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An Evolutionary Algorithm Frame Work with Potential Enhancement in Selection, Cross over and Mutation Operators for a Nurse Scheduling Problem

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Abstract: Generating the best nurse schedule is an ever challenging effort for many decades.The real world scenario sare influenced by external factor srelated to hospital environment and internal factors characterized by the nurse personnel themselves. The effort is being further hindered by the complexity of the nurse scheduling problem which trigge red numerous potential scheduling approaches thus far. Hence, joining the race to search for the most suitable approach,this study proposed an Evolutionary Algorithm (EA) frame work with embedded enhancement in its selection, cross over and mutation operators. The evolutionary approach is expected to generate and produce the best suitable nurse working schedule for a highly constrained setting. Supported by the current scheduling trend in the approaches, some fruitful nurse scheduling models are in the pipe line of future work.

Key words: Nurse scheduling problem, scheduling techniques, Evolutionary algorithm, health care management, human resource management

INTRODUCTION

With improved lifestyles and abetter 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 increasein 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 ofhealth 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 simulationin modeling health care problems. In the domain of ED, several researchers have successfully adopted and implemented simulation to solve ED problems that are related to resource allocation, improving patient flow and reducing patients' waiting time (Komashie and Mousavi, 2005; Ruohonen *et al*., 2006; Gunal and Pidd, 2007; Powell, 2007; Ahmad and AlKhamis, 2008; Brenner *et al*., 2010). Other researchers have also taken advantage of the flexibility of simulation approaches by integrating simulation with other techniques like integer linear programming, genetic algorithm and optimization algorithm (Ahmad and AlKhamis, 2008). Many of these simulation studies highlighted the applicability of Discrete Event Simulation (DES) to identify bottlenecks, to model complex patient flows, to provide detailed operational characteristic, to evaluate current health care system performance and to design a new health care systemof 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

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patients in terms of the 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: From literature, it is apparent that waiting time has become a frequent topicof investigation and often becomes one of the performance measures in ED modeling. For instance, Panayiotopoulos and Vassilacopoulos (1984) proposed queuing theory approach to study the effect of waiting times on ED. However, in order to capture the complex behavior and stochastic nature of ED many researchers have applied computer simulation to address the waiting time problems (Blake *et al*., 1996; Mahapatra *et al*., 2003; Takakuwa and Shiozaki, 2004; Eskandari *et al*., 2011). The developed models enabled ED administrators to identifythat 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 waitingtime.

In addition to waiting time, researchers also studied the length of stay experienced by patients in ED. For instance, Blasak *et al*. (2003) presented asimulation study of the operations between the Medical Telemetry Unit and ED at Rush North Shore Medical Center. The model was developed using Arena Software that depicts the current operations and allows the administrators to evaluate proposed changes to reduce the length of stay and to improve operations. Similarly, Samaha *et al*. (2003) developed a simulation model of the operation in the ED of Cooper Health System to reduce the length of stay.

They introduced a fast-track center that is able to expedite flows of non-critical patients through the system and ultimately reduce the length of stay. An application of DES modeling to determine the impact of critical resources (beds, doctors and nurses) on key performances (queuing time and length of stay) has been discussed by Komashie and Mousavi (2005). 5 scenarios were tested by altering the number of critical resources and removed impact of admission to ED process. The results show that 20% reduction of patients' waiting time isobtained when admission blockage is removed. Ruohonen *et al*. (2006) discussed the application of the simulation model in describing the operations in the ED of aspecial health care at Jyvaskyla, Finland. The study tested the impact of a triage-team method on key performances (waiting times and throughput time). Results from the model showed that the new triage approach is able to improve over 25% of the operations of the ED if implementation and all necessary tasks are properly considered.

On the contrary, Patvivatsiri (2006) focused on the impact of ahypothetical bioterrorist attack on ED capacity. Her model suggested that staffing strategy at two bottle necked areas of the hospital's treatment facility would allow asignificant reduction in patients' total time in the ED and an improvement on theutilization of resources.

Baesler *et al*. (2003) described the application of DES model in estimating future capacity of an ED in a private hospital. They used the DES model to predict the behavior of patient's time in the system and estimate the maximum possible demand that can be absorbed by the system using its capacity. Similarly, Wiinamaki and Dronzek (2003) developed a DES model to predict the number of beds required for expanding the current ED at Sarasota Memorial Hospital in Florida.

One similarity of the a fore mentioned 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 and coauthors.

Another study doneby 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 ED sim 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). 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 operated 24 h every day a week and receives an average of 1554 patients weekly. The process flow begins with patient arrivals. Typically, patients arrive either by ambulance or as walk-in cases. At the same time a medical assistant will triage the patients. However, critical patients 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 waiting to be called for treatment. If there is an availability of a doctor, the patient moves to the treatment area and sees the doctor. Delay of doctor to patient contact depends on severity of illnesses. Doctors will decide if the patient needs further tests such as clinical lab tests or X-rays. Results obtained will be reviewed by doctors and a decision is made upon the results. Discharged patients can either be released to go home or send to hospital wards for further treatment as shown in Fig. 1.

The developed model includes activities that are typical in hospital EDs. In addition to the several different areas of the hospital, including registration, triage, reception and beds, special cases such as emergency calls, doctor and nurse schedules are modeled. The administrators of an ED are interested to find the optimal staffing levels to serve the incoming patients within the specified target time. The ED must be able to treat its patients in a timely manner, yet not be overstaffed (which costs the hospital a lot of money).

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 solution and to determine the extent to which the DES is effectively able to solve the ED problems. Arena Software is able to bring the power of modeling and simulation to business environment as it is designed for analysing the impact of changes that involve significant and complex redesigns associated with manufacturing, business processes, supply chain, logistics, distribution and warehousing and service systems.

There are three main components in DES, i.e., the entities, the resources and the processes. Entities are the moving parts that 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 operating rooms, hospital beds, medical equipment, etc. In addition, both patients and resources can be assigned with attributes, like illness, age, gender, availability and capacity. The processes, on the other hand, are the services required by the entities, i.e., the treatments or diagnostic tests required by patients. The model considers a three-step process that is purposefully simplified:

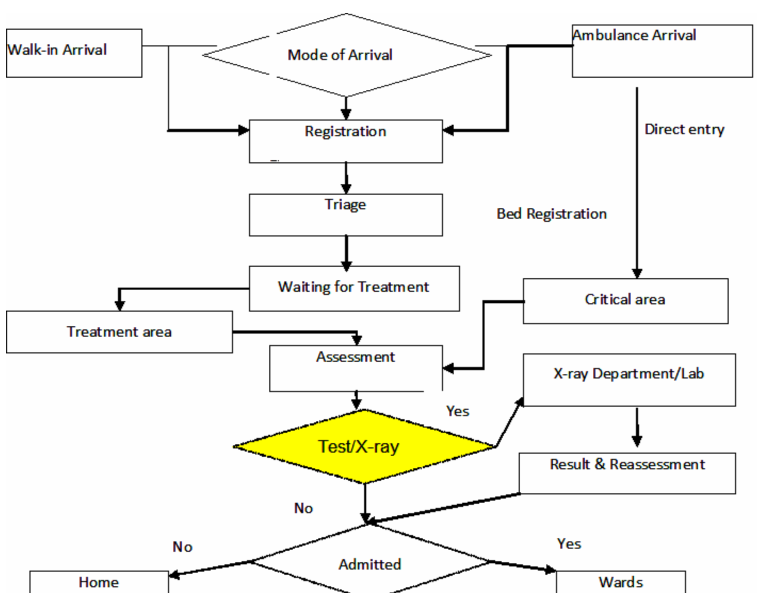

Fig. 1: The primary process

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

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 arrive to the emergency room either through the entrance door or via ambulance. The simulation model groups these patients into four categories: level 1-4. Level 1 patients (Red triaged) such as heart attacks victimsare considered the most critical and need to be treated immediately. Levels 2 and 3 patients (Yellow and Green triaged) go through a triage process where the medical staffs make an initial assessment of their injuries. Level 4 patients (Blue triaged) refer to patients that appear non-critical and are sent to triage for evaluation. All patients are then transferred to an available bed for treatment. Each patient needs to go through a registration process either before or after treatment depending on the severity of his/her injury. After initial medical treatment, the hospital can release the patient or assign him/her to a bed in the hospital for a longer stay (Fig. 3).

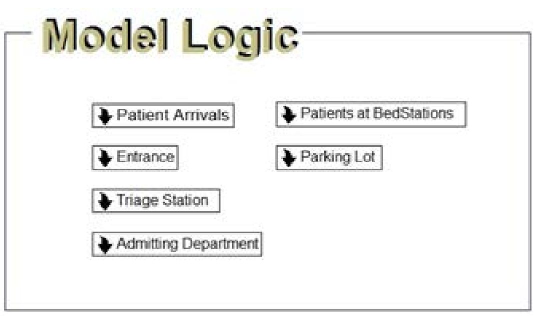

Fig. 2: Primary model logic of the ED healthcare process

The ED needs to be adequately staffed to meet the number of incoming patients. Historical data was used to simulate the number of incoming patients, categorized into arrivals by day, evening and morning and the severity of their injuries. To satisfy 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. In order to find the optimal levels of these resources, the Arena optimization tool, OptQuest was applied to the emergency room model. The objective for OptQuest was to "maximize the beds in use" which would in effect reduce the number of unneeded resources and beds.

OptQuest ran 15 iterations of the emergency room model and the optimal results are presented in Table 1 as follows: The obtained optimal values of staffing levels were applied to the emergency room model and the associated cost was determined. In addition, Arena Dashboard was used to graphically illustrate the proposed staffing levels by showing the "Bed Usage" and "Number of Patients Waiting". The Dashboard clearly showed that the use of the optimal values of resources in the emergency room would provide a timely and appropriate service for all incoming patients.

Data collection: The data collected in this study came from both the primary and secondarydata sources. Most of the data were gathered through visits to the ED under study. Unlike, the hospitals in overseas, patient information system in Malaysia lacks some of the

Table 1: Result from OptQuest

Resource	Optimal result
Administrative clerk	4
Nurse	6
Patient Care Technician (PCT)	4
Physician	6
Emergency beds	16

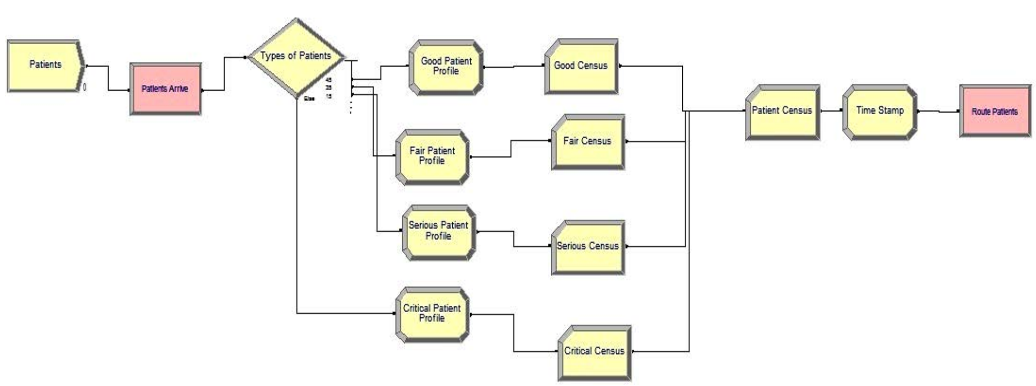

Fig. 3: Patients arrival at the emergency room

important data like the processing times experienced by each patient. Further, most of the important data collected such as arrival time and exit time are manually recorded in log books. This study deployed 3 methods of data collection, namely observations, interviews and document analysis.

RESULTS AND DISCUSSION

The gathered data was analyzed using Arena 12 input and output analyzers and the output obtained for one week (7 working days 24h) were as follows: Since patients are issued at the counter, their arrival patterns are influenced by the arrival times. The number of patients' 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 10 replications and the average values for the number of patients treated, the doctors' process time, the patients' waiting time and the percentages of doctors' 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 eachtype 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.

Doctors' process time: The comparisons between the actual data and the simulation output of the doctors' 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.

Patients' waiting time: The comparisons between the actual and simulated data of the patients' 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 <4%. Again, these results show that both the actual and simulated data seem to closely correspond to one another and are in good agreement.

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

	Mean total patient's arrivals			
Days	Red	Yellow	Green	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	92	254	481	665

Table 3: The Distributions of Doctors' Service Times for Monday-Friday

Treatment	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)

Table 4: Comparisons of Number of patients for each type treated

Day	Patient' type											
	Patient level 1 (Red)			Patient level 2 (yellow)			Patient level 3 (Green)			Patient level 4 (Blue)		
	Act	Sim	Diff (%)	Act	Sim	Diff (%)	Act	Sim	Diff (%)	Act	Sim	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	4.	4.50	66.2	68	2.65	90.3	93	2.90

Table 5: Comparisons of mean doctors' process time

Day	Tpyes of doctor	Act	Sim	Diff (%)
Sunday	Speacialist	17.10	17.6	2.8
	Senior	20.10	20.0	0.5
	Jounior	24.50	24.4	0.4
Monday	Speacialist	19.90	19.6	1.5
	Senior	24.90	24.8	0.4
	Jounior	27.90	28.7	4.7
Tuesday	Speacialist	18.80	18.8	0.0
	Senior	22.20	22.3	0.4
	Jounior	27.90	28.7	2.8
Wednesday	Speacialist	20.50	20.2	2.5
	Senior	24.50	23.5	4.3
	Jounior	29.50	28.4	3.9
Thursday	Speacialist	18.50	18.1	2.2
	Senior	25.50	24.9	2.4
	Jounior	31.50	30.2	4.3
Friday	Speacialist	16.20	15.9	1.9
	Senior	25.40	24.7	2.8
	Jounior	28.00	27.6	1.4
Saturday	Speacialist	21.40	21.2	0.9
	Senior	25.17	24.8	1.5
	Jounior	27.60	26.9	2.6

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

	Mean patient' waiting time(minute)											
	Patient level 1 (Red)			Patient level 2 (yellow)			Patient level 3 (Green)			Patient level 4 (Blue)		
Day	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	1.3

Utilization of doctors: The comparisons between the actual data and the simulation output in terms of percentageforutilization 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. If 30 min is set as the standard patien' waiting time as suggested by Valdivia and Crowe, then the waiting time for Level 4 patients is unsatisfactory where patients have to wait >30 min, except for Monday where the patients' 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 <85%, the desired level set by the ED management. Since, patients waiting time is unsatisfactory and doctors are not fully utilized, 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 patients' 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 4.5-10.4%. With these changes, the desired level of 85% utilization for certain types of doctors is met while for the remaining doctors, their utilization rates are approaching the desired

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

	Utilizatio								
	Speacialist			Senior			Junior		
Day	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	96.9	28.3	70.1	72.4	3.2
hursday	74.5	77.9	4.4	78.5	78.5	12.9	72.5	74.5	3.8
Friday	77.7	80.1	3.0	89.9	89.9	11.7	74.5	81.3	8.4
Saturday	72.4	73.5	1.5	76.2	76.2	2.1	71.5	73.5	2.7

Table 9: Comparisons of Patients' Waiting Time between the Current System and New Scenario.

	Waiting time(minute)											
	Patient level 1 (Red)			Patient level 2 (yellow)			Patient level 3 (Green)			Patient level 4 (Blue)		
Day	Crnt	New	Diff (%)	Crnt	New	Diff (%)	Crnt	New	Diff (%)	Crnt	New	Diff (%)
Sunday	36.2	39.2	7.65	22.3	24.3	8.23	76.3	79.6	4.15	53.2	57.1	6.83
Monday	33.6	37.1	9.43	18.5	20.4	9.31	56.5	62.5	9.60	40.8	41.3	1.21
Tuesday	26.4	29.3	9.90	23.9	28.4	15.85	106.5	120.1	11.32	97.7	104.4	6.42
Wednesday	29.6	33.4	11.38	24.2	25.2	3.97	121.8	131.4	7.31	97.7	104.4	6.42
Thursday	37.6	40.1	6.23	26.3	29.3	10.24	114.0	117.2	2.73	83.2	85.4	2.58
Friday	19.6	21.4	8.41	27.4	28.3	3.18	87.7	88.3	0.68	96.4	99.2	2.82
Saturday	24.3	26.3	7.60	23.1	24.5	5.71	95.1	97.3	2.26	78.3	81.2	3.57

level. However, as expected, patients' waiting times increased by as low as 1.2% and as high as 18.8%.

CONCLUSION

With the advantages of simulation techniques to mimic a real-world system, this study incorporates the use of Arenasimulation softwareto 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 see the impact on doctors' utilization. Results from the experiment have shown an increase in doctor utilization but at the same time increased patients' waiting time. Therefore, further works need to be done in determining effective ways to reduce patients' waiting time and at the same time optimizing the available resources. In addition, future works need to give concern on the data collection as the output obtained from this study was only based on data collected over a period of 3 weeks. For better accuracy, data should be collected for a period longer than 3 weeks.

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