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A Generic Simulation Optimization Model of Emergency Department Resource Capacity

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Abstract: This study discusses the development of a discrete event simulation model for an Emergency Department (ED) in a government hospital. We present a generalized ED model that is developed by using discrete event simulation which can be adapted by other EDs in Malaysian government hospitals. Generalization in the model refers to the modeling of patients in terms of the primary process flow, patient prioritization and resource allocation. The developed model can be used to test different process scenarios, provide useful insights for possible areas of improvement, direct specific resource allocation for maximal impact and perform activity based on cost analysis. From a case study on ED the computational results show that the estimates of the distribution parameters are as accurately as the simulated results obtained which are consistent with actual data.

Key words: Emergency department, discrete event simulation, health care modeling, actual data, Malaysia

INTRODUCTION

With improved lifestyles and a better accessibility to health care, Malaysians have shown significant increase in the average life expectancy (Thomas *et al*., 2011). Yet, it has also contributed in enlarging the pool of patients who will require more health care. As such there is a growing need to tightly manage resources in the health care system. Similarly, in the context of Emergency Department (ED) resource capacity planning is essential for an effective management. Lack of resource capacity may lead to an increase in medical errors and long waiting times. With restricted financial support from the government it is increasingly difficult for the administrators to ensure that adequate resources either manpower or equipment are available to maintain a quality of health delivery in ED. Due to this, ED administrators require a tool that can help them to make sure that the key resources such as doctors in the department are best-utilized.

One such tool that can tackle the complexity and uncertainties associated with the health care systems is simulation modeling. A significant amount of health care studies has testified the use of simulation in modeling health care problems. In the domain of ED there have been several successful simulation studies conducted to solve ED problems such as overcrowding, extended waiting time and staffing allocation (Komashie and Mousavi, 2005; Ruohonen *et al*., 2006; Gunal and Pidd, 2007; Ahmed and Alkhamis, 2009; Brenner *et al*., 2010). There are also studies that integrate simulation with other operations research methods like integer linear programming (Centeno *et al*., 2003), genetic algorithm and optimization algorithm (Ahmed and Alkhamis, 2009). Many of these simulation studies highlighted the applicability of Discrete Event Simulation (DES) in identifying bottlenecks, improving complex patient flows, portraying detailed operational processes, evaluating system performance and configuring a new system structure of ED.

Realistic modeling of an ED can be difficult and time-consuming. Therefore, for initial exploration of ED modeling, the development of a generic and flexible simulation model is needed. As the structures and procedures in government hospitals in the country are basically similar, we present a generic ED model using DES to evaluate the resource utilization and system performance periodically. The model aims to determine the staffing requirements in ED. Take note that generalization in the model does not mean total similarities between different EDs but simply focus on common characteristics shared by the EDs. In this study, generalization in the model refers to the modeling of patients in terms of the

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primary process flow, patient prioritization and resource allocation. The primary application of this model is government EDs but it can easily be extended to other EDs with some modifications.

Literature review: As ED patients arrive with different levels of urgency, waiting time has always become the concern of many researchers in ED modeling. Panayiotopoulos and Vassilacopoulos (1984) and Cooke *et al*. (2004) have demonstrated an analytical approach of queuing theory to study the effect of waiting times on ED. However, to better capture the complex behavior and unpredictable demand of ED, many computer simulation studies have been applied to mitigate long waits in EDs (Blake *et al*., 1996; Samaha *et al*., 2003; Takakuwa and Shiozaki, 2004; Holm and Dahl, 2009; Eskandari *et al*., 2011). Some of the models enabled ED administrators to identify that one of the key driver for long waiting time is inadequate staff. In addition, the models also provide a better understanding of ED delivery process among staff and help them to determine effective strategies to resolve patients waiting time.

In addition to waiting time, researchers also studied the Length of Stay (LOS) experienced by patients in ED. For instance, Baesler *et al*. (2003) presented a DES model to investigate the minimum LOS using available resources when ED receives maximum demand. Findings from the model revealed that LOS was influenced by the number of beds and physicians. Similarly, Samaha *et al*. (2003) demonstrated the impact of additional beds and space towards patient flow in ED but the results were in contrast as they identified that additional beds and space has less impact to the LOS. In addition, they concluded that LOS and other problems in the ED was not resource dependent but was process related. Other study by Khare *et al*. (2009) also investigated the impact of number of beds towards LOS. Their findings showed that an increased number of beds increases the average LOS. On the other hand they found that reducing the boarding time of admitted patients in ED will reduce the average LOS.

Apart from beds, researchers also studied the impact of other critical resources on ED performance such as doctors and nurses. Komashie and Mousavi (2005) developed a DES model to determine the impact of beds, doctors and nurses on queuing time and LOS. They tested five scenarios by altering the number of critical resources and omitted the impact of admission to ED process. The obtained results demonstrated 20% reduction of patient's waiting time when admission blockage is removed. Alternatively, Ahmed and Alkhamis (2009) implemented a hybrid DES and system dynamics model of a government ED to determine the impact of demand increase towards medical assistants, nurses and beds. The study tested three scenarios to determine the impact when patient volume is increased with varying staffing numbers and beds. Results from the model showed that medical assistants are the critical resources in the ED and adding bed capacity is necessary when increasing the medical assistant.

Some studies are concerned to reduce the waiting times of less severity patients through the introduction of fast track queue. Mahapatra developed a DES model to show the impact of fast track route in ED for non-critical patients. The result showed that the average waiting time was improved by 10% when fast track unit is added to the base case model. With similar aim, Holm and Dahl (2009) developed a DES model to show the effect of including physician triage on patient waiting time in an ED. The study showed that introducing physician triage did not affect the average LOS. Rather they found that the rate of Left Without Being Seen (LWBS) in the ED and total time spent resulted from ambulance diversion decreased.

One similarity of the aforementioned studies is that the developed models are problem-specific. In other words, such studies have been directed to solve specific issues of concern to the institutions. However, there are a few who believe that a more general or flexible model should be established in modeling health care systems. The earlier study that promotes the need of flexible and reusable ED model is written by Miller *at al*. (2003). Another study done by Sinreich and Marmor developed a simulation model using Arena simulation software that is reusable to evaluate the performance of ED in hospitals. In a similar vein Ferrin *et al*. (2007) developed a reusable DES model called EDsim to improve the operations of EDs. These researchers claimed that a generic flexible model can reduce time and cost of study. For that reason, various EDs in the UK have used flexible ED simulation model as a decision tool to improve the operations of ED (Fletcher *et al*., 2007). As for our study, we believe that by developing the flexible model it will improve the process of learning and understanding of the clients. With client involvement in the modeling process, a successful simulation study can be attained.

In this study, we also aware the need to integrate simulation with optimization approach. This is because the simulation model only provides estimate values and not the exact values. In order to determine the optimal staffing number to meet the incoming demand, optimization approach should be incorporated with the simulation model. Several studies emphasize the need for simulation-optimization to evaluate health care system performance and analyze the outcome of different situations (Blasak *et al*., 2003; Ahmed and Alkhamis, 2009). Similarly, in this study, we determine the optimal resource levels in order to enhance system performance within the constraints imposed by ED resource capacity.

MATERIALS AND METHODS

System description: The ED under study is a non-terminating system that operates 24 h, seven days a week and receives more than a thousand patients weekly. The general process flow in the ED begins with patient arrivals as shown in Fig. 1. Typically, patients enter the ED either by ambulance or as walk-in cases. As patients arrive they need to register at the registration counter. At the same time a medical assistant will triage the patients. In contrast, critical patients bypass this process and will be sent directly to the critical area and bedside registration will be performed at a later time by the registrar. Once triaged, the patient moves to the waiting area and wait for an availability of a doctor. As soon as a doctor becomes available the patient leaves the waiting area and sees the doctor at the treatment area. The doctor examines the patient and will decide if the patient needs additional tests such as clinical lab tests or X-rays. Once results from the test are available and reviewed by the doctor, a decision is made upon the results. The doctor will decide whether the patient is to be discharged for home or admitted to the hospital for further treatment.

The developed model includes activities that are typical in hospital EDs. In addition to the general processes in ED like registration, triage, reception and beds, special cases such as emergency calls, doctor and nurse schedules are also modelled. Generally, the main challenge of ED administrators is to find the optimal staffing levels to serve the incoming patients within the specified target time. Therefore, this model is developed to better capture patient flow in ED and to understand how resource availability affect the performance of ED.

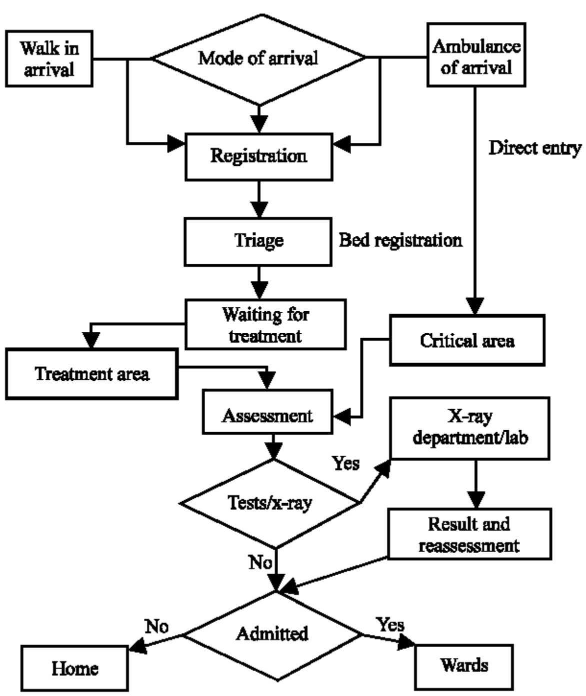

Fig. 1: The primary process

Model of the emergency department processes ("As-Is"): A basic simulation model of the ED was built in Arena in order to find the optimal staffing level and to determine the extent to which the DES is effectively able to solve the ED problems. Arena software is chosen due to its flexible modelling tools and clear animated run that tend to ease communication between modeller and the system owner. In our study the graphical tools and animation of moving entities help the ED administrator identify bottlenecks in the system.

There are three main components in DES, i.e., the entities the resources and the processes. Entities are the moving elements that are being simulated and need to be served by the resources. Typically, in health care systems the entities are usually the patients and the resources can either be human such as doctors, nurses, etc. or physical resources that include observation rooms, hospital beds, diagnosis facilities, etc. Using DES, special features of both patients and resources like illness, age, gender, availability and capacity can be modelled. The processes, on the other hand are the services provided by the resources i.e., the triaging process or diagnostic tests required by patients. The model considers a three-step process that is purposefully simplified:

- Patients arrive at a regular rate
- Three medical staffs each perform an activity (triage, assess, treat)
- Patients that are discharged after treatment is finished

The simulation model represented the current process (As-Is) and is categorized into six sub-models, each one representing one-step of the ED health care process (Fig. 2). Patients enter the ED either by walk in or

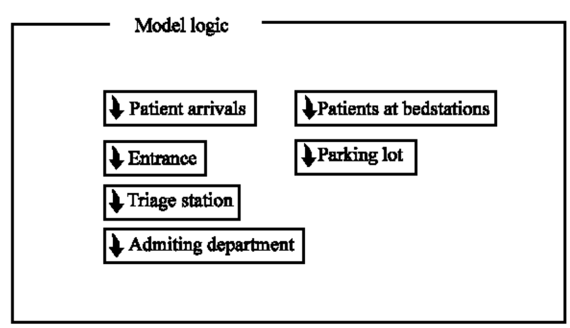

Fig. 2: Primary model logic of the ED healthcare process

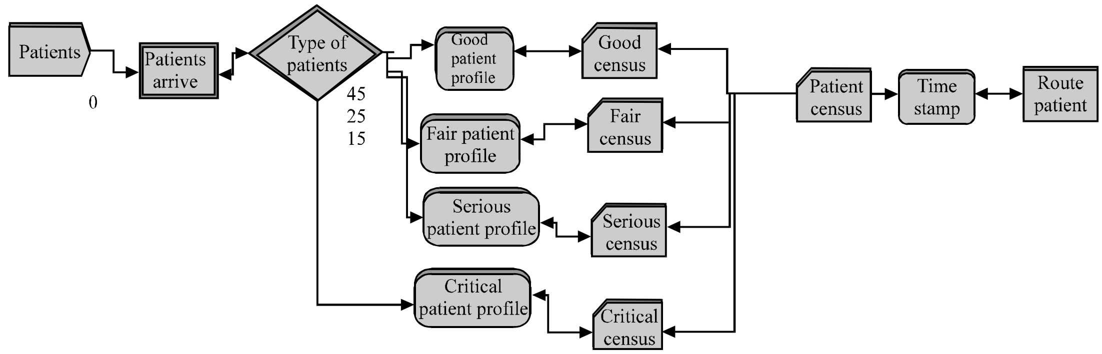

Fig. 3: Patients arrival at the emergency room

Table 1: Result from OptQuest

Resource	Optimal result
Administrative clerk	4
Nurse	6
Technician	4
Physician	6
Beds	16

via ambulance. The simulation model groups these patients into four categories: level 1-4 (Fig. 3). Level 1 patients (red triaged) such as unresponsive critically injured trauma victims are considered the most critical and need immediate life-saving intervention. Levels 2 and 3 patients (yellow and green triaged) go through a triage process where the medical staffs make an initial assessment of their severity of illnesses. Level 4 patients (blue triaged) refer to patients that appear non-critical and are sent to triage for evaluation. All patients are then moved to an available bed for treatment. Each patient needs to be registered either before or after treatment depending on the severity of his/her injury. After health condition of a patient is already stabilized, doctors can decide to discharge the patient or assign him/her to a bed in the hospital for further review.

It is vital for the ED to have a sufficient number of staff to meet the number of incoming patients. In the model the number of incoming patients was generated based on historical data which is classified into arrivals by day, evening and morning and the triage groups. To serve these arrivals, some of the resources have fixed levels for example: 1 charge nurse, 1 triage nurse and 13 wheelchairs while others do not. The arena model was used to find the optimal levels of the resources that do not have fixed levels.

To determine the optimal levels of these resources, the embedded optimization tool in arena, OptQuest was applied to the ED model. The objective function of the OptQuest was set to "maximize the beds in use" which would in effect reduce the number of surplus resources and beds. The optimal results obtained after 15 iterations are presented in Table 1.

The obtained optimal values of staffing levels were applied to the ED model and the associated cost was determined. For ease of communication with ED administrators, arena dashboard provides graphical animation of the proposed staffing levels by showing the "Bed Usage" and "Number of Patients Waiting". Using the optimal values of resources the dashboard displayed that the ED would provide a timely and appropriate service for all incoming patients.

Data collection: The data involved in this study came from both the primary and secondary data sources. Three methods of data collection were deployed, namely observations interviews and document analysis. Unlike the hospitals in overseas, patient information system in Malaysian hospitals lacks some of the processing times experienced by each patient. For some available data such as arrival time and exit time of patients from the ED they are manually recorded in log books. Therefore, a data collection team was hired to collect the processing times as well as accessing the hardcopy documents at the ED under study.

RESULTS AND DISCUSSION

The gathered data was analyzed using arena 12 input and output analyzers and the output obtained for 1 week (7 working day 24 h) were as follows: since patients are issued at the counter their arrival patterns are influenced by the arrival times. The number of patient's arrival is as described in Table 2. Treatment times of doctors vary depending on their experience their specialization and the type of emergency case treated. The treatment times of doctors for the seven days follow a certain distribution as shown in Table 3.

These distributions were then used as inputs for the simulation model developed based on the process described earlier in Fig. 3. The model was run for

Table 2: The mean total patient arrival for each patient type for a week

Days	Mean total patient's arrivals			
	Patient level 1 (red)	Patient level 2 (yellow)	Patient level 3 (green)	Patient level 4 (blue)
Sunday	11	41	64	100
Monday	14	32	66	88
Tuesday	12	35	70	98
Wednesday	16	33	73	103
Thursday	12	37	71	94
Friday	14	36	69	89
Saturday	13	40	68	93
Total	92	254	481	665

Table 3: The distributions of doctor's service times for Monday-friday

Treatments	Treatment distribution	Expression
Specialists		
Sunday	Normal	NORM (17.1, 2.29)
Monday	Triangular	TRIA (10.5, 20.6, 28.5)
Tuesday	Erlang	10.5+ERLA(2.09, 4)
Wednesday	Triangular	TRIA (12.5, 21.4, 30.5)
Thursday	Triangular	TRIA (11.5, 19.6, 29.5)
Friday	Normal	NORM (16.2, 3.27)
Saturday	Triangular	TRIA (11.3, 23.4, 29.5)
Senior doctors		
Sunday	Beta	14.5+11*BETA (2.13, 2.06)
Monday	Triangular	TRIA (14.5, 24.6, 35.5)
Tuesday	Normal	NORM (22.3, 4.22)
Wednesday	Triangular	TRIA (18.5, 25.4, 35.5)
Thursday	Triangular	TRIA (17.5, 23.6, 33.3)
Friday	Triangular	TRIA (16.3, 25.3, 34.6)
Saturday	Triangular	TRIA (15.2, 23.8, 36.5)
Junior doctors		
Sunday	Beta	18.5+11*BETA (2.23, 1.83)
Monday	Weibull	21.5+WEIB (9.46, 2.77)
Tuesday	Triangular	TRIA (16.5, 31, 38.5)
Wednesday	Normal	NORM (22.3, 4.22)
Thursday	Triangular	TRIA (17.5, 23.6, 33.5)
Friday	Triangular	TRIA (14.6, 32, 36.5)
Saturday	Triangular	TRIA (15.4, 30, 37.5)

10 replications and the average values for the number of patients treated the doctor's process time the patient's waiting time and the percentages of doctor's utilization were recorded. The detailed results will be discussed in the following subsections.

Number of patients treated: The comparisons between the actual data and the simulation result of total patients of each type that are treated for one week are as shown in Table 4. Table 4 shows that the differences between the simulation outputs and the actual data are between 1.13 and 9.17%. The differences are <10% the maximum value of the standard total differences allowed for a simulation model to be considered as acceptable and valid (Stedinger and Taylor, 1982).

Doctor's process time: The comparisons between the actual data and the simulation output of the doctor's process times for a week are as shown in Table 5. Since, the largest difference is only 4.7% the small differences between these values show that both the actual and simulated data seem to closely correspond to one another and are in good agreement.

Patient's waiting time: The comparisons between the actual and simulated data of the patient's waiting time for a week are as shown in Table 6. Note that there are only small differences between the values of the actual and simulated data with all the differences less than four percent. Again, these results show that both the actual and simulated data seem to closely correspond to one another and are in good agreement.

Utilization of doctors: The comparisons between the actual data and the simulation output in terms of percentage for utilization of doctor are as illustrated in Table 7. Similarly, the differences between the values of the actual and simulated data are <10%, well within the acceptable limit.

In summary, for the entire comparisons the differences between the actual data and the data obtained from the simulation output are below 10%. This means that the simulation output can be considered as valid. The simulation results show: junior doctors take the longest time while the specialists take the least time to treat patients. The differences between their treatment times are between 5.7 and 12.1 min.

According to the suggestion of Ramirez and Crowe (1997) the standard patient's waiting time should not exceed 30 min. Thus, the waiting time for level 4 patients is considered unsatisfactory where patients have to wait >30 min, except for Monday where the patient's mean waiting time is recorded as <29.5 min.

The average utilization rate of doctors is 74.5, 78.5 and 79.5% for the specialists, senior doctors and junior doctors, respectively. The utilization of each type of doctors is below 85% the desired level set by the ED management. Based on these findings, several measures have to be taken by the ED management.

Model experimentation: Since doctors are underutilized, we considered a scenario of increasing the number of patients by 10%. When the number of patients in each time block was increased by 10% the effects of these changes on doctor utilizations and patient's waiting times are as shown in Table 8 and 9, respectively.

By increasing the number of patients by 10% the doctor utilization rates are increased from 1.4-12.9%. With these changes the desired level of 85% utilization for certain types of doctors is met while for the remaining

Table 4: Copmarisons of number of patient for each type treated

	Patient types											
	Patient level 1 (red)			Patient level 2 (yellow)			Patient level 3 (green)			Patient level 4 (blue)		
Days	Sim.	Act	Diff.	Sim.	Act	Diff.	Sim.	Act	Diff.	Sim.	Act	Diff.
Sunday	10.6	11	3.64	39.6	41	3.41	61.7	64	3.59	98.1	100	1.90
Monday	12.9	14	7.86	30.5	32	4.69	64.7	66	1.97	86.3	88	1.93
Tuesday	10.9	12	9.17	32.7	35	6.57	68.4	70	2.29	96.7	98	1.33
Wednesday	14.7	16	8.13	32.2	33	2.42	71.4	73	2.19	101.3	103	1.65
Thursday	11.3	12	5.83	35.3	37	4.59	70.2	71	1.13	92.7	94	1.38
Friday	12.8	14	8.57	34.4	36	4.44	67.7	69	1.88	86.5	89	2.81
Saturday	12.4	13	4.62	38.2	40	4.50	66.2	68	2.65	90.3	93	2.90

Table 5: Comparisons of mean doctor's process time

Day	Type of doctors	Act	Sim.	Diff. (%)
Sunday	Specialists	17.1	17.6	2.8
	Senior doctors	20.1	20.0	0.5
	Junior doctors	24.5	24.4	0.4
Monday	Specialists	19.9	19.6	1.5
	Senior doctors	24.9	24.8	0.4
	Junior doctors	30.9	29.5	4.7
Tuesday	Specialists	18.8	18.8	0.0
	Senior doctors	22.2	22.3	0.4
	Junior doctors	27.9	28.7	2.8
Wednesday	Specialists	20.5	20.0	2.5
	Senior doctors	24.5	23.5	4.3
	Junior doctors	29.5	28.4	3.9
Thursday	Specialists	18.5	18.1	2.2
	Senior doctors	25.5	24.9	2.4
	Junior doctors	31.5	30.2	4.3
Friday	Specialists	16.2	15.9	1.9
	Senior doctors	25.4	24.7	2.8
	Junior doctors	28.0	27.6	1.4
Saturday	Specialists	21.4	21.2	0.9
	Senior doctors	25.17	24.8	1.5
	Junior doctors	27.6	26.9	2.6

Table 6: Comparisons of patient's waiting time for each type of patients

	Patient types											
	Patient level 1 (red)			Patient level 2 (yellow)			Patient level 3 (green)			Patient level 4 (blue)		
Days	Act	Sim.	Diff.	Act	Sim.	Diff.	Act	Sim.	Diff.	Act	Sim.	Diff.
Sunday	4.2	4.3	2.33	11.2	11.3	0.88	21.7	21.9	0.91	35.3	35.6	0.84
Monday	5.4	5.6	3.57	12.4	12.5	0.80	24.5	24.7	0.81	29.2	29.5	1.02
Tuesday	3.6	3.7	2.70	13.2	13.4	1.49	23.4	23.6	0.85	37.1	37.3	0.54
Wednesday	6.1	6.2	1.61	10.4	10.6	1.89	21.7	21.8	0.46	39.3	39.6	0.76
Thursday	4.2	4.3	2.33	15.6	15.7	0.64	26.8	26.9	0.37	38.4	38.7	0.78
Friday	5.7	5.8	1.72	17.4	17.6	1.14	22.1	22.8	3.07	31.4	31.7	0.95
Saturday	4.9	5.1	3.92	16.1	16.3	1.23	27.4	27.9	1.79	32.5	32.6	0.31

Table 7: Comparisons of percentage for utilization of doctors

	Average utilization (%)		
Type of doctors	Act	Sim.	Diff
Specialists	75.5	74.5	1.3
Senior	76.9	78.5	2.1
Junior	81.4	79.5	2.4

Table 8: Comparisons of doctor utilization between the current system and new scenario

	Utilization (%)								
	Specialists			Senior			Junior		
Days	Crnt.	New	Diff.	Crnt.	New	Diff.	Crnt.	New	Diff.
Sunday	75.6	76.7	1.4	73.5	74.8	1.7	78.2	79.9	2.1
Monday	73.7	77.1	4.4	77.1	81.8	5.7	78.4	81.9	4.3
Tuesday	77.5	83.4	7.1	80.2	87.5	8.3	81.0	88.1	8.1
Wednesday	69.2	78.0	11.3	69.5	70.9	2.0	70.1	72.4	3.2
Thursday	74.5	77.9	4.4	68.4	78.5	12.9	72.5	75.4	3.8
Friday	77.7	80.1	3.0	79.4	89.9	11.7	74.5	81.3	8.4
Saturday	72.4	73.5	1.5	74.6	76.2	2.1	71.5	73.5	2.7

Table 9: Comparisons of patient's waiting time between the current system and new scenario

	Patient types											
	Patient level 1 (red)			Patient level 2 (yellow)			Patient level 3 (green)			Patient level 4 (blue)		
Days	Crnt.	New	Diff.	Crnt.	New	Diff.	Crnt.	New	Diff.	Crnt.	New	Diff.
Sunday	4.3	3.9	10.3	11.3	10.2	10.8	21.9	19.2	14.1	35.6	32.4	9.9
Monday	5.6	4.3	30.2	12.5	11.2	11.6	24.7	22.1	11.8	29.5	27.2	8.5
Tuesday	3.7	2.8	32.1	13.4	9.8	36.7	23.6	21.3	10.8	37.3	33.8	10.4
Wednesday	6.2	5.4	14.8	10.6	9.7	9.3	21.8	20.3	7.4	39.6	36.8	7.6
Thursday	4.3	3.7	16.2	15.7	14.4	9.0	26.9	24.5	9.8	38.7	35.6	8.7
Friday	5.8	5.1	13.7	17.6	15.6	12.8	22.8	19.8	15.2	31.7	28.6	10.8
Saturday	5.1	4.3	18.6	16.3	14.7	10.9	27.9	23.5	18.7	32.6	28.7	13.6

doctors their utilization rates are approaching the desired level. However, as expected, patient's waiting times increased by as low as 7.4% and as high as 36.7%.

CONCLUSION

With the advantages of simulation techniques to mimic a real-world system this study incorporates the use of Arena simulation software to develop a flexible DES model of an ED. The generic model is developed with the aims to improve the understanding of staffs about their system and to help them in analyzing the performance of the current system. The developed model is useful in decision making as the administrators can perform changes to the current system without affecting the existing operations.

In this study, we conducted an experiment by increasing the number of patients by 10% in order to see the impact on doctor's utilization. Results from the experiment have shown an increase in doctor utilization but at the same time increased patient's waiting time. Therefore, further works need to be done in determining effective ways to reduce patient's waiting time and at the same time optimizing the available resources.

SUGGESTIONS

In addition, future works need to give concern on the data collection as the output obtained from this study was only based on three weeks data collection. For better accuracy, more data is needed and perhaps in future the ED staffs should be engaged in the data collection team.

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