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Estimating Emergency Department Maximum Capacity using Simulation and Data Envelopment Analysis

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Abstract

Recently, the number of Emergency Department visits in UKM Medical Centre has increased rapidly. This has encouraged several healthcare problems occur in the emergency department such as overcrowding. A study was conducted to estimate the maximum possible demand that able to serve by the emergency department with current number of resources. Discrete Event Simulation method was applied to model the Emergency Department system. The model was used to study the behavior of waiting time of the emergency department visits and predict the maximum demand. Finally, combination of Data Envelopment Analysis methods (BCC input-oriented and Super-efficiency-BCC) was used in order to determine the new configuration of number of resources (doctor and nurse) required to maintain their efficient services. Results assume that the Emergency Department capable to accommodate 230 patients per day with an additional doctor to Yellow Zone Treatment Area and new schedule time for Green Zone doctors.

Keywords: Data Envelopment Analysis, Discrete Event Simulation, Emergency Department Overcrowding, Healthcare Modelling

1. Introduction

Emergency Department (ED) crowding can be defined as an extremely busy situation occurs in ED caused by imbalance condition between medical resources supply and demand for quick and quality service by patients[1]. The main reason for overcrowding in the ED are increasing volume of ED visits, delay for hospital admission caused by insufficient inpatient bed capacity, seasonal illnesses and lack of staffs. Therefore, it usually leads to variety negative effects to happen such as treatment delays, long waiting time[2], patient dissatisfaction, medical error, high utilization rate of ED resources, patient mortality and patient leaving without being seen[3].

Universiti Kebangsaan Malaysia Medical Centre (UKMMC) who is located in the heart of Kuala Lumpur, Malaysia also has experienced the similar dilemma. Receiving more than 72,000 patients annually or an average of 200 patients per day through ED has made the hospital one of the busiest hospitals in Kuala Lumpur. Overcrowding issues has been identified occur regularly in the ED. According to a case report wrote by[1], UKMMC experienced the most terrible overcrowding situation on Wednesday 21st March 2012. On that day, ED UKMMC

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has been operating by taking only critical and semi-critical patients. This situation happened since large numbers of admitted patients unable to be transferred to hospital ward as the whole ward are fully occupied. Thus, they were temporarily placed throughout the ED and remained there for more than 24 hours. Thus, the ED has become overcrowded and raises the utilization rate of their staffs.

Related to that incident, hospital management begin to implement various measures to deal with overcrowding issues. One of the hospital concerns is to estimate maximum number of ED visits that they able to serve by maintaining the efficiency of their services. By doing so, it can help the hospital management able to perform early and right decisions before the ED system become worst.

Therefore, Discrete Event Simulation (DES) method is applied in the first phase in order to model daily operation of ED UKMMC system. The method is chosen since it is a powerful technique that capable to model a complex system like ED[4]. It is also the most cost-effective way to solve problem as possible modification can be tested without disturbing the operation of actual system[5]. Moreover, it can help us to get a clear picture of the behavior of our system. In that case, bottlenecks can be identified and several possible improvements can be proposed to increase the efficiency of the system.

In the second phase, a graph is constructed in order to get estimate maximum demand of ED visits. In the last phase, a maximum demand simulation model is design. Results from the actual system model are compared to the maximum demand model. Some feasible improvements are suggested to overcome the bottlenecks occurred in the maximum demand model. Then, Data Envelopment Analysis (DEA) approach is used to select the best improvement to be implemented in the ED system.

The purposes of this study can be summarized as follows; to model the ED UKMMC system, to predict the maximum demand that ED UKMMC is able to serve without increasing the waiting time over an acceptable

Table 1. Triage categorisation system and target time

Triage zone	Case	Target time	Presentation
Red Zone	Critical	Immediate	Cardiac arrest Respiratory arrest Unconsciousness Severe trauma
Yellow Zone	Emergency/ Semi-critical	Within 30 minutes	Severe chest pain Severe dyspnoea Severe pain Major trauma Severe bleeding Hyper-pyrexia
Green Zone	Non-critical	Within 3 hours	Moderate trauma Acute pain Bleeding Irritable child Minor condition

level and to determine the new configuration of number of resources required to handle with this level of demand.

2. Materials and Methods

2.1 System Description

ED treatment area in UKMMC can be divided into three colour triage zone, namely Red Zone (critical), Yellow Zone (semi-critical) and Green Zone (non-critical). All ED visits will be triaged and attended by treatment team according to target time mentions in Table 1.

Currently, the 24 hours operation of the ED involves one medical assiatance at Primary Triage counter and two nurses at Secondary Triage counter. In treatment zone, the number of nurses are difference where five in red, four (night shift) to six (day shift) in yellow and one in green. There are one Red Zone's doctor and two Yellow Zone's doctor. All of them work by shift which is starting at 0700 to 1400, 1400 to 2100 and 2100 to 0700 on the next day. Meanwhile, at Green Zone there are nine doctors who work by schedule; one starting at 0700 until 1000, three from 1000 to 1700, three from 1700 to 2300 and two at 2300 to 0700 on the next day.

2.2 Simulation Model

Development of ED UKMMC simulation model starts by study and investigate the system which include analyse of ED layout, patients flow and available recourses. This being done by interview the ED management and perform several visit to ED to get the view of how the system operates. It help us to understand the whole system clearly, process involved and required data for developing the ED model. After familiar with the system, data collection is conducted. We designed a data collection form that is used by data collection team. The data was collected by the team in one month for 24 hours. Data collected involve patient's arrival time, processing time at every process, number of patients in each zone and doctor final decision for each patient.

ARENA software is used to model the ED UKMMC. All data are gathered and ARENA Input Analyzer is used to determine the appropriate distribution to be used during modelling process. Then, the distributions are included to the modules in ARENA. The modules is linked together and run for 12 replication in order to get average and accurate results. In this model, capacity of each arrival patient is assumed as a single. Besides, animation of the model also has been created for the purpose of verification checking on the next step.

Finally, the simulation model undergoes a verification and validation test to make sure that it is valid and represent the actual operation system. Verification test is a process of ensuring the model is free from any logical error[6]. Therefore, the ED model and the animation have been shown to ED management. The model is reviewed by them in order to trace any logical error occur in the model before accepting the model as valid. Once verified, validation test is performed to the model. Validation test is a process of ensuring that the model behaves as the actual system[6]. Thus, all the results are presented to ED management and they will decide the validity of the result based on their experience. Since the results are considered reliable, thus it can be used to conduct further analysis. Besides, we also perform validation check using the following mathematical formula below. The model is run for 7 days period. Results obtained are compared to actual 7 days data and shown in Table 2 in the next section. This is done in order to reinforce the validity of the model.

$$\text{Difference}(\%) = \frac{|\text{Simulation output} - \text{Actual data}|}{\text{Actual data}} \times 100\%$$

2.3 Data Envelopment Analysis

DEA is one of a linear programming methodology that used to calculate efficiency of a group of entities or multiple Decision-Making Units (DMUs). It was first introduced by Charnes, Cooper and Rhodes in 1978. DEA has two types of model orientations which are input-oriented model and output-oriented model. Input-oriented model is used when we aim to get a minimum level of input to the given output. In contrast, the objective of output-oriented model is to get a maximum level of output to the given input. There are various DEA models that have been constructed in order to calculate efficiency for instance DEA-BCC model. DEA-BCC model is seen be recommended for evaluating efficiency in healthcare sector[7]. Therefore, based on the usual hospital objective that prefers to provide high quality services by using minimum resources, the BCC model input-oriented is used. The model is explained below:

$$Max\ \theta_0 = \sum_{j=1}^{m} u_j y_{j0} + u_0$$

$$subject\ to \sum_{i=1}^{s} v_i x_{i0} = 1$$

$$\sum_{j=1}^{m} u_j y_{jk} - \sum_{i=1}^{s} v_i x_{ik} + u_0 \leq 0$$

$$v_i \geq 0,\ u_j \geq 0,\ u_0\ free\ in\ sign$$

where θ_0 is the relative efficiency score for DMU_0, x_{i0} is the vector of input at DMU_0, y_{j0} is the vector output at DMU_0, x_{jk} is the actual value of input i used by DMU_k, y_{jk} is the actual value of output j produced by DMU_k. Meanwhile, u and v are the weights attached to inputs and outputs. DMU is efficient when $\theta_0 = 1$.

Sometime when dealing with DEA, it may occur that more than one DMU are efficient. Thus, Super-efficiency-BCC technique is used to rank the efficient DMUs. This technique modifies the BCC model above by eliminate constrain related to DMU that is being calculated. The highest Super-efficiency-BCC score is selected as the best DMU to be applied to the system.

3. FPGA

The model is run for 7 days period. Results obtained are compared to actual 7 days data as shown in Table 2 using the above mathematical formula. The percentage difference between simulation output and actual data must not exceed 10% in order to achieve the level of sufficient accuracy[8]. Since all difference values are less than 10%, we conclude that the ED UKMMC model is valid.

The second objective of this study is to predict the maximum demand that ED UKMMC is able to serve without increase patients waiting time. In order to solve the objective, the ED simulation model has been run in 6 different level of demand. Table 3 illustrates the percentage of demand increase and total arrival patients related to that particular level of demand. Meanwhile, Table 4 summarized waiting time results obtained after running these 6 scenarios. By considering the waiting for Green

Table 2. The difference between simulated and actual data

Phase	Simulation output	Actual data	Difference (%)
Total arrival patients	1356	1400	3
Number of patients in Red Zone	49	51	4
Number of patients in Yellow Zone	429	438	2
Number of patients in Green Zone	875	892	2

Table 3. Changes in demand

% Demand Increase (scenarios)	Distribution	Number of arrival patients (per day)
0 (Actual model)	-0.5 + LOGN(7.98, 6.39)	195
12	-0.5 + LOGN(7.24, 5.51)	218
19	-0.5 + GAMM(2.86, 2.44)	232
28	-0.5 + LOGN(6.38, 4.51)	249
33	-0.5 + LOGN(6.18, 4.35)	259
41	-0.5 + LOGN(5.93, 7.53)	275
54	-0.5 + WEIB(5.73, 1.18)	301

Table 4. Waiting time results for each zone (minutes)

% Demand increase (Scenarios)	Red Zone	Yellow Zone	Green Zone
0 (Actual model)	0	9	129.72 (2.2h)
12	0	10	153.56 (2.6h)
19	0	14	183.33 (3.1h)
28	0	14.2	212.35 (3.5h)
33	0	14.5	226.54 (3.8h)
41	0	16	230.74 (3.9h)
54	0	17	276.17 (4.6h)

Zone (refer Table 1), a graph (Figure 1) has been plotted to estimate the level of demand that generates the average waiting time in ED UKMMC of 3 hours.

Linear regression model of $y = 0.0228x-2.2527$ shows that for an average waiting time of 3 hours, there will be 230 patients per day. It is an increase of 17% of the existing number of patients per day. Hence, based on the model we estimated that the maximum demand that ED UKMMC is able to serve without increasing the waiting time of patients over an acceptable level is approximately

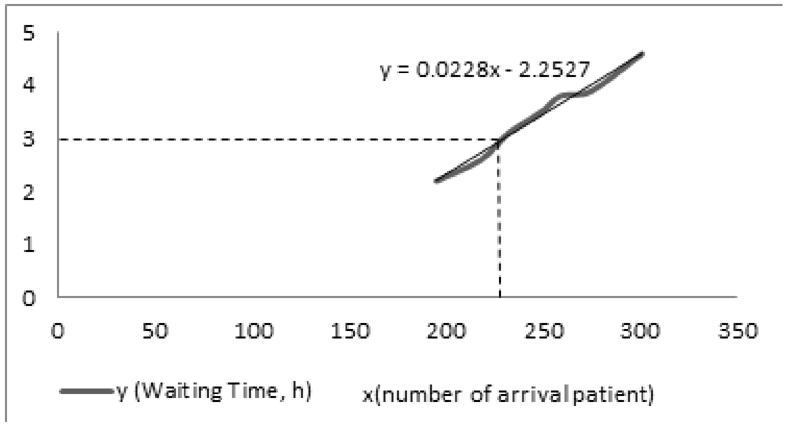

Figure 1. Demand graph.

17% increase or up to 230 patients per day. If the arrival patient is greater than this quantity, the similar overcrowding situation that mention before may be happened if appropriate decision not be implemented promptly. Then, a distribution of patient arrival that generates 230 patients is included to the actual simulation. The new model is known as maximum demand model. After run the model, results are analysed in order to study the consequences that occur to the model as number of arrival patient change.

Table 5 presents results of the total arrival patients to ED, the average waiting time before seeing the doctor, the length of stay in the system as well as the average resource utilization rate. The table shows the scenarios that happen in actual system and when total arrival patients has reached the maximum level that can be accommodated by the ED. It is noted that the waiting time at each treatment zone has increased as the total arrival patient increase. An obvious increase can be seen in Green Zone

Table 5. Simulation results of actual model and maximum demand model

Phase	Actual system model	Maximum demand model	Difference (%)
Total arrival patient	195	230	18
Waiting time (minutes):- ○ Yellow Zone ○ Green Zone **Total average**	 9 129.72 (2.2h) **172.41**	 10 178.15 (3h) **233.3**	 11 36
Average length of stay (minutes):- ○ Yellow Zone ○ Green Zone	 526.33 221.82	 588.06 283.33	 12 28
Average utilization (%):- ○ Doctor ○ Nurse	 66 55	 68 57	 3 4

area where the waiting time is increased by 36%. Each patient has to wait an average 3 hours instead of 2.2 hours to get treatment. Moreover, the waiting time in Yellow Zone also rises up by 11%. With regard to length of stay, results display that Green Zone patients spend an average 588.06 minutes and 283.33 minutes respectively in the maximum demand model. This shows an increase of 12% and 28% respectively. Furthermore, the utilization rates of ED recourses in maximum demand model shows higher value than the actual system. Utilization rate of doctor rise by 3% while for nurse, the rate rise by 4%. In this study, we do not observe the simulation outputs for Red Zone patients since they are first priority in ED system. The clinical treatment will be given immediately as soon as they arrive in the ED.

In conclusion, numerous bottlenecks began to occur once arrival patient has achieved 230. It can be seen that the bottleneck occur primarily at Green Zone area which causes patients have to wait longer to seek medical advices by doctor. In addition, average waiting time patient at Yellow Zone should also be enhanced in order to improve ED's efficiency. This can be done by adding or reallocating staffs at the appropriate area. By doing so, it is indirectly can lower the staffs utilization rate. For that reason, several modifications to maximum demand model are suggested in the next section.

3.1 Model Improvement

Several modifications to maximum demand model are suggested in order to improve the model. This being done by adding staffs at the appropriate area, reallocating them and reschedule the existing staff's timetable. Based on the modification, six improvement models has been developed and presented in Table 6. The proposed ED improvement models are known as DMU.

All the DMUs are run for twelve replications to get accurate results in average. The outputs after run those DMUs are analyzed. The comparison among those models is mention in Table 7. This output is used to evaluate the efficiency of each DMU.

Table 6. Proposed improvement to maximum demand model

Improvement model (DMU_i)	Additional doctor		Additional nurse at Yellow Zone
	Yellow Zone	Green Zone (Schedule)	
DMU1	1	1 (7 am – 10 am)	1
DMU2	1	2 (7 am – 10 am)	0
DMU3	1	2 (8 am – 10 am)	0
DMU4	1	1 (8 am – 10 am)	0
DMU5	1	1 (8 am – 10 am)	1
DMU6	1	0*	0

*No additional doctor, however doctor who work from 7 am to 10 am is schedule to work from 7 am until 2 pm

Table 7. Simulation results of different DMU

Improvement model (DMU_i)	Number of Doctor	Number of Nurse	Total average waiting time (minutes)	Average utilization of Doctor (%)	Average utilization of Nurse (%)	Number of patient served
DMU1	7	13	173.9	65	57	128
DMU2	8	12	165	65	56	128
DMU3	8	12	164.5	63	56	126
DMU4	7	12	193.1	64	56	127
DMU5	7	13	182	63	57	126
DMU6	6	12	172.4	64	55	130

The best improvement model is determined by DEA BCC input-oriented model. Number of doctor, number of nurse, total average patient waiting time is set as inputs. Meanwhile, average utilization of doctor, average utilization of nurse, number of patient served is set as outputs. The objective of this method is to reduce total average waiting time of the model using minimum number of resources with the given average utilization rate of resources and number of patient served. All of this data are included to the DEA BCC input-oriented model. Then, it is solved using LINGO 12.0 software. The results are presented in Table 8.

Table 8. Results of BCC input-oriented and super-efficiency

Improvement model (DMU_i)	BCC input oriented score	Super- efficiency score	Rank
DMU1	0.99067		
DMU2	1	1.03071	2
DMU3	1	1.00304	3
DMU4	1	1	4
DMU5	0.952071		
DMU6	1	1.1849	1

The efficiency scores show that DMU2, DMU3, DMU4 and DMU6 are efficient DMUs. Since more than one model is efficient, Super-efficiency-BCC will be used. The method ranks DMU6 as the higher followed by DMU2, DMU3 and DMU4. Therefore, DMU6 is selected as the best improvement model.

4. Discussion

The above method suggests that the DMU6 is the best improvement model. It is suggested that to add only a doctor at Yellow Zone Treatment Area when overcrowd situation start to occur in the ED. No additional doctor is needed at Green Zone Treatment Area. However, one of the doctors who work at 7 am to 10 am is scheduled to work until 2 pm. By implementing this improvement, it can reduce the expenses incurred by administration if hiring more additional staff to the ED. Such expenses can be used for other things such as buy new hospital equipment or expand the hospital capacity.

Table 9 displays the average waiting time patient has reduced by 26%. This happened due to several modifications being done to the ED staffs. As a result, the process of getting treatment become faster and patient has to spend less time in the ED system. At the same time, the number of patient served also improves by 8%. [9]Suggests that two indicators that indicate patient flow of an ED is efficient namely a low waiting time and short length of stay. Therefore, we can conclude that the ED service become efficient as the both factors have been met by enhance the above improvement.

The time when the number of patients to ED is increase, the workload among ED staffs increase. This situation will cause the staff's utilization rate also increase. Higher human utilization rate are proven capable to decrease quality of care by increases the potential medical errors[10]. Therefore, by performing such improvement, the utilization rate of doctor as well as the nurse is seen reduce by 4% and 2% respectively. Besides, all the staffs will not be burdened with lots of workload and have time to rest within each job. In conclusion, DMU6 is chosen as the best improvement model to improve overcrowd situation and maintain the efficiency of the ED.

5. Conclusion

This paper presents a study to predict maximum demand that can be accommodated by ED UKMMC without increasing the waiting time of patients over an acceptable and to optimize numbers of staffs required to handle the situation. The actual daily operation of the ED system has been developed using DES method. The maximum demand value is predicted by run the simulation model with different level of demand. By considering the waiting for Green Zone, a graph has been plotted and estimate that the ED able to serve approximately 17% increase or up to 230 patients per day.

Table 9. Comparison results of the DMU6 model and maximum demand model

Model	Number of Doctor	Number of Nurse	Total average waiting time (minutes)	Average utilization of Doctor (%)	Average utilization of Nurse (%)	Number of patient served
Maximum demand	5	12	233.3	67	56	120
DMU6	6	12	172.4	64	55	130
Difference (%)	20	0	26	4	2	8

A modification that generates 230 total arrival patients has been made to the actual model and called as maximum demand model. Results from the actual model and the maximum demand model are compared in order to see the impact occur to the ED system as total number of patient increase. Several possible improvements have been designed to overcome bottlenecks occur in maximum demand model. The best improvement is determined by using DEA BCC-input oriented method and Super-efficiency method. The suggested improvement can be used as initial benchmark for hospital administration to perform right decision when addressing overcrowding issues. Hopefully, the efficiency of the ED system also can be increased in order to provide high-quality services to their customer.

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