Journal of Quality Measurement and Analysis *JQMA* 17(1) 2021, 153-163
e-ISSN: 2600-8602 *http://www.ukm.my/jqma*

ESTIMATING THE BEST RESOURCE ALLOCATION AT AN EMERGENCY DEPARTMENT'S GREEN ZONE USING BCC SUPER EFFICIENCY AND BI-OBJECTIVE MCDEA BCC MODELS

(Menganggarkan Pengagihan Sumber yang Terbaik di Zon Hijau Jabatan Kecemasan Menggunakan Model Kecekapan Super BCC dan Dwi-Objektif MCDEA BCC)

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ABSTRACT

Hospitals are healthcare institutions that provide medical and surgical treatment and nursing care for sick or injured people. Hospitals are generally divided into different types of departments, such as emergency, outpatients, and inpatients. The emergency department (ED) is one of the busiest departments, especially during weekends and public holidays as it handles various sorts of emergency cases. The Green Zone of an Emergency Department, which provides treatment for non-critical cases, is known to be a contributor to the extensive waiting period of patients and overcrowding. As one of the busiest departments, many patients have experienced a long waiting period before being able to receive treatment while enduring the congestion in the ED due to overcrowding of patients. This study aims to estimate the best resource allocations for improving the Emergency Department's Green Zone services. Forty resource allocations including the current and proposed allocations, have been analysed using the Data Envelopment Analysis models. Based on the comparison, the DMU36 proposed by the BCC Super Efficiency model is selected as the best and efficient resource allocation compared to the DMU18 proposed by the Bi-Objective MCDEA-BCC model in order to improve the current services in the Emergency Department's Green Zone during weekends and public holidays. The proposed resource allocation suggests the combination of four doctors and four nurses compared to the previous resource allocation of two doctors and two nurses in every shift. The result shows that the patients' waiting time before treatment at the Emergency Department's Green Zone reduces drastically from 177.80 minutes to 11.47 minutes. The findings also improved the utilisation rates of resources and managed to increase the number of patients served during weekends and public holidays.

Keywords: BCC input-oriented model; bi-objective MCDEA-BCC model; efficiency scores; super efficiency model

ABSTRAK

Hospital merupakan sebuah institusi penjagaan kesihatan yang menyediakan rawatan perubatan dan pembedahan serta penjagaan kejururawatan bagi orang yang sakit dan cedera. Secara amnya, hospital terbahagi kepada beberapa jabatan seperti kecemasan, pesakit luar, dan pesakit dalam. Jabatan kecemasan merupakan satu daripada jabatan yang paling sibuk terutamanya pada hujung minggu dan cuti umum kerana menangani pelbagai kes kecemasan. Zon Hijau bagi Jabatan Kecemasan yang menyediakan rawatan untuk kes-kes yang tidak kritikal, dikenali sebagai penyumbang kepada kesesakan dan tempoh menunggu pesakit yang lama. Sebagai jabatan tersibuk, banyak pesakit mengalami tempoh menunggu yang lama sebelum mendapat rawatan selain terpaksa bersesak disebabkan bilangan pesakit yang ramai. Kajian ini bertujuan untuk menganggarkan peruntukan sumber terbaik bagi menambah baik servis di Zon Hijau Jabatan Kecemasan. Empat puluh peruntukan sumber termasuk peruntukan semasa dan cadangan telah dianalisis menggunakan model Analisis Penyampulan

Data (APD). Berdasarkan perbandingan, DMU36 yang dicadangkan oleh Model Kecekapan Super BCC dipilih sebagai peruntukan sumber yang terbaik dan berkesan berbanding dengan DMU18 yang dicadangkan oleh Model Dwi-Objektif Analisis Penyampulan Data Pelbagai Kriterium bagi menambah baik servis semasa di Zon Hijau Jabatan Kecemasan pada hujung minggu dan cuti umum. Peruntukan sumber yang dicadangkan menunjukkan gabungan empat doktor dan empat jururawat berbanding dengan peruntukan sumber sebelumnya, iaitu dua doktor dan dua jururawat dalam setiap syif. Hasilnya menunjukkan bahawa masa menunggu pesakit sebelum rawatan di Zon Hijau Jabatan Kecemasan berkurang secara drastik daripada 177.80 minit kepada 11.47 minit. Hasil kajian juga dapat menambah baik kadar penggunaan sumber dan berjaya meningkatkan jumlah pesakit pada hujung minggu dan cuti umum.

Kata kunci: model berorientasikan input BCC; model dwi-objektif analisis penyampulan data pelbagai kriterium; skor kecekapan; model kecekapan super

1. Introduction

The emergency department (ED) is one of the busiest departments in a hospital as it handles emergency cases, provides health aid services for patients, and managing critical and non-critical cases for 24 hours daily, especially during weekends and public holidays (Ireen Munira *et al.* 2018; Komashie & Mousavi 2005; Nazhatul Sahima *et al.* 2018a). As the busiest department, many patients endure a long waiting period before receiving treatment while having to tolerate the congestion in the ED due to the large crowd of patients and their extended families. This often occurs due to the drastic increase in demand from the public for ED's services in public hospitals, particularly during weekends and public holidays (Wan Malissa *et al.* 2016a; 2016b). Reflectively, as the number of patients increases, the waiting time for obtaining treatment becomes more extensive and results in congestion in ED. As a result, some patient even leaves without being treated (Nazhatul Sahima *et al.* 2018b). Besides that, another critical issue that most ED has to combat is the shortage of resources such as medical staff namely doctors and nurses.

Likewise, similar problems are faced by the Emergency Department's Green Zone of Hospital Universiti Sains Malaysia (EDHUSM), as it is one of the busiest hospitals located in the capital city of Kelantan, Malaysia. Evidently, EDHUSM's Green Zone failed to achieve the targeted Key Performance Indicator (KPI) that is set at 120 minutes on waiting period due to key problems such as high patient volume which leads to congestion during the weekend and public holidays (Nazhatul Sahima *et al.* 2018a; 2018b; Selasawati *et al.* 2004). Although EDHUSM's Green Zone has five consultation rooms, only two rooms are in operation currently with two doctors and are supported by two nurses for each shift. According to Selasawati *et al.* (2004), patients visiting EDHUSM gradually increase towards the weekend and hit the peak during weekends. Basically, the demands are higher during weekends and public holidays as compared to weekdays due to the closure of all outpatient departments and healthcare clinics on weekends (Nazhatul Sahima *et al.* 2018b). Ironically, although the number of patients increases, the allocation of doctors and nurses are similar to what's allotted during the weekdays.

Conferring to Wan Malissa *et al.* (2016a), Ireen Munira *et al.* (2014), Norazura *et al.* (2012), who corroborated that insufficient resource allocations are one of the main reasons of failure to achieve KPIs by an ED's Green Zone. The shortage of manpower leads to extensive patients' waiting time which eventually contributes to the congestion in the Green Zone. As a result, the utilisation of doctors and nurses is at its peak and almost maximized which is beyond the recommended utilisation level of 70% to 80% utilisation rate for the service sector

(Louis 2004; Mohd *et al.* 2016). Irrefutably, this condition overburdened the doctors and nurses as it left them with no time to rest. Consequently, this overwhelming burden leads to a decrease in performance, which is reflected in the failure to achieve KPIs, fewer patients served, and the health of the doctors and nurses. Therefore, to overcome these problems, proper resource allocation of doctors and nurses for each shift is required to ensure improvement in current patients' waiting time, proper utilisation of doctors and nurses, achieve the set KPIs and increase the number of patients aided.

2. Method of Study

Previously, multiple studies were conducted using various methods in determining the best resource allocations. Researchers alike Blasak *et al.* (2003), Siddhanta *et al.* (2003), Takakuwa and Shiozaki (2004), Tijen *et al.* (2006), Wiinamaki and Dronzek (2003), have applied single methods such as Discrete Event Simulation (DES), Data Envelopment Analysis (DEA) and System Dynamics Simulation (SD) in solving problems in the ED. Meanwhile, some researchers have also introduced hybrid methods by integrating two or more methods to identify the best resource allocations in the ED (Al-Refaie *et al.* 2014; Norazura *et al.* 2014; Weng *et al.* 2011; Brailsford *et al.* 2010; Chahal & Eldabi 2008). A previous study conducted by Wan Malissa *et al.* (2018) applied the Bi-Objective Multiple Criteria Data Envelopment Analysis BCC (Bi-Objective MCDEA-BCC) and Cross Efficiency models in DEA to measure the efficiency score and to determine the best resource allocation of the Emergency Department of Pusat Perubatan Universiti Kebangsaan Malaysia's (EDPPUKM). Whereas Weng *et al.* (2011) have applied the BCC input-oriented model to identify the best resource allocation in the Emergency Department of Taiwan Hospital.

Comparatively, the BCC model is deemed to be more suitable compared to CCR model for measuring efficiency in hospitals as the performance in ED services is not always linear and most healthcare facilities aim to achieve a higher level of service for the patients by using fewer resources. Therefore, this study will compare the best resource allocations proposed by using BCC Super Efficiency and Bi-Objective MCDEA-BCC models to measure the efficiency score and suggest the best resource allocation of doctors and nurses per shift for weekends and public holidays in EDHUSM's Green Zone. The findings derived from this study are anticipated to improve the average patients' waiting time which subsequently ensures the achievement of KPIs and improves the level of utilisation of doctors and nurses during weekends and public holidays in EDHUSM. There are 40 DMUs or resource allocation alternatives that have been suggested in this study for weekends and public holidays improvement to resolve patients' congestion, reduce patients' waiting time for treatment as well as utilise resources optimally in the Emergency Department. The suggestion is based on the discussions with the management of EDHUSM according to the department's budget allocation and also possible number of doctors and nurses in each shift. DMU1 is referred to the current resource allocation while DMU2 until DMU40 are the proposed resource allocations for improvement in EDHUSM.

In addition, a total of three inputs and three outputs were selected in this study. The inputs and outputs selected in this study are guided by the inputs and outputs used by previous researchers such as Al-Refaie *et al.* (2014), Wan Malissa *et al.* (2018) and Weng *et al.* (2011) in problem solving in the Emergency Department. The number of doctors, number of nurses and patient waiting time in the Green Zone were set as inputs, while the utilisation of doctors, utilisation of nurses and number of patients completed in the Green Zone were set as outputs. In order to obtain more efficient and accurate scores, the number of DMUs measured is more than twice the sum of the number of inputs and outputs used (Cooper *et al.* 2007; Wan

Malissa *et al.* 2018). Therefore, the suggestion of 40 DMUs is coincidental as it exceeds twice the sum of the number of inputs and outputs used in this study, which is (6 + 6) x 2 = 24. Constructively, the Lingo 14 Software will be used to determine the best resource allocation alternative by getting the best efficiency score for each DMUs using both DEA models.

2.1. *BCC Input-Oriented and Super Efficiency Model*

The most widely used technique for efficiency measurement is the non-parametric technique namely the DEA. This technique is mainly based on the frontiers' analysis concept, which uses a mathematical programming method to estimate the relative efficiency scores of a specific set of DMU. It was proven from the study conducted by Rebba and Rizzi (2007), Wan Malissa *et al.* (2018) and Weng *et al.* (2011), that the DEA method was successfully used for measuring hospital's performance. The DEA method could invariably guide a hospital's management team to identify potential sources of inefficiency by using different weights to re-run linear programming. This is possible because the DEA method allows for the inclusion in the analysis of a wide range of inputs and outputs. Wan Malissa *et al.* (2016a) stated that the BCC model is recommended for evaluating efficiency in the healthcare sector. Thus, the BCC input-oriented model is used based on the common hospital's objective that prefers to provide high-quality services while using minimum resources. Eq. (1) until (4) shows the BCC input-oriented model.

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

subject to:

$$\sum_{i=1}^{s} v_i x_{i0} = 1 \tag{2}$$

$$\sum_{j=1}^{m} u_j y_{jk} - \sum_{i=1}^{s} v_i x_{ik} + u_0 \leq 0, k = 1, \ldots, n \tag{3}$$

$$u_{j,} v_i \geq 0 \tag{4}$$

where θ_0 is the efficiency score for DMU_0 that is evaluated, x_{i0} is the vector of input DMU_0, y_{j0} is the vector output DMU_0, x_{ik} is the actual amount of input i for DMU_k, y_{jk} is the actual amount of output j produced by DMU_k, and u is the weights attached to inputs and v is the weights attached to the output. By using this model, a DMU is considered as efficient if θ_0 equals to 1, while an inefficient DMU happens when θ_0 are not equal to 1 (Cooper *et al.* 2007). As this model only gives the value 1 as an efficient score, it might be difficult to determine which DMU gives the best resource allocation. In order to rank these DMUs, the Super Efficiency model is used as its ability to discriminate the second constraint by eliminating constraints related to DMU that is under evaluation (Nazhatul Sahima *et al.* 2018b; Cooper *et al.* 2007). The BCC Super Efficiency model is as per Eq. (5) until (8).

$$\text{Max } \theta_0 = \sum_{j=1}^{m} u_j y_{j0} + u_0 \tag{5}$$

subject to:

$$\sum_{i=1}^{s} v_i x_{i0} = 1 \tag{6}$$

$$\sum_{j=1}^{m} u_j y_{jk} - \sum_{i=1}^{s} v_i x_{ik} + u_0 \leq 0, k = 1, \dots, n, k \neq 0 \tag{7}$$

$$u_{j,} v_i \geq 0 \tag{8}$$

The DMUs are ranked by highest to lowest efficiency score. DMU with the highest score is deemed to be the most efficient resource allocation combination to be applied by EDHUSM's Green Zone.

2.2. *Bi-Objective MCDEA BCC Model*

The Bi-Objective MCDEA-BCC model that was introduced by Ghasemi *et al.* (2014) was applied in this study as shown in Eq. (9) until (15).

$$\text{Min } h = (w_2 M + w_3 \sum_j d_j) \tag{9}$$

subject to:

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \tag{10}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j + c_0 = 0, \; j = 1, \dots, n \tag{11}$$

$$M - d_j \geq 0, \; j = 1, \dots, n \tag{12}$$

$$u_r \geq \epsilon, \; r = 1, \dots, s \tag{13}$$

$$v_i \geq \epsilon, \; i = 1, \dots, m \tag{14}$$

$$d_j \geq 0, \; j = 1, \dots, n \tag{15}$$

where h is the efficiency score for inefficient DMU, M is the maximum quantity for all variable d_j $(j = 1, \dots, n)$, d_j is the variable deviation for DMU_j, u_r is the weightage for r output, v_i is the weightage of i input, x_{ij} is the value of input i from DMU_j, y_{rj} is the value of output r from DMU_j, c_0 is the free sign, n is the number of DMU_s, s is the number of outputs and m is the number of inputs. A DMU is said to be efficient when the efficiency score is equal to 1, while otherwise would have shown less than 1. The ways of getting the value of 1 is relatively a little different for the Bi-Objective MCDEA BCC model as compared to other models where calculation of $1 - d_j$ must be used.

3. Results and Discussion

Efficiency score analysis is able to reflect the level of efficiency of service operations and the productivity of EDHUSM's Green Zone. The efficiency score measurements for each of the 40 DMUs in this study were measured using the BCC input-oriented and Bi-Objective MCDEA-BCC models. Subsequently, the Super Efficiency model was used to improve the results of the efficiency decisions obtained to determine the best resource allocation by ranking the efficient DMUs measured by BCC input-oriented and Bi-Objective MCDEA-BCC models.

Table 1 shows the efficiency scores obtained using the BCC input-oriented and Super Efficiency models, while Table 2 illustrates the efficiency scores obtained using the Bi-Objective MCDEA-BCC and Super Efficiency models for 40 DMUs on weekends and public holidays. DMU1 is the current schedule while DMU2 until DMU40 are the proposed resource allocations for improvement based on the discussions with the management of EDHUSM according to the department's budget allocation.

In reference to Table 1, the results show that the BCC input-oriented models have produced 17 efficient DMUs with an efficiency score of 1. This indicates that the results produced are parallel with the studies that have been conducted by Doyle and Green (1994), Sarkis (2000) and Wan Malissa *et al.* (2018), who also get a large number of efficient DMUs when the BCC model is used. As this model only gives the value 1 as an efficient score, it might be difficult to determine which DMU suggest the best resource allocation. In order to rank these DMUs, the Super Efficiency model is used as its ability to discriminate the second constraint by modifies the model in equation Eq. (5) until Eq. (8) by eliminating constraints that related to DMU that is under evaluation (Wan Malissa *et al.* 2014). This situation makes each DMU that is assessed as efficient obtains an efficiency score worth more than one (θ_0> 1) or has no solution. DMU with the highest efficiency score is considered the most efficient DMU, while DMU with the lowest efficiency value is considered the most inefficient DMU. The highest Super-efficiency score is selected as the best DMU to be applied by Green Zone EDHUSM for improvement.

Therefore, DMU 36 was selected as the most efficient DMU with the highest Super Efficiency value. This alternative proposes the addition of two doctors and two nurses per shift. The number of doctors and nurses in each shift totals up to four compared to the current allocation, which is two in each shift for the improvement. This is because the number of doctors and nurses required for weekend and public holidays is higher than weekdays since all the outpatient departments and healthcare clinics are non-operative and closed during weekends and public holidays (Nazhatul Sahima *et al.* 2018a; 2018b).

Whereas, based on Table 2, only two out of 40 DMUs for the Bi-Objective MCDEA-BCC model were rated as efficient with an efficiency score of 1 which is DMU13 and DMU18. The number of efficient DMUs obtained through this model is very less compared to the number of efficient DMUs obtained from the BCC Super Efficiency model. This is due to the improvement made by Ghasemi *et al.* (2014) on previous DEA models. According to Wan Malissa *et al.* (2018), the impact of the improvement has shortened the calculation process and reduce the occurrence of an error during the efficiency value calculation. In addition, it is able to increase the discriminatory ability of DMUs and eventually reduce the number of efficient DMUs. The efficiency score of Bi-Objective MCDEA BCC is calculated by the formula of $1- d_o$ and the Super Efficiency score is used to rank the score in obtaining the best DMUs.

Therefore, DMU18 was selected as the most efficient DMU which is able to reduce the congestion problem in Green Zone EDHUSM by giving the best resource allocation. This shows that the best schedule is 3 doctors and 3 nurses for morning and evening shifts, while 2 doctors and 2 nurses are required for night shifts. It means that only one doctor and one nurse need to be added for the morning and the evening shifts in order to reduce the patients' congestion at EDHUSM's Green Zone.

Table 1: Results of BCC input-oriented and Super Efficiency Models for Weekends and Public Holidays

DMU	Number of doctors	Number of nurses	Average waiting time	Average utilisation of doctor	Average utilisation of nurse	Number of patients served	BCC score	Super efficiency score	Super efficiency rank
1	(2,2,2)	(2,2,2)	177.80	93.00	98.00	92	1.000	1.193	2
2	(2,2,2)	(3,2,2)	164.93	95.00	91.00	98	1.000	1.048	8
3	(2,2,2)	(3,3,3)	182.72	98.00	72.00	101	1.000	1.063	6
4	(2,2,3)	(2,2,3)	137.63	90.00	97.00	105	0.942	-	-
5	(2,2,4)	(2,2,4)	107.84	86.00	93.00	116	0.882	-	-
6	(2,3,2)	(2,3,2)	117.28	90.00	97.00	104	0.977	-	-
7	(2,3,2)	(3,3,2)	98.53	92.00	90.00	107	1.000	1.017	12
8	(2,3,3)	(2,3,3)	88.91	87.00	95.00	115	1.000	1.135	3
9	(2,3,3)	(3,3,3)	70.81	86.00	85.00	117	1.000	1.077	5
10	(2,3,4)	(2,3,4)	67.98	82.00	89.00	124	0.955	-	-
11	(2,4,2)	(2,4,2)	72.67	89.00	96.00	113	1.000	1.003	17
12	(2,4,3)	(2,4,3)	52.14	83.00	90.00	121	0.979	-	-
13	(2,4,3)	(3,4,3)	39.79	82.00	81.00	122	1.000	1.022	11
14	(2,4,4)	(2,4,4)	40.98	77.00	83.00	124	0.952	-	-
15	(3,2,2)	(3,2,2)	128.15	89.00	95.00	100	0.947	-	-
16	(3,2,3)	(3,2,3)	92.77	86.00	94.00	113	0.903	-	-
17	(3,2,4)	(3,2,4)	73.04	83.00	90.00	124	0.941	-	-
18	(3,3,2)	(3,3,2)	67.99	87.00	94.00	112	1.000	1.003	16
19	(3,3,3)	(3,3,3)	45.49	82.00	90.00	121	1.000	1.014	13
20	(3,3,4)	(3,3,4)	33.81	75.00	82.00	123	0.969	-	-
21	(3,4,2)	(3,4,2)	42.79	84.00	91.00	117	1.000	1.045	9
22	(3,4,2)	(4,4,3)	47.04	87.00	75.00	121	1.000	1.008	15
23	(3,4,3)	(3,4,3)	27.33	77.00	84.00	124	1.000	1.049	7
24	(3,4,3)	(5,5,4)	16.58	74.00	59.00	121	1.000	1.100	4
25	(3,4,4)	(3,4,4)	19.88	69.00	76.00	123	0.995	-	-
26	(3,4,4)	(5,4,4)	14.45	68.00	65.00	121	0.996	-	-
27	(3,4,4)	(5,4,5)	12.84	68.00	59.00	121	1.000	1.029	10
28	(4,2,2)	(4,2,2)	99.85	86.00	91.00	102	0.880	-	-
29	(4,2,3)	(4,2,3)	66.58	81.00	89.00	113	0.913	-	-
30	(4,3,2)	(4,3,2)	46.40	82.00	89.00	112	0.986	-	-
31	(4,3,3)	(5,4,4)	24.44	76.00	64.00	121	0.972	-	-
32	(4,3,3)	(5,5,5)	30.11	79.00	56.00	124	0.966	-	-
33	(4,3,4)	(4,3,4)	19.80	68.00	74.00	121	0.996	-	-
34	(4,3,4)	(5,5,5)	21.40	70.00	55.00	123	0.913	-	-
35	(4,4,2)	(4,4,2)	28.70	78.00	86.00	119	1.000	1.009	14
36	(4,4,4)	(4,4,4)	11.47	65.00	71.00	127	1.000	1.354	1
37	(5,2,2)	(5,2,2)	90.44	83.44	91.20	111	0.840	-	-
38	(5,2,4)	(5,2,4)	57.43	71.23	76.79	120	0.811	-	-
39	(5,3,3)	(5,3,3)	28.71	69.06	75.51	120	0.919	-	-
40	(5,3,4)	(5,3,4)	23.43	63.52	69.28	120	0.899	-	-

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Table 2: Efficiency Scores for Bi-Objective MCDEA-BCC and Super Efficiency Models

DMU	Number of doctors	Number of nurses	Average waiting time	Average utilisation of doctor	Average utilisation of nurse	Number of patients served	Bi-O MCDEA BCC score	Super efficiency score	Super efficiency rank
1	(2,2,2)	(2,2,2)	177.80	93.00	98.00	92	0.842	-	-
2	(2,2,2)	(3,2,2)	164.93	95.00	91.00	98	0.875	-	-
3	(2,2,2)	(3,3,3)	182.72	98.00	72.00	101	0.801	-	-
4	(2,2,3)	(2,2,3)	137.63	90.00	97.00	105	0.875	-	-
5	(2,2,4)	(2,2,4)	107.84	86.00	93.00	116	0.879	-	-
6	(2,3,2)	(2,3,2)	117.28	90.00	97.00	104	0.931	-	-
7	(2,3,2)	(3,3,2)	98.53	92.00	90.00	107	0.991	-	-
8	(2,3,3)	(2,3,3)	88.91	87.00	95.00	115	0.933	-	-
9	(2,3,3)	(3,3,3)	70.81	86.00	85.00	117	0.999	-	-
10	(2,3,4)	(2,3,4)	67.98	82.00	89.00	124	0.928	-	-
11	(2,4,2)	(2,4,2)	72.67	89.00	96.00	113	0.988	-	-
12	(2,4,3)	(2,4,3)	52.14	83.00	90.00	121	0.965	-	-
13	(2,4,3)	(3,4,3)	39.79	82.00	81.00	122	1.000	1.847	2
14	(2,4,4)	(2,4,4)	40.98	77.00	83.00	124	0.911	-	-
15	(3,2,2)	(3,2,2)	128.15	89.00	95.00	100	0.899	-	-
16	(3,2,3)	(3,2,3)	92.77	86.00	94.00	113	0.921	-	-
17	(3,2,4)	(3,2,4)	73.04	83.00	90.00	124	0.916	-	-
18	(3,3,2)	(3,3,2)	67.99	87.00	94.00	112	1.000	1.892	1
19	(3,3,3)	(3,3,3)	45.49	82.00	90.00	121	0.983	-	-
20	(3,3,4)	(3,3,4)	33.81	75.00	82.00	123	0.927	-	-
21	(3,4,2)	(3,4,2)	42.79	84.00	91.00	117	0.984	-	-
22	(3,4,2)	(4,4,3)	47.04	87.00	75.00	121	0.977	-	-
23	(3,4,3)	(3,4,3)	27.33	77.00	84.00	124	0.945	-	-
24	(3,4,3)	(5,5,4)	16.58	74.00	59.00	121	0.904	-	-
25	(3,4,4)	(3,4,4)	19.88	69.00	76.00	123	0.878	-	-
26	(3,4,4)	(5,4,4)	14.45	68.00	65.00	121	0.885	-	-
27	(3,4,4)	(5,4,5)	12.84	68.00	59.00	121	0.848	-	-
28	(4,2,2)	(4,2,2)	99.85	86.00	91.00	102	0.900	-	-
29	(4,2,3)	(4,2,3)	66.58	81.00	89.00	113	0.913	-	-
30	(4,3,2)	(4,3,2)	46.40	82.00	89.00	112	0.965	-	-
31	(4,3,3)	(5,4,4)	24.44	76.00	64.00	121	0.904	-	-
32	(4,3,3)	(5,5,5)	30.11	79.00	56.00	124	0.879	-	-
33	(4,3,4)	(4,3,4)	19.80	68.00	74.00	121	0.875	-	-
34	(4,3,4)	(5,5,5)	21.40	70.00	55.00	123	0.829	-	-
35	(4,4,2)	(4,4,2)	28.70	78.00	86.00	119	0.933	-	-
36	(4,4,4)	(4,4,4)	11.47	65.00	71.00	127	0.830	-	-
37	(5,2,2)	(5,2,2)	90.44	83.44	91.20	111	0.855	-	-
38	(5,2,4)	(5,2,4)	57.43	71.23	76.79	120	0.797	-	-
39	(5,3,3)	(5,3,3)	28.71	69.06	75.51	120	0.854	-	-
40	(5,3,4)	(5,3,4)	23.43	63.52	69.28	120	0.796	-	-

b

Meanwhile, Table 3 summarizes the comparisons between current resource allocations DMU1 and the high ranking DMU36 based on BCC input-oriented and Super Efficiency models and high ranking DMU18 based on Bi-Objective MCDEA-BCC and Super Efficiency models. Conversely, by selecting the resource allocations proposed by DMU36, the finding shows a drastic decrease in average patients' waiting time from 177.8 minutes to 11.47 minutes, equivalence to a 93.55% decrease. This decrease is evidently due to the allocation of more doctors and nurses on each shift which reflects positively on more patients being served parallelly at the same time, hence, directly decreases the waiting period of patients seeking for treatment and reduces congestion in EDHUSM's Green Zone, especially during weekends and public holidays. On the other hand, comparing with the resource allocations proposed by DMU18, the finding reveals that the average patients' waiting time is reduced from 177.8 to 67.99 minutes. Although the average patients' waiting time proposed by DMU18 achieves the targeted KPI for EDHUSM' Green Zone, which is set to be below 120 minutes but patients are still required to wait for more than an hour to be treated.

Succeeding forward, DMU36 also shows that the percentage of utilisation reduces from 93% to 65% for doctors, while 98% to 71% for nurses, respectively. Hence, if DMU36 is selected, the utilisation of both resources is at its optimal level and very close to meet the recommended resource utilisation level in the service sector, which is around 70% to 80% as deliberated by (Mohd *et al.* 2016; Louis 2004). Whereas, DMU18 only shows a slight decrease in the percentage of utilisation, from 93% to 87% for doctors, while 98% to 94% for nurses. Although DMU18 shows the utilisation rates decrease for both the resources, the optimal utilisation rates for both resources are still high and not anywhere close to the recommended utilisation rates.

Constructively, by selecting DMU36 as the best resource allocation, the number of patients treated sees a significant increase from 92 patients to 127 patients, while DMU18 records an increase from 92 patients to 112 patients treated. This shows that DMU36 enables more patients to be treated as compared to DMU18 in EDHUSM's Green Zone.

Table 3: Comparison between DMU1 (Current DMU) and two efficient DMUs (DMU18 for Bi-Objective MCDEA BCC Model and DMU36 for BCC Super Efficiency Model)

Items	DMU1	DMU18	DMU36
Number of Doctor	6	8	12
Number of Nurse	6	8	12
Patient's Waiting Time	177.80	67.99	11.47
Number of Served Patient	92	112	127
Utilisation of Doctor	93	87	65
Utilisation of Nurse	98	94	71

4. Conclusion

In conclusion, although the Bi-Objective MCDEA BCC model only recommends an additional of 8 staff as compared to the BCC input-oriented model that recommends an allocation of 12 staff daily, it's still ineffective as the utilisation of doctors and nurses is higher than the recommended level. Therefore, DMU36 from the Super Efficiency BCC model is selected as the best resource allocation as it meets all the requirements of this study generally and by EDHUSM's Green Zone specifically. Despite the higher number of staff proposed by DMU36 as compared to DMU18, it does not exceed EDHUSM's budget allocation, which is in the range of two to four doctors and nurses working per shift. Reflectively, the finding will be able to assist the management in choosing the best resource allocations suggested by adding new doctors and new nurses within their permitted budget and reschedule the resources in EDHUSM's Green Zone. This would inevitably solve EDHUSM's Green Zone issues by reducing patients' waiting time and achieving the KPIs set while providing the doctors and nurses with more rest and personal time during weekends and public holidays.

Acknowledgement

The author would like to thank the Emergency Department of Hospital Universiti Sains Malaysia (EDHUSM) for granting permission to conduct this study.

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Received : 16 March 2021
Accepted : 21 July 2021

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