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Optimising the service of emergency department in a hospital

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Abstract: Nowadays, the rapidly increasing healthcare cost has become a serious problem because of inefficient usage of medical resources. The Emergency Department (ED) plays a vital role in the hospital system and has critical effects on the overall efficiency in a hospital. The ED deals with patient's arrival, triage, physician assessment, imaging and laboratory studies, treatment planning, nursing procedures, decisions to discharge or admit access to inpatient beds and physicians. These activities generally occur in a sequential manner and the delayed activities of the patient flow can cause bottlenecking and reduce the service level. Optimising the service of the ED is challenging because the arrival times of patients are dynamic and their expected treatment times are volatile. This paper develops a new ED optimisation model using stochastic mathematical programming approach under limited budget and resource capacity. The objectives of the proposed model are for increasing the system efficiency, serving more patients in specific time, or providing the same quality of the service with the use of less medical resources. A numerical investigation is presented and demonstrates that high-quality solutions are obtainable for industry-scale applications in a reasonable time. Computational experiments have been conducted using CPLEX and ExtendSim to solve the ED-Stochastic Optimisation Mixed Integer Programming model and ED-Simulation model sequentially. Real data for Royal Brisbane and Women's Hospital (RBWH) is used in this paper to validate the proposed solution approach.

Keywords: *Emergency department, healthcare optimisation, mathematical programming, simulation*

1. INTRODUCTION

Increased demand for more medical services under limited resources is stretching the capacity of current healthcare delivery in many hospital locations, causing long wait times and poor service quality (Vissers and Beech 2005). As a result, there is an urgent need to improve efficiency which means increasing the quality of the service using fewer resources, and increase the capacity which means serving more patients in a specific time (Vissers and Beech 2005). One unit of a healthcare system that is essential to a hospital's capacity is the Emergency Department (ED). The ED is perhaps one of the most challenging components of the healthcare system and requires the capacity to deal with mass casualty and critical situations. ED services provide immediate treatment to patients who need urgent medical care and determine the time which is required by the patient to move to the next health unit if necessary. Patients arrive at the ED through different ways such as ambulance, walk-in or drive-in. Information about the patient is collected to triage (prioritise and stabilise) by a receptionist and a nurse. By completing the treatment time in ED, the patient can be admitted to another unit where they may encounter more processes and delays. Finally, the beds are prepared for the next patient after the discharge process (Hall et al. 2013), where the patients are discharged from the ED.

In this research, the patient emergency pathway in the ED will be optimised in an integrated framework to maximise patient flow and reduce the length of stay for patients in the ED and the whole system. An objective mathematical model will be developed considering the constraints and limited resources of the ED to satisfy several performance criteria. The simulation and optimisation techniques are integrated to solve the proposed ED model under many performance criteria. The impact of the developed model on waiting time performance, patient length of stay in ED, and the entire system will be analysed and discussed. The resources utilisation of beds and doctors will be optimised and validated using the real data.

2. RESEARCH PROBLEM

Inefficiencies within the ED can cause congestion by delaying transmission between medical units and home. Some EDs' capacities are not sufficient to accommodate significant surges in patient numbers (Green 2005). This leads to the ED congestion that negatively affects patient flow throughout the emergency care pathway (Rais and Viana 2011). As a result, maximising the patient flows throughout the emergency care patient pathway is one of the most important objectives in a healthcare system (Diefenbach and Kozan 2010).

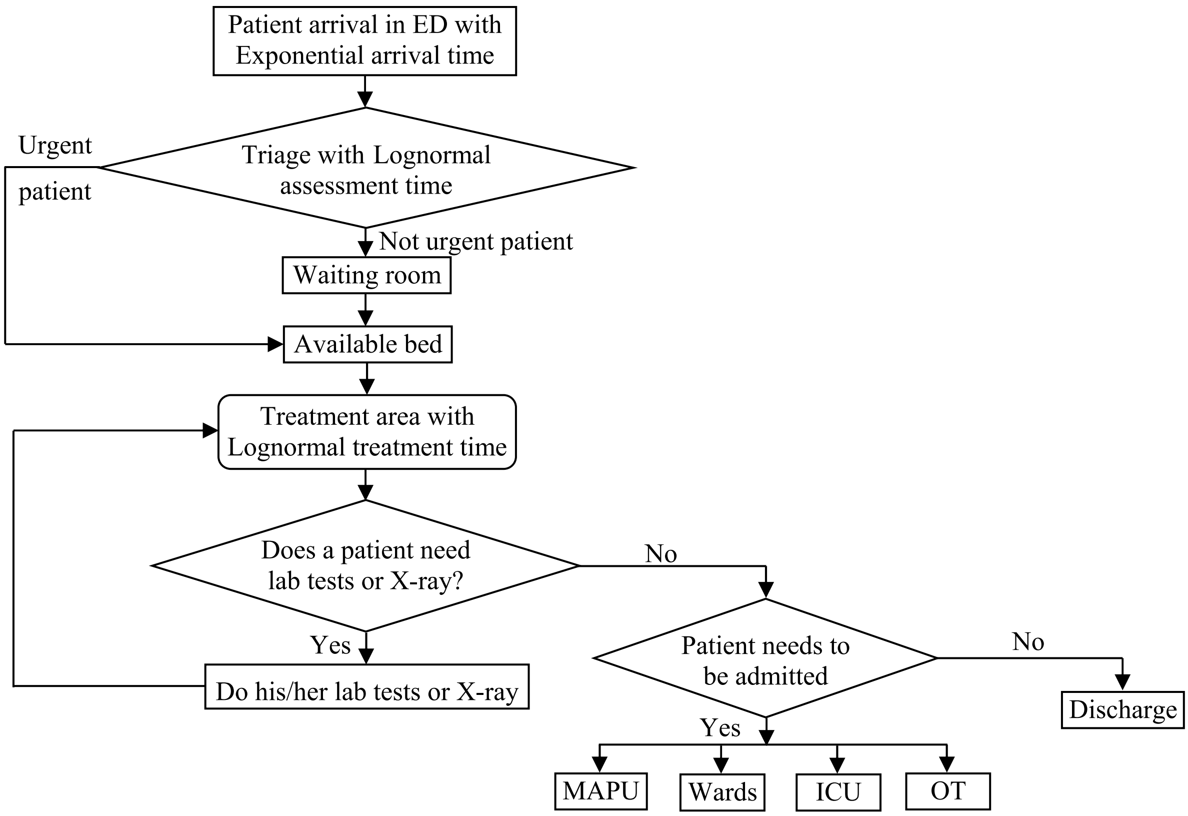


Figure 1. Flowchart of ED operations.

However, the congestion of the ED is also affected by the resources and operations in other units, particularly for inpatient pathways (Jones et al. 2009). Due to the interconnection of the units' operations and patient flow, the decisions made for one unit can significantly affect others regarding patient waiting time and patient departure time (Hall et al. 2013; Bryant and Hopper 2016). In the light of the strong interconnection between the ED and other units, the optimal number of finite resources (e.g. number of beds and doctors) of the ED could has a positive impact on the utilisation. Therefore, there could be a significant reduction in the costs associated with these resources and hospital capital budgeting, as well as better medical outcomes. Many benefits will be gained by applying the proposed approach on healthcare performance measurements such as the reduced patient length of stay and the reduced patient waiting time. Additionally, the proposed approach will lead to a considerable reduction in the costs associated with the medical resources and hospital capital budgeting, as well as better medical outcomes.

3. STOCHASTIC MATHEMATICAL FORMULATION MODEL

The Stochastic Optimisation Mixed Integer Programming (SOMIP) approach is applied to formulate the ED optimisation problem as an ED-SOMIP model (Liu and Kozan 2016; Masoud et al. 2016). In this model, the objective function is constructed to optimise the patient total waiting time under limited budget. In the proposed mathematical model, many stochastic elements will be included and optimised such as patient's arrival and patient's service time, where the exponential distributed interarrival times and lognormal distributed treatment times are used according to the real-world data collected from the RBWH. Figure 2 shows the ED system with stochastic elements used in the proposed ED-SOMIP model.

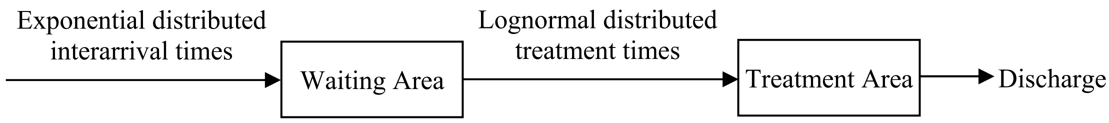


Figure 2. Stochastic elements of the ED-SOMIP model.

Parameters

n Number of patients

i Index of a patient; $i = 1, 2, \dots, n$

K Number of operations (1: Triage staff; 2: Doctor; 3: Nurse)

k Index of an operation; $k = 1, 2, 3$

C Number of staff

c Index of staff in each operation; $c = 1, 2, \dots, C$

$p_{i,k}$ Lognormal distributed processing time of patient i for operation k

r_i Arrival time of patient i ($r_i - r_{i-1}$ is Exponential distributed)

B Upper bound on the number of beds in the ED

b_i Type of bed required for patient i, $b_i \in \{1, \dots, B\}$

M An arbitrary large positive number

Decision variables

$s_{i,k}$ Starting time of operation k for patient i

$$y_{i,k,b} = \begin{cases} 1, & \text{if patient } i \text{ requires bed } b \text{ to implement operation } k \\ 0, & \text{otherwise} \end{cases}$$

$$z_{i,k,c} = \begin{cases} 1, & \text{if patient } i \text{ schedules for staff } c \text{ during operation } k \\ 0, & \text{otherwise} \end{cases}$$

$$t_{i,i',k} = \begin{cases} 1, & \text{if patient } i \text{ procedes patient } i' \text{ for operation } k \\ 0, & \text{otherwise} \end{cases}$$

$$q_{i,k,k'} = \begin{cases} 1, & \text{if patient } i \text{ requires operations } k \text{ and } k' \text{ where operation } k \text{ precedes operation } k' \\ 0, & \text{otherwise} \end{cases}$$

Objective function

The main objective function is minimising the total waiting time f_W, where total waiting time includes the initial waiting time of patients before admitting to ED and the waiting time of patients between operations in ED

$$Min\ f_W = \sum_{i=1}^{n}(s_{i,2} - r_i) + \sum_{i=1}^{n}\sum_{k=2}^{K-1}\left(s_{i,k+1} - (s_{i,k} + p_{i,k})\right) \quad (1)$$

Constraints

Constraint (2) ensures that the ready time of each patient precedes the first operation in ED where ready time less than or equal the starting time of the first operation in the ED.

$$r_i \leq s_{i,1} \qquad i = 1,2,\dots,n \quad (2)$$

Constraint (3) ensures that operation k precedes operation $k+1$

$$(s_{i,k} + p_{i,k}) \leq s_{i,k+1} \qquad i = 1,2,\dots,n;\ \ k = 1,2,\dots,K \quad (3)$$

Constraints (4), (5) and (6) address the sequence of different patients, i and i' on same operation k.

$$s_{i,k} \geq s_{i',k} + p_{i',k} - M * (1 - t_{i',i,k}) \quad (4)$$

$$s_{i',k} \geq s_{i,k} + p_{i,k} - M * (1 - t_{i,i',k}) \quad (5)$$

$$t_{i',i,k} + t_{i',i,k} = 1 \quad (6)$$

Constraint (7) ensures that bed b is only occupied by one patient i at a given time

$$\sum_{i=1}^{n} y_{i,k,b} \leq 1 \qquad k = 1,2,\dots,K; b = 1,2,\dots,B \quad (7)$$

Constraint (8) ensures that patient i only occupies one bed b in ED

$$\sum_{b=1}^{B} y_{i,k,b} \leq 1 \qquad i = 1,2,\dots,n; k = 1,2,\dots,K \quad (8)$$

Constraint (9) makes sure the patient i is scheduled to one operation k

$$\sum_{k=1}^{K} y_{i,k,b} \leq 1 \qquad i = 1,2,\dots,n; b = 1,2,\dots,B \quad (9)$$

Constraint (10) ensures that patient i is assigned to operation k using one staff c

$$\sum_{c=1}^{C} z_{i,k,c} \leq 1 \qquad i = 1,2,\dots,n; k = 1,2,\dots,K \quad (10)$$

Constraints (11-12) to ensure that the patient are scheduled correctly on different beds and staff (operations)

$$s_{i,k'} \geq s_{i,k} + (y_{i,k,b} * p_{i,k}) - M * (1 - q_{i,k,k'}) \quad (11)$$

$$i = 1,2,\dots,n;\ \ k = 1,2,\dots,K;\ \ k' = 1,2,\dots,K';\ \ b = 1,2,\dots,B$$

$$s_{i,k'} \geq s_{i,k} + (z_{i,k,c} * p_{i,k}) - M * (1 - q_{i,k,k'}) \quad (12)$$

$$i = 1,2,\dots,n;\ \ k = 1,2,\dots,K;\ \ k' = 1,2,\dots,K';\ \ c = 1,2,\dots,C$$

4. SOLUTION APPROACH

The main contribution of this paper is developing a stochastic optimisation ED model to validate the developed ED-simulation model. The developed simulation model has used the result of ED optimisation model as input data and a target-supervised framework to improve the simulation model output regarding the patient waiting time. Number of resources such as doctors, nurses and beds has been optimised using ED-SOMIP model and then will be used as input data in the ED-Simulation model. Figure 3 shows the main proposed solution approach for the ED system. ExtendSim software was used to run the ED-Simulation process, while the CPLEX software was used to solve the ED-SOMIP model. In the proposed framework of the integrated Optimisation-Simulation approach for the ED system, the statistical distributions are applied to produce stochastic variables such as patient interarrival and treatment times. The variance rates of two models for small-size case study (50 patients) are calculated to adapt the ED-Simulation model to improve the accuracy of this model. Based on the improvement of the total waiting time of hospital real data, the proposed model will be generalised to solve large-scale problem.

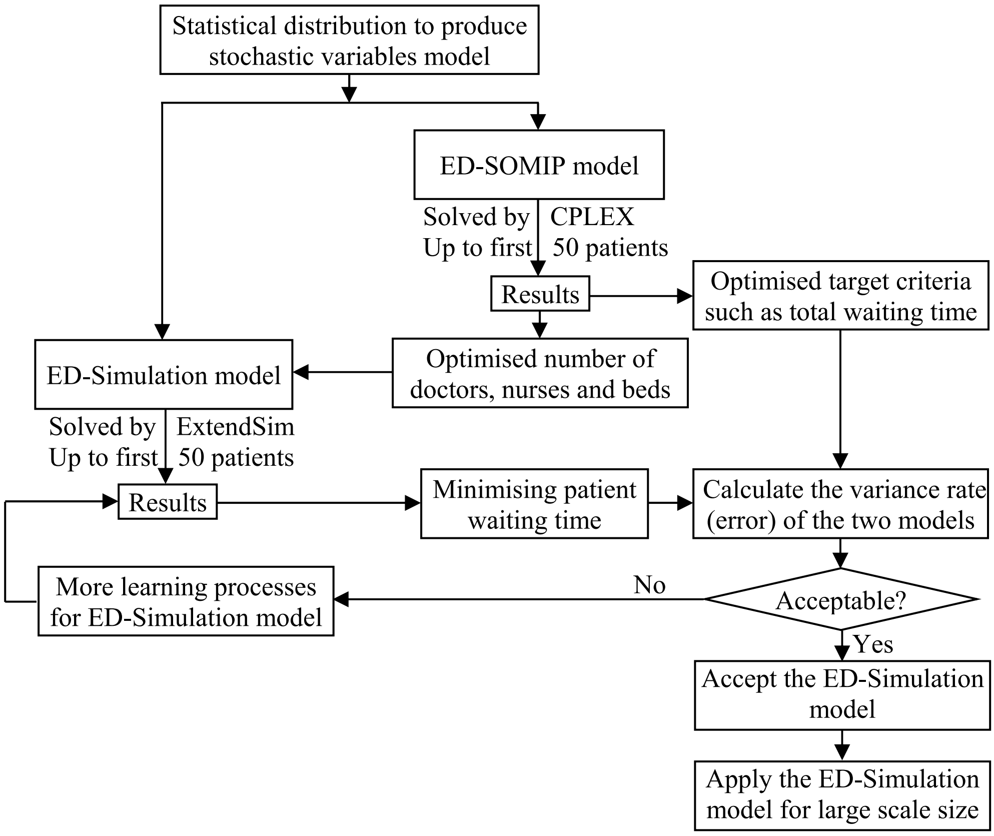


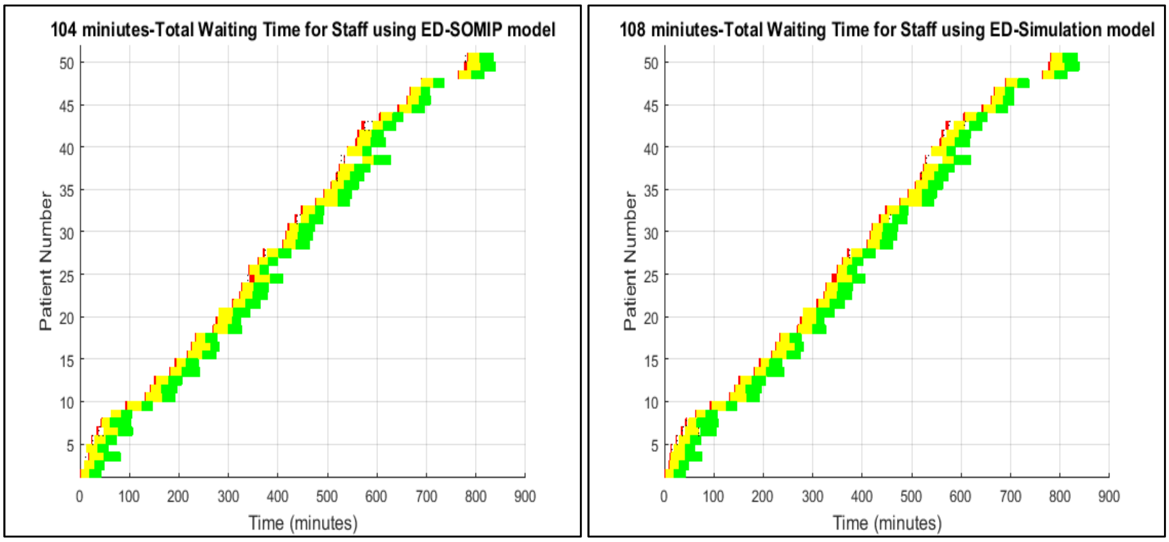
Figure 3. The framework of the integrated Optimisation-Simulation approach for the ED system.

5. COMPUTATIONAL RESULTS

The ED-SOMIP and ED-Simulation models are solved using CPLEX and ExtendSim software sequentially. The results of several patient groups, up to first 50 patients, are shown in Table 1 under several criteria in column 1. The patient total waiting time and the staff utilisation such as triage, doctor and nurse. Furthermore, the utilisation of resources such as Resuscitation, Acute and Fast track beds has been shown, where no patient in the first 50 arrivals has assigned for the Resuscitation bed. Consequently, the utilisation of Resuscitation is zero in Table 1. The validation of the proposed ED-Simulation model depends on the results of the average of standard errors in the last column. The squared standard error shows the accuracy of the ED-Simulation comparing with the results of the ED-SOMIP model. Figure 4 shows the Patient Scheduling using ED-Simulation and ED-SOMIP model, where each patient is served within three operations in ED, triage (Red colour), doctor (Yellow colour) and nurse (Green colour). The total waiting time for 50 patients is shown in Figure 4 for the two proposed models with 0.1% as a squared standard error. Figure 5 is a close up of the ED operations for patient scheduling that includes triage, doctor and nurse with clarifying the patient waiting time before assigning for any of these operations. As shown in Table 1, the value of the standard error is small, which implies the ED-Simulation model is constructed in a good manner and this model is applicable for large-size cases as shown in Figure 6. The results of the extended ED-Simulation model have been analysed in Figure 6 for serving 2895 patients by different types of resources within one month. The total waiting time of all patients has been determined to be 7001.8 minutes with improvement 28.5 % (9793 minutes) in comparison to the current practice and the resources utilisation has been analysed with average percentage value for each type of resource.

Table 1. Results of ED-SOMIP and ED-Simulation Models

	ED-SOMIP model										Average squared standard error (%)
Number of patient	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**	
Total waiting time of all patient in min	11	22	22	22	26	31	40	75	101	104	
Average Resuscitation bed utilisation (%)	0	0	0	0	0	0	0	0	0	0	
Average Acute bed utilisation (%)	56.2	53	47	50.4	51	51.8	51	52.8	54	53.1	
Average Fast track bed utilisation (%)	26	22	41	46	51	55	55	58	51	43	
Triage utilisation (%)	12.4	12	13.1	14	16.3	16.9	16.4	16.5	16.8	15.6	
Average Doctor utilisation (%)	44.9	41.2	42.7	47.6	50	51.1	51.1	53.5	52.5	49.1	
Average Nurse utilisation (%)	47.3	44	48	50	52.4	54.6	53.2	55.8	54.2	50.5	
	ED-Simulation model										
Number of patient	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**	
Total waiting time of all patient in min	11	24	24	24	32	37	45	80	106	108	1
Average Resuscitation bed utilisation (%)	0	0	0	0	0	0	0	0	0	0	0
Average Acute bed utilisation (%)	62	54.5	48.3	51.4	52.4	52.5	51.7	53.6	55.7	54.2	0.1
Average Fast track bed utilisation (%)	31	23	42	46	52	55	55	59	51	43	0.3
Triage utilisation (%)	12.4	12	13.1	14	16.3	16.9	16.4	16.5	16.8	15.6	0
Average Doctor utilisation (%)	48.2	41.3	42.7	47.7	50.4	51.2	51	53.5	52.5	49.1	0
Average Nurse utilisation (%)	50.6	44.2	48.1	50.2	53	54.7	53.2	55.9	54.3	50.5	0



(a) ED-SOMIP model (b) ED-Simulation model

Figure 4. Patient scheduling using ED-Simulation and ED-SOMIP models.

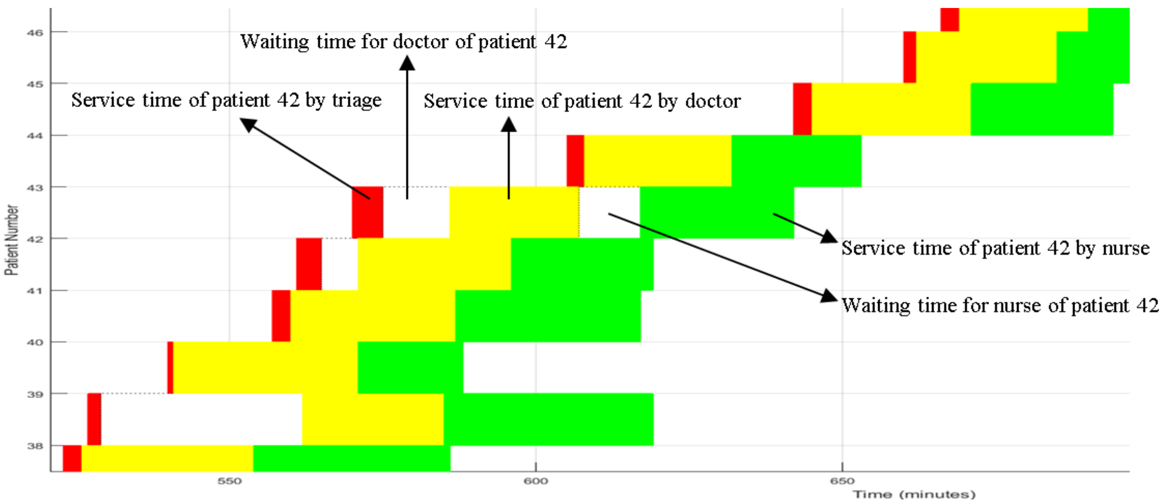


Figure 5. Close up of ED operations for patient scheduling.

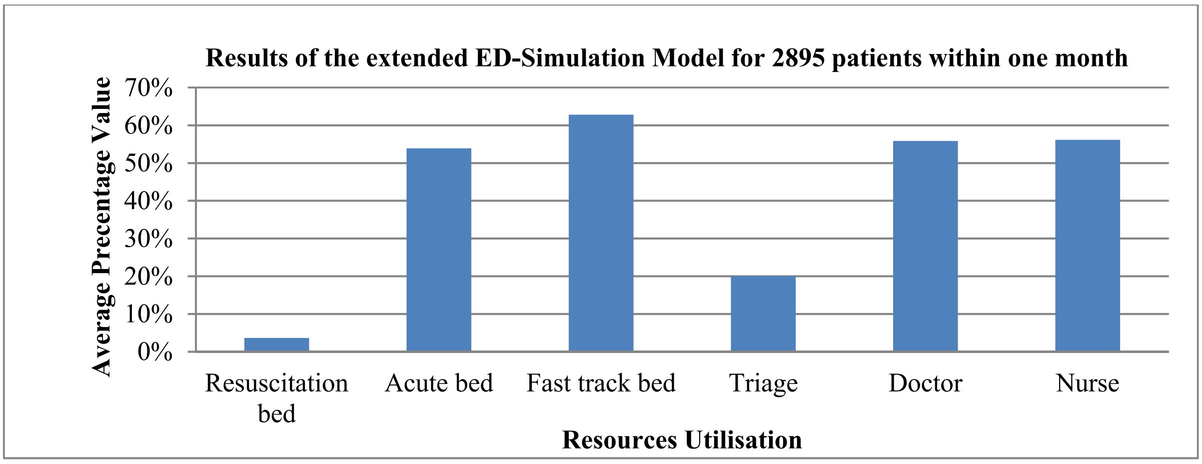


Figure 6. Results of the extended ED-Simulation model for 2895 patients within one month.

6. CONCLUSION

The paper addressed ED problem through stochastic optimisation and simulation approaches. The ED-SOMIP model has been developed to validate the proposed simulation model using small case study up to first 50 patients. The ED has been modelled mathematically using stochastic MIP and CPLEX has been used to solve the proposed model. The ExtendSim software has been used to develop and solve the proposed ED-Simulation model. The standard error for the two models has been calculated to extend the ED-Simulation model to be reliable and solve large size case study of ED. The results of the extended model has been improved and used for validating the produced results and the constructed model. The real data of one month at the ED has been experimented where 2895 patients are served with the total waiting time of 7001.8 minutes that brings an improvement of 28.5% in comparison to the current practice.

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