in a smaller resilience triangle and, consequently, in a higher degree of resilience. Figure 1 represents a case where the loss is immediate at time t_0, and the recovery is linear with a duration of T.

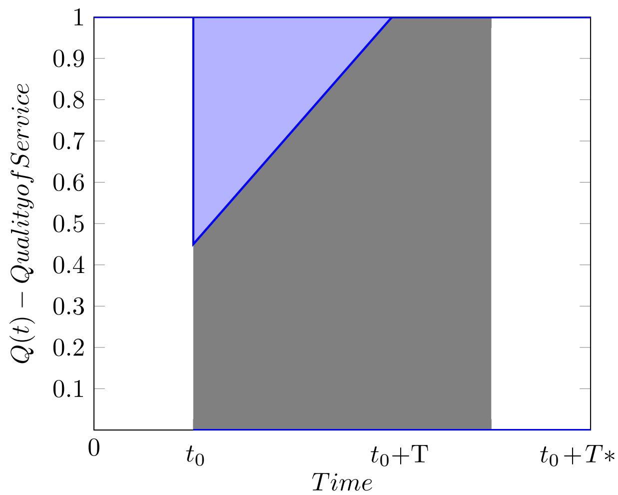


Figure 1: Predicted resilience adapted from (Davis et al. 2020).

The research findings of Davis et al. (2020) comprehensively analyze the NEDOCS score, delineating its functionality and the functionality of the components. To improve the efficiency of the ED, it is necessary to invert and rescale the NEDOCS scores, exemplified by Equation (2). Rescaling ensures that an increase in functionality indicates an improvement in the ability to function efficiently. Equation (3) calculates the functionality of the residual component of the ED with respect to the number of beds occupied.

$$\text{Functionality} = 1 - \left(\frac{\text{NEDOCS Score}}{\text{Historical Max NEDOCS Score}}\right) \tag{2}$$

$$\text{Component Functionality} = 1 - \left(\frac{\text{Total number of patients in the ED occupying beds}}{\text{Historical Max Total number of patients in the ED occupying beds}}\right) \tag{3}$$

The use of discrete-event simulation (DES) to simulate MCIs in EDs has previously been explored. Research has been conducted by formulating a simulation-optimization approach to measure ED resilience in times of crisis, in which seven crisis scenarios and one scenario of the ED system in a normal situation are simulated, with interarrival times acting as the driver of workload (Farahi and Salimifard 2021). An optimization model determines the optimal configuration to improve the resilience of healthcare. Additionally, research was conducted in a hospital in Italy to simulate unusual conditions in an ED that cause a sudden increase in patient arrivals (Fava et al. 2022). The main aim is to reduce waiting times and improve service quality through extensive scenario analyses to define emergency plans to be activated in the event of mass casualty disasters.

The ED and other outpatient clinics are included in the DES in evaluating the seismic resilience index for healthcare facilities. Using Anylogic 8, changes in patient waiting time before and after the earthquake are predicted (Niazi et al. 2021). The authors proposed a plan to increase the system's resiliency and reduce waiting times by up to 35%. Another method focuses on the ED infrastructure and measures a quantified performance value, which is the waiting time (Favier et al. 2019). Depending on their injury, the pathways of patients inside the ED are modeled using DES and the accumulated waiting time is calculated and considered in the risk management of the essential ED infrastructure.

Finally, other tools can be merged with DES to cope with MCI. For instance, DES and system dynamics were used to assess adaptive resource allocation strategies of different hospitals in responding to an MCI, with the primary goal of improving the resilience of the ED during demand surges (Faccincani et al. 2022). A set of performance metrics was developed to assess the effectiveness of healthcare delivery and the spikes in MCI events. The authors provide a robust and reliable approach, practical strategies, and new perspectives to complete plans for dealing with MCIs.

Despite the availability of DES utilization in the context of ED and MCI, the literature on this topic still needs to be improved in terms of examining the constituent elements of resilience through the use of DES. Specifically, the resistance and recoverability of resilience have not yet been thoroughly investigated. This new understanding of resilience expands on previous ideas by allowing us to look more closely at the different aspects, allowing for more detailed analysis and a better understanding of disasters. Additionally, the functionality of these components within EDs and the development of a resilience triangle based on data generated from DES simulations have not yet been fully explored. To address these gaps, current research aims to investigate these aspects of resilience in the context of EDs. Doing so can achieve a more detailed analysis and understanding of disasters, particularly in organizational resilience.

3 METHODOLOGY

This methodology involves developing a conceptual model based on the patient pathway and using it to create a simulation model for testing different scenarios and measuring the ED's emergency response capability. The model incorporates patient flow data, staffing levels, and resource availability from the ED, and is validated against real-world data to identify areas for improvement.

3.1 Conceptual Modeling

To conduct the research, it is necessary first to understand the flow of patients in the ED. This study measures the flow of patients from medium-acuity adult patients to the ED, excluding life-threatening cases. Figure 2 illustrates the general flow of patients, and the resources required at each step are noted after consulting a group of medical staff. The waiting times before being assigned to a bed are shown in the figure, while the waiting times for labs, doctor visits, or discharge after being transferred to a bed are not displayed, since the patient already has a bed and will wait there. Most adult patients in the ED follow one of two paths: either they move directly to a bed or are triaged or checked by a nurse prior triage due to limited availability of beds. In this study, 70% of the patients are assumed to undergo triage. The essential timestamps collected from actual data are arrive-to-doctor (AtD), arrive-to-triage (AtT) and LOS, which help to understand patient time in the ED.

3.2 Simulation Modeling

This research presents the simulation model developed using AnyLogic 8. Figure 3 shows a screenshot of the software, showcasing patient flow in the ED and identifying available resources, including doctors, nurses, and beds. The simulation enables the generation of time stamps that represent the patients' time at different points in the ED, as well as the status of the ED. These time stamps can be used to understand the performance of the ED and its allocation of resources. Additionally, simulation can also be used to

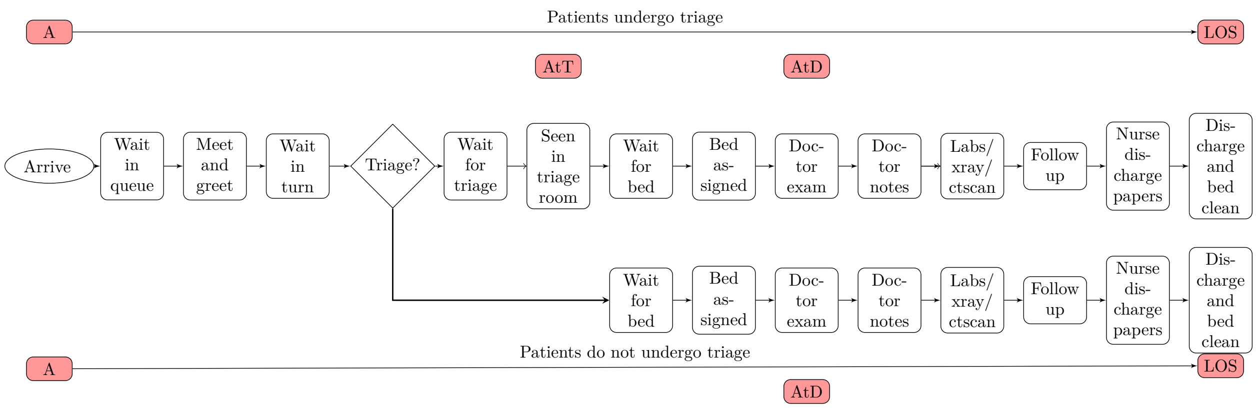


Figure 2: General adult patient flow; AtT denotes arrive-to-triage, AtD denotes arrive-to-doctor, LOS denotes length of stay.

test different scenarios and assess possible changes in ED processes and resources. Overall, the simulation model allows for a comprehensive analysis of the ED's performance and identifies areas for improvement.

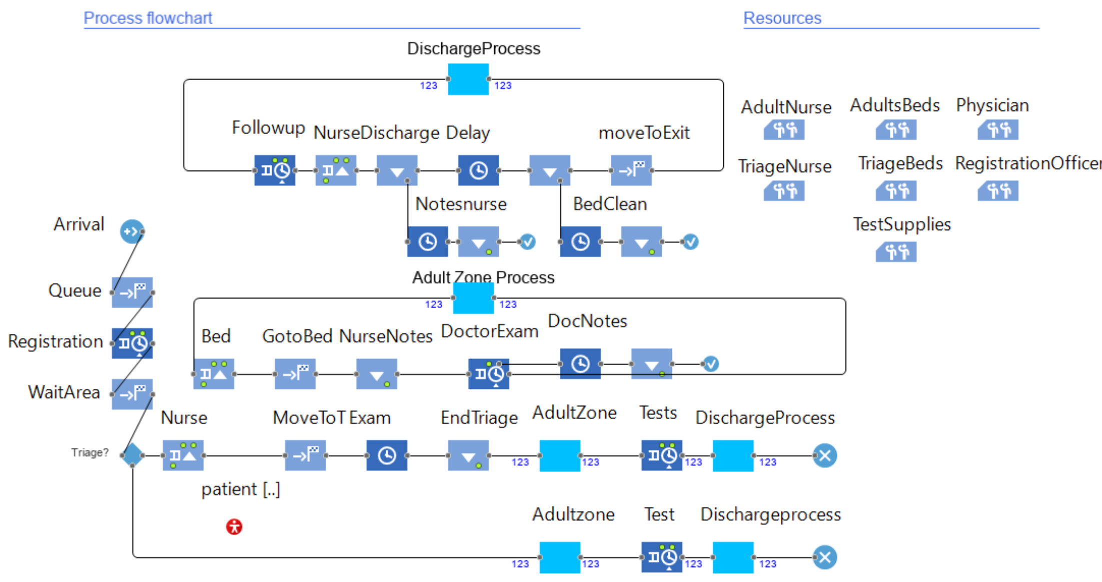


Figure 3: Anylogic view of patient flow.

3.3 Model Validation

The validation of the simulation model used in this research is a crucial step to ensure the reliability and accuracy of the obtained results. In this study, various measures were taken to verify, validate, and calibrate the model, ensuring its robustness and alignment with real-world ED operations.

To verify the model, face-to-face verification sessions were conducted with medical personnel from a UAE hospital. These sessions involved detailed discussions and evaluations of the model's representation of the ED patient flow, ensuring that it accurately captured the key operational aspects. For calibration, hospital real-time stamps were collected and integrated into the simulation model using the OptQuest Optimization Engine. This allowed for fine-tuning and adjustment of the model parameters to better reflect the actual ED environment and its dynamics.

To validate the simulation model, the service time distribution was extracted and the simulated data was compared to the actual data using the percentage difference formula (Equation 4) (Ibrahim et al. 2018). The average percentage difference over a six-month simulation period, as shown in Table 1, demonstrated a reasonably good level of agreement between the simulated and actual data.

However, it is important to acknowledge that there may be various factors contributing to the observed differences between the simulated and actual data. These factors include inherent variability in the ED operations, stochastic events that are difficult to predict, challenges in data collection and measurement, and assumptions and simplifications made during model development. These factors can introduce variations and uncertainties, which warrant further investigation to better understand their influence on the simulation model's validity.

To ensure the simulation model's validity, we inputted parameters and probability distributions carefully as the foundation for running the model. To establish a steady and stable state within the simulation, a 10-day warm-up period was incorporated in each simulation run. The 10-day warm-up period was chosen based on a thorough understanding of the ED system's unique characteristics. Operating continuously without interruptions, the ED needs this period to attain system stability. The warm-up period enabled the simulation to accurately represent patient arrival rates and resource availability, crucial for evaluating the ED's performance. During the simulation's initial phase, the simulation began at zero patients in the ED. However, transient effects, caused by system initialization or changes, could introduce deviations from steady-state behavior. To address this, a 10-day warm-up period was included in the simulation to mitigate these effects and enhance result reliability and accuracy.

$$\text{Percentage Difference} = \left| \frac{Simulated - Real}{Real} \right| \times 100 \tag{4}$$

Table 1: Mean time in minutes; LOS1 denotes length of stay of patients triaged, LOS2 denotes length of stay of patients not triaged.

Measured Variable	**Arrive-to-Triage**	**Arrive-to-Doctor**	**LOS1**	**LOS2**
6 Months (Real Data)	15	80	197	224
Multiple Simulations (Average)	15	91	233	225
Percentage Difference	0%	14%	18%	0%

3.4 Design of Experiments

Traditional analysis of NEDOCS scores provides insight into the severity of overcrowding in the ED, but fails to explain the underlying causes of its fluctuation. To gain a deeper understanding of overcrowding dynamics, this study uses an examination of component resilience using NEDOCS scores. By doing so, the study aims to identify the specific factors that contribute most significantly to the duration and severity of overcrowding. This approach equips EDs with valuable information on how to implement changes that enhance resilience and mitigate overcrowding.

The second phase of this study focuses on applying the resilience concept to the ED by analyzing its component functionality. Considering that the number of occupied beds can be easily quantified, it is considered to be more closely associated with the resistance of the system (Davis et al. 2020). On the other hand, waiting times are primarily related to throughput or delays, indicating their connection to the recoverability of the system. Therefore, Equation (5) is used to assess the recoverability of the ED, while Equation (3) is used to examine its resistance. It is important to note that in these equations, the historical maximum represents the highest value observed since the start of the simulation, thereby capturing the peak performance under normal operational conditions.

$$\text{Component Functionality} = 1 - \left(\frac{\text{Waiting time}}{\text{Historical Max Waiting time}} \right) \tag{5}$$

The derived equations enable the construction of a resilience triangle plot, which provides a holistic perspective on the overall resilience of the ED. By examining the individual elements of resilience and their respective functionality within the ED, a comprehensive understanding of the ED's resilience can be achieved. This improved understanding facilitates a more effective management of patient care and resource allocation during times of disaster.

The initial simulation model is carefully constructed to accurately depict the normal operating conditions of the ED, effectively simulating the average patient demand experienced. To ensure the model accurately captures the dynamics of the ED system, multiple runs are performed, incorporating a warm-up period to account for the system's standard conditions and stabilize the simulation. Figure 4 visually presents the arrival rates observed during normal operating conditions, providing valuable information on the expected flow patterns of the patient. To further assess the resilience of the ED and its ability to handle extreme scenarios, the simulation model is modified to simulate a single-day peak arrival scenario. This scenario represents an MCI where there is a significant surge in patient arrivals, creating a large influx of people entering the ED. The impact of this surge is reflected in the simulation by showcasing a second arrival pattern in Figure 4. This modification allows the simulation model to accurately reflect the increased demand and resource pressures experienced during surge events or crowd-level disasters.

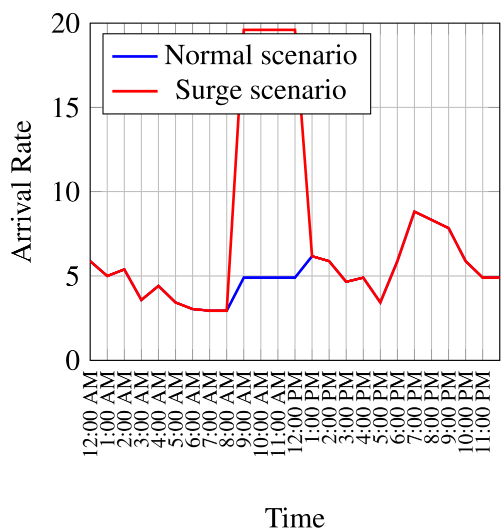


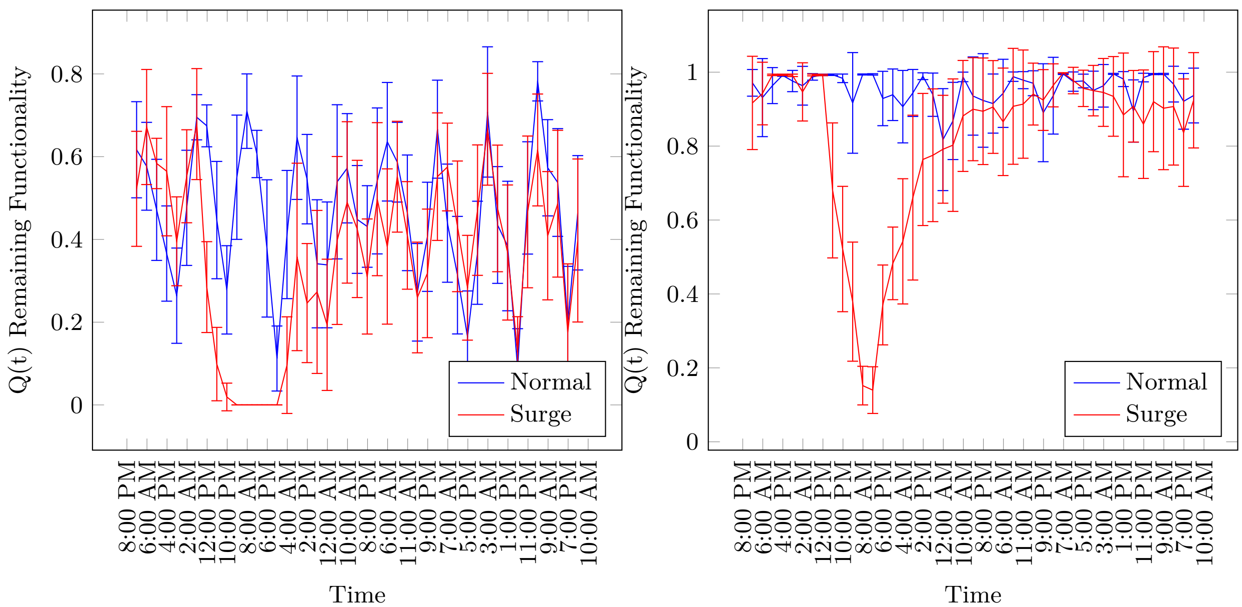
Figure 4: Comparison of the daily arrival rate per hour of patients over time in normal and surge scenarios.

The resulting data obtained from the simulation model and analysis are then analyzed and plotted. The objective is to track the duration required for the ED to recover and return to normal conditions, effectively measuring the time needed for it to revert to its pre-surge state. This analysis provides valuable information on the resilience of the ED in handling peak arrival scenarios and informs strategies to enhance its ability to respond effectively to such events.

4 EXPERIMENTAL RESULTS

This section presents numerical and simulation results of the methodology used in this study. The findings of the simulation model used to measure the resilience of the ED based on the flow and arrival rates of different patients are discussed. First, a simulation was conducted to assess the impact of surge demand on the ED. Specifically, the simulation considered a high rate of 40 patients per hour for 4 hours, followed by a medium rate of 25 patients per hour for 2 hours. The simulation recorded the number of beds occupied in the ED every 10 minutes. Ten simulation runs were performed, and a 90% confidence interval was calculated for each experiment. Using Equation (3), the functionality of the components was plotted and presented in Figure 5a. Since the number of beds is assumed to remain constant and all beds are occupied, the resulting graph appears rectangular with zero repetition.

Additionally, the waiting time for patients was recorded, and the triage-to-bed wait time was calculated using Equation (5). This represents the time patients wait after triage until they receive a bed. Due to the limited number of beds in the hospital, this waiting time can be long, leading to patient frustration. Once patients have a bed, they can sleep and feel more assured, so the threshold for waiting is likely to be higher. The functionality of this component was plotted and presented in Figure 5b. Since the maximum waiting time is variable, the resulting graph appears triangular. Figure 5 illustrates the resilience of the system in the event of a disaster.



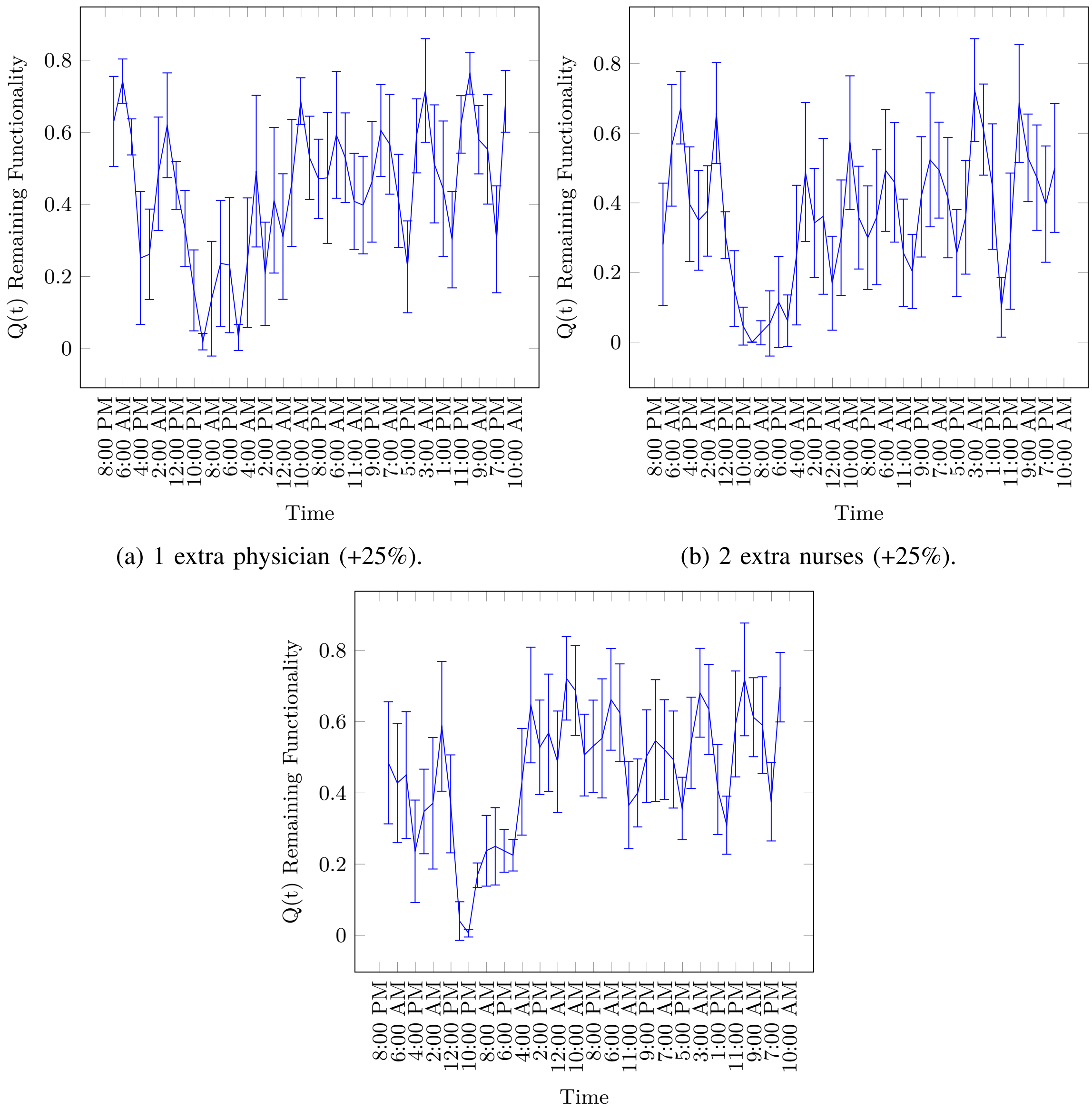
(a) (b)

Figure 5: Emergency resilience profile with disaster-level crowding and no scheduled interventions. (a) Resistance profile: remaining functionality of the "bed occupation" component. (b) Recoverability profile: remaining functionality of the "waiting time" component.

Additionally, the study aimed to investigate the potential impact of various resources on reducing the time required for the system to return to normal conditions. To explore the impact of resource interventions on the system's resilience, simulations were conducted by changing the availability of resources, physicians, nurses, and beds, by 25% in every experiment to understand their individual effects.

Equations (3) and (5) were used to calculate the component functionality plots for each scenario, similar to previous work done without any intervention. For the resistance component of this study, the resulting plots of adding beds, nurses, and physicians are presented in Figure 6. Similarly, the recoverabilty element was also calculated using Equation (5) and plotted in Figure 7.

Furthermore, to determine the predicted resilience of the system, the area under the curve is calculated and divided by the area under the curve assuming normal conditions. This enables the measurement of the system's component resilience and its changes in different scenarios. The simulation-generated results of these calculations are summarized in Table 2, indicating that beds and physicians are crucial factors that



(a) 1 extra physician (+25%).

(b) 2 extra nurses (+25%).

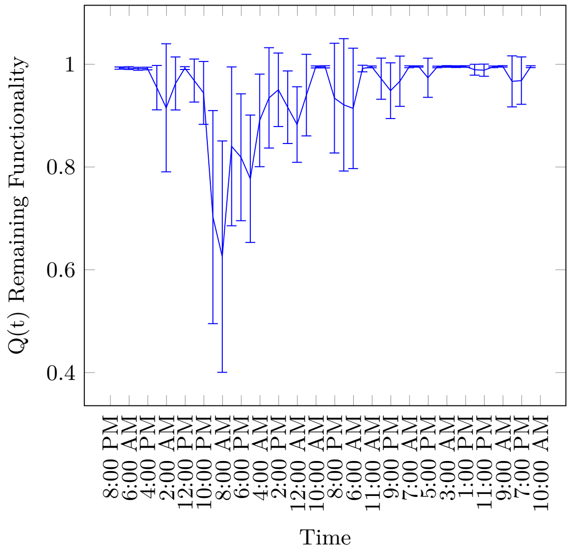
(c) 6 extra beds (+25%).

Figure 6: Resistance profile; remaining functionality of the "bed occupation" component.

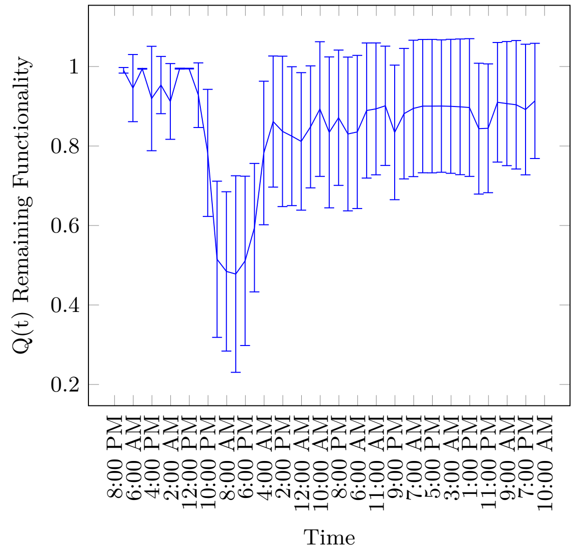
can enhance throughput and improve the recoverability and resistance components of the system, ultimately contributing to overall resilience.

5 CONCLUSION AND FUTURE PERSPECTIVE

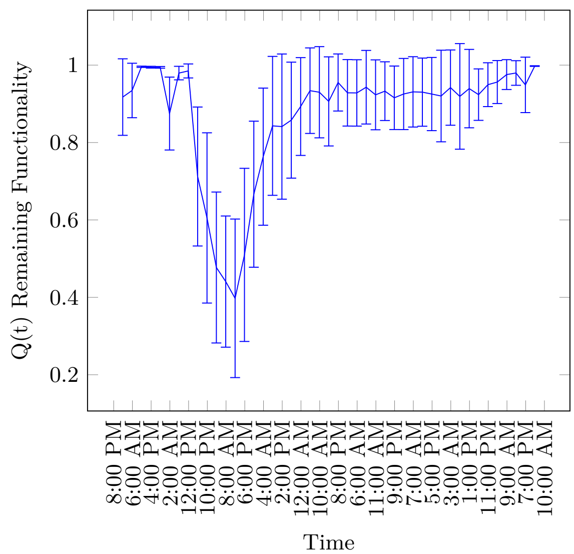
The findings of this study have significant managerial implications for improving the resilience of EDs in response to peak arrivals or surge demands. The developed DES model provides valuable information for managers to comprehensively understand the resilience of the ED system. This knowledge can guide resource allocation decisions and the development of surge response plans, ensuring that the ED is adequately prepared to handle future surge demands. Furthermore, managers can take a holistic approach to system



(a) 1 extra physician (+25%).



(b) 2 extra nurses (+25%).



(c) 6 extra beds (+25%).

Figure 7: Recoverability profile; remaining functionality of the “waiting time” component.

Table 2: Component predicted resilience at different scenarios.

Scenario	**Component predicted resistance and recoverability**	
	Resistance: Occupied beds	Recoverability: Waiting time
Normal schedule	0.10	0.65
1 extra physician (+25%)	0.40	0.85
2 extra nurses (+25%)	0.17	0.73
6 extra beds (+25%)	0.47	0.83

design considering the impact of potential changes on staff scheduling, thus improving overall resilience and promoting improved patient outcomes and organizational efficiency.

This research introduces a methodology that uses simulation modeling to study the resilience of the ED and facilitate the development of emergency response plans for hospital managers. Patient flow and resource requirements were illustrated at each step of the ED process, and engineering principles were applied to assess the ED's ability to withstand surge demands. The simulation model was developed using AnyLogic 8 software and calibrated using real-time stamps obtained from a hospital in the UAE.

The results of the simulation model were presented under normal conditions and during peak demand, revealing that the ED takes considerable time to recover to normal conditions without intervention. Furthermore, the impact of resource additions, such as physicians, nurses, and beds, on the resilience of the ED was investigated. The increase in the number of physicians and beds was found to have a more pronounced effect on reducing recovery time compared to the increase in the number of nurses.

These findings have practical implications for ED managers and policy makers, allowing them to assess the resilience of their ED and identify interventions that can strengthen resilience in the face of increased demand or other disruptions. However, this study has certain limitations that pave the way for future research. First, the simulation model used in this study is specific to the hospital setting investigated and patient flow, which may limit its generalizability to other locations. Furthermore, this work focuses solely on the effects of resource additions on system resilience, without considering the possible impacts of altering patient flow or introducing new system tracks. Resource allocation is only one aspect, and other strategies, such as changes in patient flow and a comprehensive understanding of the entire hospital setting, should be explored and tested using DES before implementation in real-life scenarios. Lastly, future research should explore the effects of broader changes in patient flow on system resilience and perform a comprehensive evaluation of the general crowding score using DES.

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