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A New Look at Patient Waiting Time in an Australian Emergency Department using Simulation

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Abstract

Emergency Department (ED) is an important part of a hospital that provides 24-hour emergency care to patient who need immediate attention. However, long waiting times are common in this environment which can negatively impact patients' health and experiences. This study aimed to simulates the system operations of an ED in an Australian hospital using the Arena simulation software to identify where the patients may experience long waiting times, find pilot test solutions, supporting hospital administrator's decision-making in operation and improve efficiency**.** This study uses the data from government public websites and educated randomly generated data (dummy data) to simulate the system operations. Discrete event simulation, using Arena simulation software (version 16.10), was used to model the current operating system, simulate patients' movements through various zones of ED and optimise waiting times. Five ED zones are defined to reflect the severity of a patient's illness: Resuscitation (T1), Emergency (T2), Urgent (T3), Semi-Urgent (T4) and Non-Urgent (T5). Two simulation models were created, and the analysis found that: On weekends, nurses in the Acute care zone were fully utilised whereas nurses in Resuscitation had low utilisation during weekdays. Moreover, rostering one additional nurse from Resuscitation to the Acute care zone on busier days of the week (Friday, Saturday) generated improvements in patient waiting times, across all hours (except for 7pm, additional 28 seconds (3%)). The greatest improvement in waiting time was at 7am (8.33 minutes). This change subsequently the improved length of stay (LOS) for most patients

(T2-T5) in the improved model (scenario 2). However, T1 patients experienced a slight increase in LOS this amounted to 4 hours and 41 minutes. The use of discrete event simulation software plays a significant role in assisting hospital management teams to identify system operation issues and solutions to improve patient outcomes and experiences. We have identified that efficient rostering of nursing staff as a key to improve the long wait times during busy times-frames of the ED. Further research using authentic real-time data is needed to validate this finding.

Keywords: Discrete Event Simulation, Systems Operation Research, Emergency Department

INTRODUCTION

Health service provisions are influenced by the political, economic, and social contributions of a country. In 2018, the percentage of Gross Domestic Product (GDP) for health care in Australia was 10% [1]. Providing quality health care requires efficiency in provisions to ensure services meet the needs of Australian people. For this to occur, regular evaluation of existing system operations is important to ensure efficiency and thus best possible outcomes for patients and staff [2].

As ED provides 24-hour emergency care services, seven days a week to sick or injured patients arriving independently or by ambulance, requiring the health conditions to be stabilised as acute or major, before transferring to other areas of the hospital for further treatment and/or discharge [4]. Decision-making in relation to how urgently a patient needs to be admitted can be more complex compared to general hospital admissions in other areas of a hospital. A prompt decision-making process is needed, these as patients may have life-threatening conditions that are unstable and may result in morbidity. Triage refers to a health assessment process to undertake patients as they arrive at a service site to determine the degrees of urgency for immediate care, and to prioritise the order of treatment of many patients in Emergency Department (EDs) [5]. Once a patient had entered an ED, many care decisions to take at several points as the patient progresses through the ED pathways of care system. Delays at any stage of this process, including calling for emergency assistance, can negatively impact on patient health outcomes and experiences [5]. For example, a delay in physician response time, or a shortage of beds can cause blockages in patient flow resulting in delays in patients receiving timely needed care. These types of scenarios demonstrate the necessity for EDs to continually strive to improve service provision through system analysis review to identify areas for improvement and regulate the patient flow through the ED.

The Australian Institute of Health and Welfare provide annual reports relating to the activities occurring in EDs in Australia. This shows crowding and delaying in public hospitals due to an increased inpatient demand increase the pressure on the health care system. For example, between 2014-15 to 2018-19 there was an annual demand in increase of 3.2% on EDs in Australia [3]. This rate reduced slightly by 1.4% in 2019-2020 due to COVID 19 restrictions, and overall, the median LOS increased by 16.7 minutes for the same period [3]. These findings are illustrated in the following Figure 1.

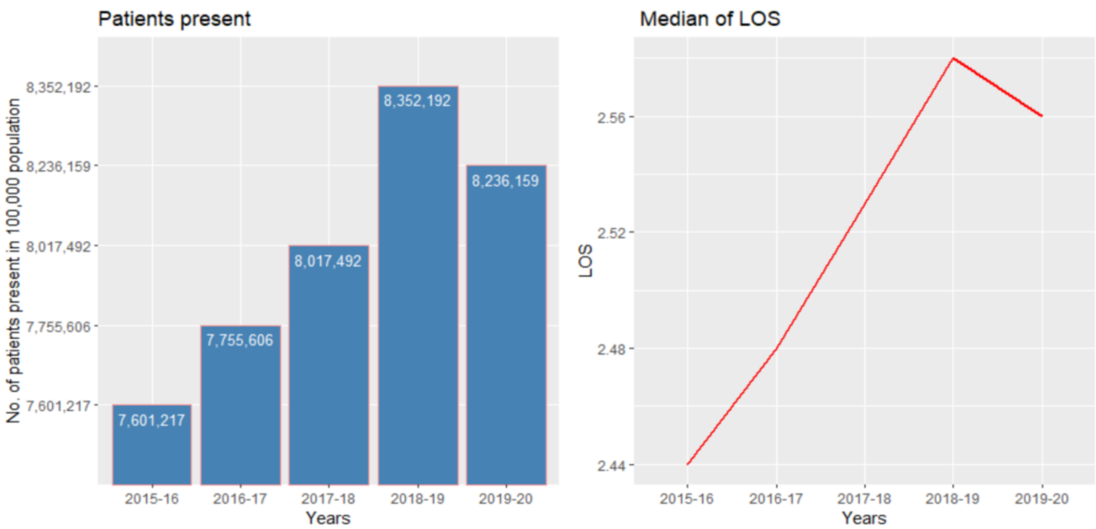

Figure 1: Number of patients present per 100,000 population and median LOS in Australia from 2015 to 2020. (Source adapted from AIHW Emergency Department presentation by state and Territory 2025-16-2019-2020 [1]**.**

Optimising the use of ED resources to improve the patient LOS is a key focus of several researchers in this field [6,7,8,9]. Multi-phase Describe Event Simulation (MDES) framework has been used to model an ED with the aim of developing improvement strategies for assessment [8,9]. These researchers concluded, the introduction of a triage system to categorise patients according to the severity of their presenting condition, adding a doctor to filter admissions and redirecting patients to priority outpatient care, produced greater efficiency, use of recourses and reductions in LOS for patients [8,9]. In contrast, Easter et al. [6] reduced patient LOS (mean 175.2 minutes), maximised bed usage (5.02 patients/bed/day) and by utilising an intake physician who split the intake of patients between two internal waiting areas. They demonstrated that “both physical design and flow type were statistically significant predictors of outcomes of interest (p-value < 0.0001)” [6, p.2186]. While the current study has considered prioritising the triage area based on patient’s condition, the study undertaken by Khanna et al. [7] in South Australia, designed a MDES model to establish efficient discharge targets. Using the National Emergency Access Target (NEAT) as their ED performance measure, they established that when 80% of patients were discharged by 11am, this produced maximum improvements in patients flow and reduced bed occupancy by 1.5%. This increased their NEAT compliance by 16%, and reduced waiting times for beds by 25% [7]. Using queuing theory Haghighinejad et al. [10] simulated the effect of increasing bed occupancy on patient length of stay in an Iranian hospital ED [10]. Running the simulations for 30 days consecutively, they found that all ED levels in the ED were overcrowded (34-50% of patients were serviced beyond the capacity of each care area in the ED). They concluded that while LOS can generate some improvements, it does not eliminate bed occupancy issues, increasing bed capacity by more than double the ED current capacity and establishing a holding unit would eliminate overcrowding. Collectively, the findings of these studies demonstrate the benefits of utilising MDES modelling software to assist in establishing solutions for patients' waiting times and LOS issues unique to specific.

The ED at the Nepean Hospital (which is the site of this research) is experiencing a primary issue of long waiting times and long queues of its patients.

The Nepean Hospital is a teaching hospital consisting of 520-bed and is a regional trauma centre situated at the Blue Mountains in Kingswood, New South Wales (NSW). It treats over 62,000 in-patients annually and provides tertiary referral services to the Blue Mountains Local Health District. The ED purpose is to build and provides a 24 - hour service to a diverse case -mix including paediatric patients. Additional multi-specialist services include: a 24-bed intensive care unit, interventional cardiology (24 hour), haematology, trauma services, neurosurgery, thoracic surgery, urology and plastic surgery, obstetrics, and gynaecology [11].

In 2020, the ED at Nepean hospital was reported to be a large busy department that accepted around 66,887 patients that year [1,11]. In Australia, patients who attend ED are categorised into one of five triage assessment groups reflecting the severity of a patient's illness: Resuscitation (T1), Emergency (T2), Urgent (T3), Semi-Urgent (T4) and Non-Urgent (T5). According to the Bureau of Health Information of New South Wales (2021) the median LOS in ED for patients in Australian hospitals (in 2020) was up to four hours. The LOS for patients in the Nepean ED has gradually increased over the past three years and can also vary across different times of the year, see Figure 2 [12]. Note: LOS data according to the five different triage assessment groups was not available.

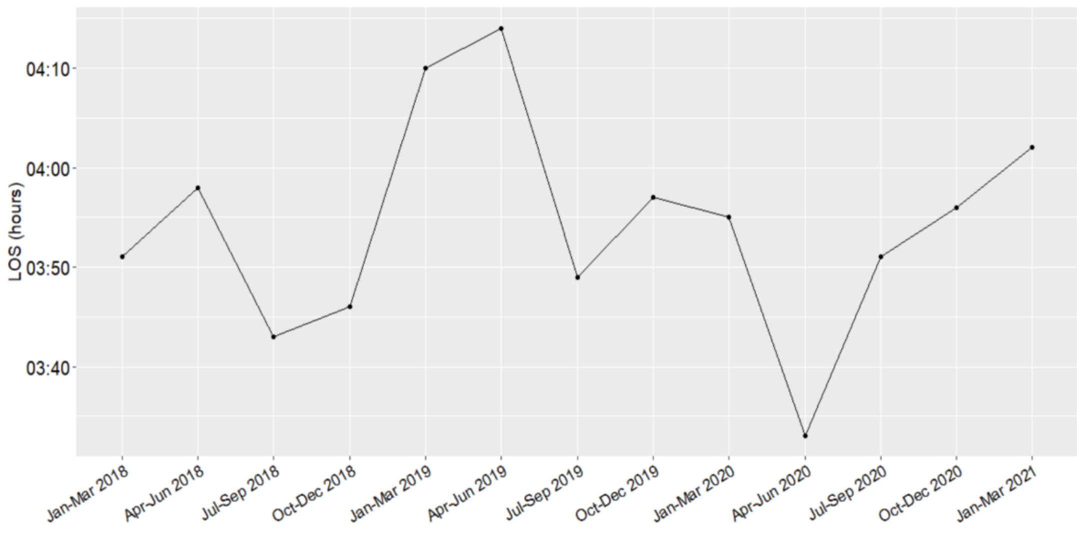

Figure 2: Patient LOS in Nepean ED Jan 2018-March 2021. (Source adapted from Bureau of health Information, 2021) [12].

ED system and boundaries

Patients can enter the ED department via ambulance entry or walk-in entry, regardless of their condition see Figure 3. Walk-in patients move directly to the registration area. A registration clerk records the patients details and registers their entry to ED prior to triage. Patients entering via ambulance move directly to the triage zone. A patient's condition is assessed by a nurse at the triage station and moves them to a relevant treatment and management zone based on the triage assessment.

There are three treatment areas in the ED, and each can deal with varying categories of patient illness: Resuscitation, Acute care, and Subacute see Figure 3. T1 patients are moved directly to the Resuscitation zone. Depending on acuity and/or if the patient is mobile, T2 patients may be sent to Recusation and/or the Acute care zone while T3 patients are sent to Acute care. If T2 and T3 patients require additional care they are sent to the Start zone. Patients in T4 and/or T5 assessed as needing care are moved to the Subacute area of ED. The triage nurse provides T1 patients priority to access the triage area for processing.

Withing the '*Diagnosis and Management"* area, patients are processed in a sequence involving the initial assessment and treatment, definitive treatment, and referral to a specialist team if required. Screening may involve pathology, radiology and review by a specialist doctor if required. A doctor, (Junior medical officers (JMOs) or an ED Registrar) then reviews the results of the patients screening tests to diagnose the patient's condition and prescribes medical treatments. Following this review the doctor my either discharge the patient from ED to home or an inpatient ward. This final decision and a medical report are completed in the patient records at this stage.

Patients who require admission are moved to '*Disposition"*. This is an observation zone in the ED to await bed availability on a ward elsewhere in the hospital. When this becomes available, the patient is then transferred to the ward for admission as an in-patient, see Figure 3.

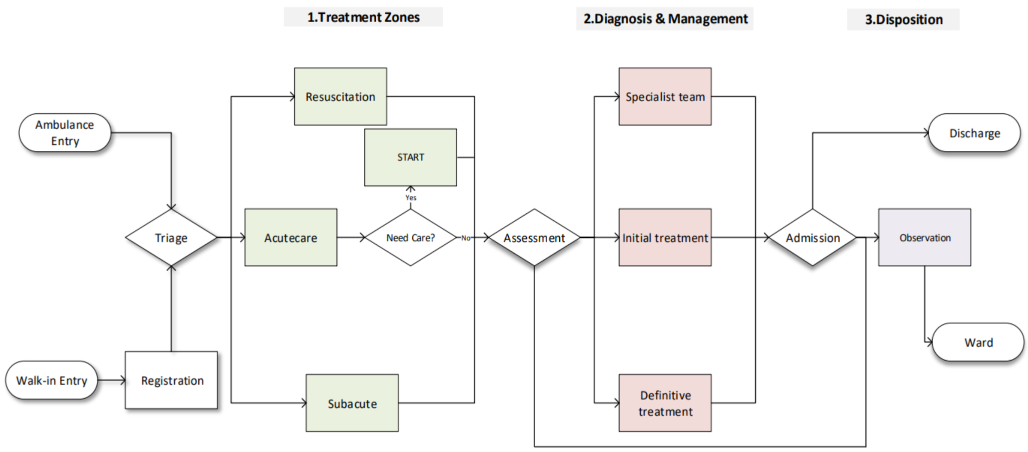

Figure 3: Layout of Nepean ED.

Modelling Methods

This study aimed to simulate the system operations of the Nepean hospital ED in NSW, to identify areas that impact patients' waiting times and bottle necks. It also aimed to improve the efficient use of available resources such as medical doctors, nurses, and beds. Two modelling methods will be presented in this paper: stochastic and discrete event simulation method.

Stochastic method

We formulated ED's aim in reducing the patients' waiting time in the ED using the stochastic integer programming model. We considered uncertainties related to the number of patients arriving in ED and how long in time, it took for the patients to receive services such as registration, triage, and entrance to the treatment zone which are of major importance in ED's. While there are numerous constraints and variables that can occur in the real-life application of an ED department, this model has focused on variables as outlined listed in (Table 1), and constraints listed below to add significant complexity for our model.

Each scenario that has been used in the optimisation model was obtained and represented by the symbol 'ω' in the distributions of the arrival and service times. Parameters, sets and decision-making variables for the model are defined in the following (Table 1).

Table 1: Definitions of parameters, sets and decision variables.

Parameters and sets	**Decision Variables:**
$\boldsymbol{p}$: Patient.	$t_{p,t}(\omega)$: Arrival time t of patient $p\epsilon\boldsymbol{P}$
$\boldsymbol{P}$: Set of patients	$e_{k,t,z}(\omega)$: The number of staff k at time $t, \forall z\epsilon\boldsymbol{Z}$
$\boldsymbol{z}$: Zone.	$g_{k,t,z}(\omega)$: The number of staff k starting at time $t, \forall k\epsilon\boldsymbol{K}, \forall z\epsilon\boldsymbol{Z}$
$\boldsymbol{Z}$: Set of all zones	$L_p(\omega)$: Random variable for LOS of patient $p\epsilon\boldsymbol{P}$
$\boldsymbol{b_n}$: maximum number of beds in zone $\boldsymbol{z\epsilon Z}$	$d_{p,t}(\omega)$: Discharge or Word time t of patient $p\epsilon\boldsymbol{P}$
$\boldsymbol{t}$: Time of event	$r_p(\omega)$: Service time of patient p in registration station
$\boldsymbol{T}$: Time of day within 24 hours	$X_p(\omega)$: Triage time of patient p in triage station
$\boldsymbol{K}$: The number of different types of staff	$y_{p,z}(\omega)$: Treatment time of patient p in $z\epsilon\boldsymbol{Z}$
$\boldsymbol{k}$: A type of staff (nurse or doctor)	$\theta_{p,n}(\omega) = \begin{Bmatrix} 1 \text{ , if Entry type } n \text{ of patient } p \text{ is walk in} \\ 0, \text{otherwise} \end{Bmatrix}$
$\boldsymbol{n}$: Entry type of patient $\boldsymbol{p\epsilon P}$	$\lambda_{p,m}(\omega) = \begin{Bmatrix} 1 \text{ , if Triage assessment } m\ of \text{ patient } p \text{ is not Resus} \\ 0, \text{otherwise} \end{Bmatrix}$
$\boldsymbol{m}$: Triage assessment of patient $\boldsymbol{p\epsilon P}$	$S_{p,t,z}(\omega) = \begin{Bmatrix} 1 \text{ , if patient } p \text{ assigent to zone } z \text{ on time } t \\ 0, \text{otherwise} \end{Bmatrix}$

Formulation:

$$\min\left\{\theta_{p,n}\lambda_{p,m}\sum_{p\,\epsilon P} r_p(\omega)+\lambda_{p,m}\sum_{p\epsilon\, P} x_p(\omega)+\sum_{z\epsilon Z}\sum_{p\epsilon P} y_{p,z}(\omega)\right\} \quad (1)$$

Subject to constraints:

$$t_{p,t}(\omega)+r_p(\omega)+x_p(\omega)+y_{p,z}(\omega)=d_{p,t}(\omega) \qquad \forall\, p\epsilon\boldsymbol{P}, \forall t\epsilon\boldsymbol{T}\,, \forall\, z\epsilon\boldsymbol{Z} \quad (2)$$

$$L_p(\omega)\geq d_{p,t}(\omega) \qquad \forall p\epsilon\boldsymbol{P}, \forall t\epsilon\boldsymbol{T} \quad (3)$$

$$t_p(\omega)\geq 0 \qquad \forall p\epsilon\boldsymbol{P} \quad (4)$$

$$\textstyle\sum_{p\in P} S_{p,t,z}(\omega)\leq b_n \qquad \forall p\epsilon\boldsymbol{P}, \forall t\epsilon\boldsymbol{T}, \forall z\epsilon\boldsymbol{Z} \quad (5)$$

$$y_{p,z}(\omega), d_{p,t}(\omega)\geq 0 \qquad \forall p\epsilon\boldsymbol{P}, t\epsilon\boldsymbol{T}, \forall z\epsilon\boldsymbol{Z} \quad (6)$$

$$S_{p,t,z}(\omega)\epsilon\{0,1\} \qquad \forall p\epsilon\boldsymbol{P}, \forall t\epsilon\boldsymbol{T}, \forall z\epsilon\boldsymbol{Z} \quad (7)$$

$$\theta_{p,n}(\omega), \lambda_{p,m}(\omega)\epsilon\{0,1\} \qquad \forall p\epsilon\boldsymbol{P} \quad (8)$$

$$e_{k,t,z}(\omega)\geq 1 \qquad \forall k\epsilon\boldsymbol{K}, \forall t\epsilon\boldsymbol{T} \quad (9)$$

$$e_{k,t,z}(\omega)\geq g_{k,t,z}(\omega)+1 \qquad \forall k\epsilon\boldsymbol{K}, \forall t\epsilon\boldsymbol{T} \quad (10)$$

The main function of this model was to build (1), a discrete-time approximation of the patient LOS gathering relevant data from all scenarios throughout. Constraint (2) represents the value of the discharge time of patient p in scenario . The discharge time $d_{p,t}(\omega)$ is equal to the arrival time $t_{p,t}(\omega)$ plus the registration time $r_p(\omega)$, triage time $x_p(\omega)$ and the treatment time $y_{p,z}(\omega)$. Constraint (3) defines the value of the LOS in each scenario. Since this needed to be minimised, $L_p(\omega)$ was set to the maximum discharge time in scenario ω which, corresponds with the discharge of the last patient. Constraint (5) limits the number of patients treated in each zone at any one time and relative to the number of available beds. Constraints (9) and (10), are operational constraints that ensure the correct members of staff from type k are working in each zone, additionally, that there is at least one staff member (doctor or nurse) from each type during every shift.

When using the stochastic integer programming model to design the ED model, transit times including the time patients spent in each zone were accounted for in the mathematical formulas. However, this modeling technique lacks feedback mechanism when patients are assigned to a bed in different zones, at varying times of day in an ED is impacted by the how busy the ED's zones can be at these times of the day. An alternative way to model ED system with feedback mechanisms is to use an operations research modelling tool such as Discrete-Event Simulation (DES). This tool has the capabilities to replicate a more accurate representation what is occurring in the system and thus, will highlight bottlenecks or blockages in the system.

Discrete-Event Simulation method

Several industries have used simulation software to model their workflows and operations for example: airlines, manufacturing, and supply chain [13]. Literature highlights the benefits of simulation software in assisting health care settings to find solutions for resource inefficiencies and supporting managerial decision-making to improve the service [14]. DES is an operations research technique that is often used to simulate scenarios within an operation system and provide analysis. It can model the intricacies of patient assignment and flow in an ED. It is also, the dominant approach used in health care simulations for single category and unit scenarios. Several authors have demonstrated its effectiveness in capturing different vitalities of interdependence, random fluctuations in patient volume and timing within discrete events [15,16]. Furthermore, it can assist in the customisations of patient assignment policies to ensure optimal patient safety through policy.

Arena simulation software 16.10 from Rockwell Automation Technology, Inc. was used to build a model that simulated patients' movement through the ED and therefore to assist in reducing patient waiting time in ED with minimum resources. Due to its compatible with several Microsoft Windows programs such as Access and Excel, Arena software is often used for the design of DES [17]. Each entity in Arena is treated individually with icons that can be used to represent each entity being processed. Visualisation of the entity's flow is achieved by monitoring the movement of the entity's icon throughout the process [17] which is an important feature of the software for debugging the model.

For these mentioned reasons, this research will utilise DES modelling to support the hospital goals in sufficient ED operation by reducing the patients' waiting time with minimum resources. Two simulation scenarios will be designed to support such goals: The first scenario represents the baseline model which is the ED's current operations system using dummy data. The second scenario tests the effect of moving resources between the ED zones. It utilises the same 'dummy data' and structure as the baseline model however, one staff resource (a nurse) was moved from the Resuscitation to the Acute care zone on the weekend only. Using Arena simulation software and **s**tatistical data obtained from the Australian Institute of Health and Welfare website were input to the simulation software to develop a baseline simulation model of the current hospital system [1]. Ethics approval was not required as data was publicly available on the AIDW website. Dummy data were used to supplement missing data required to develop the model, see (Table 2). Arrival time data of each patient will be entered once it is available to generate more accurate wait times.

Table 2: Data utilised to develop the simulation model.

Jan-Dec 2020	**Number**	**Total Number for one year**
Total number of patients for 1 year		66,887 (100%)
Total number of patients for three months	16,721 (25%)	
% Triage assessment		
T1	0.64	
T2	21.39	
T3	23.89	
T4	39.45	
T5	5.63	
Percentage of patients discharged	70	
Percentage of patients admitted as in-patient	30	
Assumed data		
Number (%) of patients entering ED via Ambulance	30	
Number (%) of patients walk into ED	70	
Arrival times data not available	0	

(Data sourced and adapted: National statistics, to simulate patient through-put in 2020 [18]).

Model resources

The ED is staffed by registered nurses/nurse practitioners and medical doctors who are at different stages of their medical career. Therefore, medical doctors can be JMO, ED registrars or a specialist ED medical doctor see (Table 3).

ED nurses are assigned to care for the patient/s carrying out assessments of vital signs, documenting the patients’ ongoing condition and conducting any immediate treatments prescribed by the doctor to promote comfort of the patient. ED nurses complete their working shift in the same zone they are assigned to at the beginning of a shift. This normally consists of two triage nurses. The Resuscitation zone has three beds. Nurse to patient staffing in this zone is based on a one-to-one basis. The Acute care section has sixteen beds staffed by four nurses. This results in a one to four, nurse to patient staffing ratio. There are two nurses in Start zone. In Subacute three nurses oversee ten beds; and three nurses work in the observation area prior to being transferred to a ward as an in-patient.

ED specialist doctors move between zones throughout the ED attending patients where needed. Doctors normally work 8- or 12-hour shifts. Newly admitted acute patients in the Resuscitation and Acute care zones are prioritised for assessment by an ED specialist. Subacute patients are seen when the doctor becomes available. Registrars work with the specialist doctor performing diagnosing and managing patients care and treatment and assist during procedures. The JMOs are medical doctors who are in the first year of their medical practice having completed their undergraduate medical degree.

Table 3: ED resources that are rostered on duty per shift each day of the week Monday-Sunday.

Resource name	Count
Specialist Doctors (SD)	3
Junior Medical Officer (JM0)	3
Registrar (R)	5
Registered nurses (RNs)	17
Registration clerk	2
Beds	32

Model execution and scenarios

Two scenarios were developed: The first was a model of the current system using data taken from the AIHW and dummy data to supplement any missing data from the AIHW statistics [1]. The second scenario made changes to staffing resources by moving a nurse from the Resuscitation to the Acute care zone on the weekend.

The first scenario was run for three months representing a total of 2016 hours. This was split between weekday hours (1440), weekend hours (576). The total number of patients generated was 15609. Authors have highlighted that, the ED can experience higher numbers of patient presentations during the weekend compared to weekdays [19]. Thus, weekends can have a higher patient arrival rate compared to weekdays. Poisson distribution defines the weekend arrival rate as having an expected mean value of 5.5 (minutes) between each patient's arrival, and a mean value of 5.8 (minutes) between each patient for weekdays. As patients arrived in ED, they were allocated a medical triage assessment attribute that used to establish their routing at decision points throughout. It was presumed that 30% of patients arriving in ED by ambulance and 70% were walk-in patients. The admission decision attribute assumed 30% of patients would be admitted to wards, and 70% would be discharged home. The attribute of triage assessment was entered as five separate percentages (Table 2) representing T1to T5.

At the triage point, patients were assessed by a triage nurse, assigned to treatment zones in consideration of their triage assessment and bed capacity. The most seriously ill patients presenting as high acuity (T1) are transferred to the Resuscitation zone initially. Patients assessed as T2 and T3, are transferred to the Acute care zone. Patients presenting as Low acuity (T4 and T5) are moved to the Subacute zone.

To moderate the degree of queueing in each treatment zone, a strategy termed "overflow routing check" is utilised by the ED. This strategy involves a triage nurse checking how many patients are Waiting in a Queue (WIQ) and how many beds are available in each treatment zone. In the Acute care zone, a queue represents more than three patients. In this instance, the triage nurse will route patients to the Resuscitation zone, providing the Resuscitation zone has no patients waiting in its queue. This strategy aims to reduce the queue in Acute care to zero and ensure T1 patient always have a bed available. T1 patients are given priority for a bed in Resuscitation therefore, they are sent directly to the Resuscitation zone.

Patients who are routed to the Subacute zone can experience longer waiting times in a queue. For the Subacute zone, a queue represents more than four patients. If this occurs, patients are then routed to the Acute care zone providing a bed is availability.

Each zone in the 'treatment zone' of ED has a specialist doctor and nurses. Once an initial assessment of the patient is undertaken by a nurse and specialist doctor, they are moved to most appropriate zone once a bed is assigned. This same process occurs in each zone. Patient treatment is prioritised according to triage assessment, and irrespective of which zone a patient is occupying. Following the initial assessment, patients are then moved to the "Diagnosis and Management" area of ED.

The model had three levels of diagnosis assigned for the routing patient percentages. These were the 'Initial treatment, definitive and specialist treatment'; and all these data were assumed. Once all tests, treatments and procedures are completed during the diagnosis stage, patients proceed to a queue where they await an ED doctor's final decision on outcome for care (disposition). There are two potential outcome options that a doctor can choose and/or for the patient to exit the simulation. Immediate discharge or re-route the patient for observation while they await admission to the hospital as an inpatient. As data used in this simulation is dummy, data for each decision were assumed. Additionally, this simulation triangulated distribution for staff service time in each zone.

Data analysis

The analysis is based on comparing the average LOS in ED for weekdays and triage assessment. The key predictors that were assesses were: arrival time, triage assessment, WIQ, admission decision LOS, exit time.

Comparisons were made between entry and exit times to determine the LOS. The average LOS was manually calculated to establish the WIQ times over a 24hour period across a three-month period. This process enabled the identification of the where the longest wait-time occurred over a 24-hour period in the system. Time attributes were assigned for two points of care, the start time (the patient is waiting to enter Resuscitation), bed assigned (the time at which the patient enters the bed in Resuscitation). The wait time was then calculated by deducing the 'bed assigned time' from the 'start time'. A series of tables and graphs were developed for each treatment zone over a 24-hour period. All tables and graphs were then analysed by comparing the data to determine average LOS and time WIQ for both weekdays and weekends.

In this research we worked on the premise that patient's arrival rates for the weekend would be more frequent compared to weekdays. Additionally, we viewed the model structure for weekends and weekdays as the same, as well as the number of resources used, see (Table 3). Additionally, it is known that WIQ can impact the LOS for a patient in the ED.

In scenario 1, the baseline model, we have found an increase in the LOS on Fridays (4.07 hours/minutes) and Saturdays (4.04 hours/minutes) while Sundays had the shortest LOS across all days of the week (3.41), see (Table 4). As most of the weekdays had lower lengths of stay, a solution to improve the LOS for the weekend was the focus of the scenario 2. This involved moving a nurse form the Resuscitation to the Acute care zone.

Table 4: Scenario 1, Baseline model - LOS per workday**.**

Days of week	Hours/Minutes
Friday	4.07
Saturday	4.04
Monday	3.50
Tuesday	3.49
Wednesday	3.44
Thursday	3.42
Sunday	3.41

The baseline model LOS for all triage assessments were higher at the weekend except T1 patients (4 hours and 10 minutes), see (Table 5). The total average for LOS over the weekend was higher by 20 minutes demonstrating a need to explore the source of delays along care pathways and to propose solutions to reduce waiting times which impact patients LOS in the ED. The longest average WIQ time was at 6am in the Acute care treatment zone (19 minutes), see Figure 4, (Table 6). There were no differences in WIQ times for weekend and weekday in the Resuscitation and Subacute zones. However, in the Acute care zone, there was an increase in WIQ time during the weekend across a 24hour period and particularly between 12 mid-night and 8 am. This was associated with patients waiting to be allocated a bed in the Acute care zone Figure 4, (Table 6).

Table 5: Comparison of LOS for scenario 1 and 2 based on triage assessment for the weekend and weekdays**.**

	Baseline mode Scenario 1		**Improved model Scenario 2**
Triage assessment	Average LOS weekday	Average LOS weekend	Average LOS weekend
T1- Resuscitation	4h 23m	4h 10m	4h 42m
T2- Emergency	3h 49m	4h 10m	4h 0m
T3- Urgent	3h 52m	4h 18m	3h 56m
T4- Semi-Urgent	3h 37m	3h 50m	3h 39m
T5- Non- Urgent	3h 58m	4h 30m	4h 10m
Total average	3h 46m	4h 6m	3h 51m

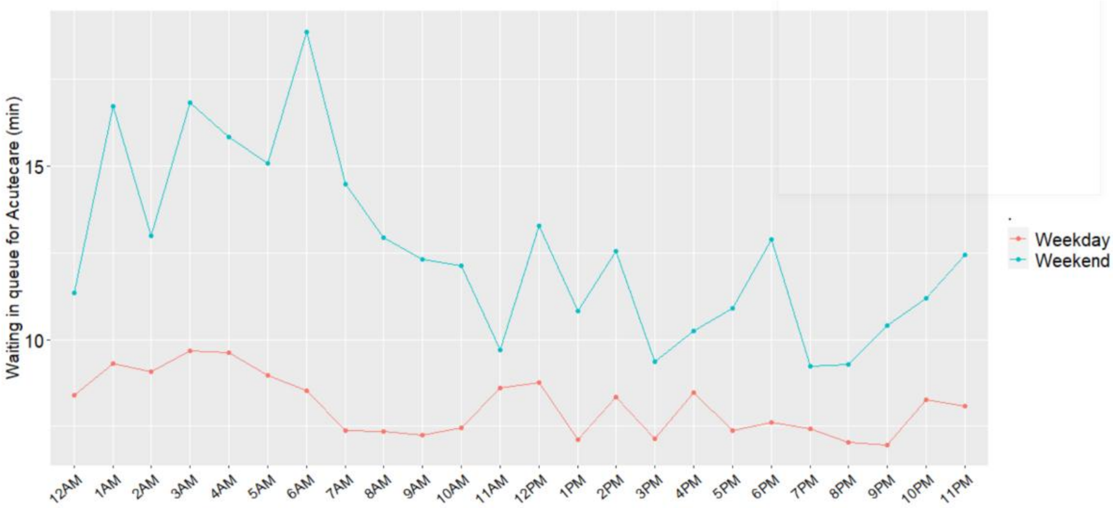

Figure 4: Scenario 1. Current ED baseline model Minute's WIQ for Acute care.

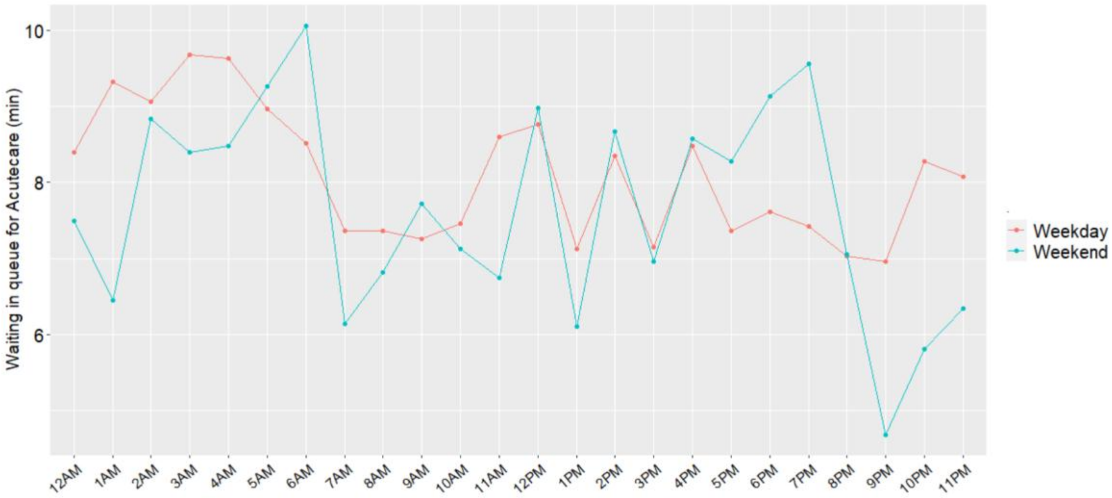

Figure 5: Scenario 2, Improved model – Nurse resource rostered from Resuscitation to Acute care zone at weekends.

Table 6: Numerical data representation of WIQ during the weekend for Acute care.

Time	Weekdays Baseline Model (minutes)	Weekend Baseline Model (Minutes)	Baseline model % increase at weekends	Weekend Scenario2 Improved (Minutes)	% Difference between Scenario 1 and 2 at weekend
12:00 AM	8.39	11.33	35%	7.49	-34%
1:00 AM	9.31	16.71	79%	6.44	-61%
2:00 AM	9.06	12.98	43%	8.83	-32%
3:00 AM	9.68	16.81	73%	8.40	-50%
4:00 AM	9.63	15.83	64%	8.48	-46%
5:00 AM	8.97	15.07	68%	9.26	-39%
6:00 AM	8.52	18.86	121%	10.06	-47%
7:00 AM	7.37	14.47	96%	6.14	-58%
8:00 AM	7.36	12.93	76%	6.82	-47%
9:00 AM	7.25	12.29	50%	7.71	-37%
10:00 AM	7.45	12.13	63%	7.13	-41%

11:00 AM	8.59	9.70	13%	6.74	-30%
12:00 PM	8.75	13.27	52%	8.97	-32%
1:00 PM	7.12	10.83	32%	6.10	-43%
2:00 PM	8.35	12.55	0%	8.66	-31%
3:00 PM	7.15	9.37	31%	6.96	-26%
4:00 PM	8.47	10.25	21%	8.57	-16%
5:00 PM	7.36	10.89	48%)	8.27	-24%
6:00 PM	7.61	12.89	69%	9.13	-29%
7:00 PM	7.42	9.22	24%	9.50	03%
8:00 PM	7.03	9.27	31%	7.05	-24%
9:00 PM	6.96	10.40	9%	4.68	-55%
10:00 PM	8.27	11.17	5%	5.80	-48%
11:00 PM	8.08	12.44	54%	6.34	-49%

A model output report demonstrated that nurses in the Acute care zone were fully utilised during the weekend. Nurses in Resuscitation zone had low utilisation of during the weekday. It was therefore proposed that one nurse from Resuscitation zone would be rostered to work in the Acute care zone on the busier days of the week (Friday, Saturday).

Improvements in WIQ were found across all hours (except for 7pm, which had an additional 28 seconds (3%)), after rostering one of the weekday nurses from the Resuscitation to Acute care zone on a weekend (Table 6). The greatest improvement in waiting time was found to be at 7am (8.33minutes) across a 24-hour period. These improvements are graphically represented in Figure 5. Additionally, this change, subsequently improved LOS for most patients (T2-T5) in the improved model (scenario 2). However, T1 patients experienced a slight increase in LOS (4 hours and 41 minutes). This may be due to T1 patients characteristically requiring higher more intensive time-consuming patient care. The waiting time for T1 patients did not change as they normally have highest priority to be assigned a bed in the treatment zone in the system.

CONCLUSION

The baseline model shows an increase in the LOS on Fridays (4.07 hours/minutes) and Saturdays (4.04 hours/minutes) while Sundays had the shortest LOS across all days of the week (3.41 hours/minutes). A solution to improve the LOS for the weekend was moving a nurse form the Resuscitation to the Acute care zone.

The baseline model LOS for all triage assessments were higher at the weekend. The total average for LOS over the weekend was higher by 20 minutes demonstrating a need to explore the source of delays along care pathways and thus to propose solutions to reduce waiting times which impact patients LOS in the ED. The longest average WIQ time was at 6am in the Acute care treatment zone. There were no differences in WIQ times for weekend and weekday in the Resuscitation and Subacute zones. However, in the Acute care zone, there was an increase in WIQ time during the weekend across a 24hour period and particularly between 12 mid-night and 8 am. This was associated with patients wait to be allocated a bed in the Acute care zone.

Model output report demonstrated that nurses in the Acute care zone were fully utilised during the weekend. Nurses in Resuscitation zone had low utilisation of during the weekday. It was therefore proposed that one nurse from Resuscitation zone would be rostered to work in the Acute care zone on the busier days of the week (Friday, Saturday). According to those improvements in WIQ were found mostly across all hours.

Further research over a longer period using actual data is needed to accurately feed in the ED's current scenario and to identify other strategies the ED may be using to address the increased in LOS on the busier days of the week.

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