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An Optimization Model for Operating Room Scheduling to Reduce Blocking Across the Perioperative Process

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An optimization model for operating room scheduling to reduce blocking across the perioperative process

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Abstract

Operating room (OR) scheduling is important. Because of increasing demand for surgical services, hospitals must provide high quality care more efficiently with limited resources. When constructing the OR schedule, it is necessary to consider the availability of downstream resources, such as intensive care unit (ICU) and post anaesthesia care unit (PACU). The unavailability of downstream resources causes blockings between every two consecutive stages. In this paper we address the master surgical schedule (MSS) problem in order to minimize blockings between two consecutive stages. First, we present a blocking minimization (BM) model for the MSS by using integer programming, based on deterministic data. The BM model determines the OR block schedule for the next day by considering the current stage occupancy (number of patients) in order to minimize the number of blockings between intraop and postop stages. Second, we test the effectiveness of our model under variations in case times and patient arrivals, by using simulation. The simulation results show that our BM model can significantly reduce the number of blockings by 94% improvement over the base model. Scheduling patient flow across the 3-stage periop process can be applied to work flow scheduling for the s-stage flow shop shop production in manufacutirng, and also Smoothing patient flow in periop process can be applied to no-wait flow shop production.

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Keywords: operating room, scheduling; optimization; simulation; statistical process control;

1. Introduction

Operating room (OR) scheduling is important. Surgical interventions are responsible for 52% of all admissions to the hospitals [1], and account for more than 40% of total expenditures of a hospital [2]. Within a hospital, the OR

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department is one of the most critical resources, which has the largest cost and revenue [3, 4, 5]. Because of the aging population, the demand for surgical services has a sharp increasing trend in recent years [6]. Therefore, hospitals must provide high quality care more effectively with limited resources by developing efficient OR schedules [3, 7].

OR scheduling is challenging, because of complexities involved in it. First, the peri-operative (periop) process consists of three stages: pre-operative (preop), intra-operative (intraop) and post-operative (postop), where the collection of patients' information and the preparation for surgeries occur in the preop stage, surgeries occur in ORs in the intraop stage, and post-anesthesia care units (PACU), intensive care units (ICU), or wards for recovery are in the postop stage. Second, there are three phases in OR scheduling including: strategic in long term, tactical in medium term, and operational in short term. The main objective of the strategic phase is to distribute OR blocks among different surgery groups, and the output is called "case mix". At the tactical phase, the objective is to develop a master surgical schedule (MSS), which determines the number and type of ORs assigned to each surgery group. The operational phase involves a detail schedule, which defines the order of cases, and start/end time of each case. These three phases are correlated with each other, because the output of the strategic phase is the input of the tactical phase, the output of the tactical phase is the input of the operational phase, and the output of the operational phase will impact the allocation of OR blocks in the strategic phase in the next period of time in long term. An MSS in the tactical phase is important to link phases in the long term and short term.

In most hospitals when OR blocks are assigned to surgery groups, there is no specific mechanism to ensure the availability of downstream resources, such as the beds in ICU or PACU [1]. Because of the unavailability of downstream resources, patients cannot be sent to the next stage, but are held in the current stage, causing blockings between every two consecutive stages. Blockings negatively impact OR management across the periop process, such as increased waiting time in each stage, increased length of stay (LoS) across the periop process, excessive overtime and overnight shifts, etc.

In this paper, we develop a blocking minimization (BM) model to reduce the number of blockings between two consecutive stages. To avoid blocking, the number of patients in each stage shouldn't exceed the number of beds in that stage. The number of patients in each stage is affected by three events:

- Patients arriving on each day from the upstream stage.
- Patients from previous days who still need to stay in the current stage.
- Patients from previous days who have spent enough time in the current stage and are ready to leave.

Our BM model provides an optimal OR block schedule by taking these three events into consideration. The BM model determines the OR block schedule for the next day by considering the current stage occupancy (number of patients in the stage) in order to minimize the number of blockings between intraop and postop stages. Therefore, our BM model balances the admission and departure of postop stage, while avoiding the accumulated number of patients exceeding the number of resources. Using simulation, we show that our BM model effectively dampens the variations in the case times and patient arrivals.

The remainder of this paper is organized as follows: Section 2 provides a literature review on OR scheduling. Section 3 describes the problem settings and our BM model. Section 4 describes a case study of simulation to test the effectiveness of our OR block schedules. Section 5 draws conclusion and proposes future work.

2. Literature review

Surgeries are categorized into two major classes: elective cases and emergency cases [3, 7]. Elective cases are scheduled several days prior to the intervention date, but emergency cases should be scheduled as soon as possible [12]. OR scheduling consists of three major phases, which challenges the OR block scheduling. Three major phases in OR scheduling are described as follows:

- **Strategic:** The main objective of the strategic phase is to provide a "case mix plan", which allocates OR blocks to surgery groups. The strategic phase is based on historical data and/or forecasts, and typically has a time horizon of one year. [7, 8, 9, 10, 11]

- **Tactical:** The main objective of the tactical phase is to provide a master surgical schedule. The MSS determines the number, type and opening hours of ORs for each surgery group. In the MSS, surgery types are clustered to surgery groups based on similar characteristics of specialties and requirement on resources, such as facilities in ORs, ICUs and PACUs. The time horizon of tactical phase usually is one to three months. The MSS is mainly based on elective cases, the number and case time of which do not vary remarkably in three months. Therefore, the MSS is cyclic and repeated in the tactical phase. Hospital administrators prefer to assign OR blocks to surgery groups instead of individual surgery types. This allows them to swap OR blocks among surgery types within the same group in case of necessity. These small swaps won't change the optimal schedule, and they don't have to develop a new schedule for any small change. Fig. 1 shows an example of MSS, where the number of available OR blocks (an OR block means daily working hours of an OR) is 6 on each day, and there are three surgery groups G1, G2, and G3. The MSS should be revised whenever the total amount of available OR blocks changes [7].

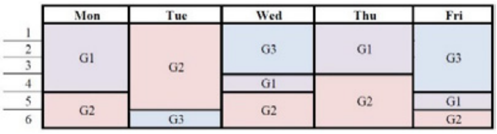


Fig. 1. An example of MSS

- **Operational:** After development of the MSS, the assignment of cases to ORs and start/end time of each case are determined on a daily basis.

To achieve high OR utilization is one of the main objectives for OR scheduling to allocate OR blocks to surgery groups. However, high variations in case times and patient arrivals may fail an OR schedule with high OR utilization at the tactical phase [1, 3, 13, 14, 15].

According to the literature, the OR utilization should be maximized to avoid underutilization costs, although due to the high variations in procedure times and patients' arrivals, highly utilized ORs are unstable [3, 16, 17]. Highly utilized ORs cannot dampen the variations because there is no time buffer; a slight variation in case or arrival time may cause high overtime cost or surgery cancellation [3].

It is important to develop an OR schedule that leads to leveled occupancy of downstream stages [3]. OR utilization has been intensively studied [18, 19, 20, 21, 22, 23, 24, 25], but few papers addressed the patient flow across the periop process. OR schedule directly affects PACU and ICU in the postop stage [1, 26].

After performing a surgery in an OR, the patient is recovered in PACU, then moved to an ICU bed to receive the required care. The amount of time that a patient stays in ICU before being moved to ward is referred as length of stay (LoS) in ICU. After spending the required time in ICU, the patient is moved to a NonICU bed in the ward. Sometimes based on the acuity level, the patient is directly moved from PACU to the ward. For those patients who don't need the ICU, we can consider their ICU LoS as zero. Fig. 2 shows the patient's path in the peri-operative process.

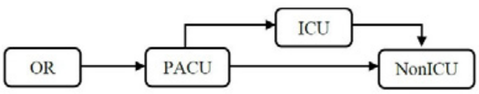


Fig. 2. The patient's path in the peri-operative process [26]

If there is no available bed in ICU, patients have to stay in the PACU [26], which is considered as blocking. OR blocking means no surgery is performed until a bed in PACU or ICU is available. OR blocking decreases the OR utilization that leads to waste of costly OR time. An efficient OR schedule not only maximizes the OR utilization, but also smooths the patient flow across the periop process, i.e., reducing the number of blockings. Price et al. [26] proposed a deterministic PACU Boarding model (hereafter we refer to this model as PB) to develop an optimal MSS that balanced the admission and discharge rate of ICU. The PB model used deterministic data for patient arrivals and ICU LoS. They used simulation to evaluate PB model under the presence of variations. According to their results, the PB can reduce the number of blockings between OR and ICU comparing to the base model of the studied hospital. Their focus was on minimizing the discrepancy between admission and discharge rate of ICU. Because in their model the current number of patients in the ICU was neglected, the role of patient accumulation in ICU has not been taken into consideration. Using simulation, Marcon and Dexter [14] examined the effect of different sequencing rules in ORs, on the PACU workload. The results showed that the case sequencing in ORs has a minor effect on the PACU workload. They stated that the best practice is to use optimization in order to match the PACU workload and its capacity.

3. BM model

We are interested in the performance of BM model in terms of weekly number of blockings and daily postop occupancy. Our BM model recursively considers the number of patients in the postop stage, in order to minimize the likelihood of blocking between ORs in the intraop stage and the postop stage. BM model takes the current postop stage occupancy into consideration to determine the OR assignment for the next day in such a way that the accumulated number of patients in postop doesn't exceed the number of beds. Using discrete event simulation, we show that our BM model outperforms the model proposed by Price et al. [26]. For the sake of simplicity, hereafter we refer to the Price et al. [26] model as PB model.

The following are the notations adopted throughout this paper.

Symbol	Description
i	Index of surgery groups, $i \in G = \{1,2,\dots,G\}$.
j,k	Index of days, $j \in D = \{1,2,\dots,D\}$.
b_{ij}	The number of OR blocks assigned to surgery group *i* on day *j*.
n_i	The total number of OR blocks that group *i* requires.
O	The number of available ORs in the intraop stage.
λ_i	The expected number of patients per block for group *i*.
μ_i	LoS in the postop stage for group *i*.
L_i	The minimum number of OR blocks that should be assigned to group *i*.
U_i	The maximum number of OR blocks that can be assigned to group *i*.
B	The number of available beds in the postop stage.
P_j	The number of patients in the postop stage on day *j*.

λ_i is the expected number of patients per block for group *i*. λ_i is estimated by dividing the length of an OR block by the mean case times plus mean set-up time plus the mean clean-up time. The set-up time is the time required to adjust equipment before the intervention, and the clean-up time is the required time to clean and disinfect the equipment after completion of a surgery. The required maximum and minimum of OR blocks for each surgery group are determined from the historical data.

Our BM model is described as follow:

$$minimize \sum_{j \in D} \left| P_j - B \right| \tag{1}$$

$$\sum_{j \in D} b_{ij} = n_i \tag{2}$$

$$\sum_{i \in G} b_{ij} \le O \tag{3}$$

$$P_j = \sum_{i \in G} \lambda_i b_{ij} X_{ij} + \sum_{\substack{k \\ k<j}} \sum_{i \in G} \lambda_i b_{ik} Y_{ik} \tag{4}$$

$$X_{ij} = \begin{cases} 1 & if\ \mu_i > 0 \\ 0 & Otherwise \end{cases} \quad \forall\, i, j \tag{5}$$

$$Y_{ik} = \begin{cases} 1 & if\ \mu_i - (j - k) > 0 \\ 0 & Otherwise \end{cases} \quad \forall\, i\ \&\ k < j \tag{6}$$

$$L_i \leq b_{ij} \leq U_i \quad \forall\, i, j \tag{7}$$

$$b_{ij} \geq 0\ and\ integer \tag{8}$$

Objective function (1) minimizes the difference between the postop stage capacity and its occupancy (number of patients). This function not only minimizes the over-occupancy in the postop stage, but also balances the daily postop occupancy. Constraint (2) imposes that the number of assigned OR blocks is equal to each group required OR blocks. Constraint (3) imposes that the number of assigned OR blocks doesn't exceed the number of available ORs. Constraint (4) recursively defines the occupancy of the postop stage on day *j*. The term $\sum_{i \in I} \lambda_i b_{ij} X_{ij}$ determines the number of arrivals from OR to the postop stage on day *j*. The BM model distinguishes between different LoSs, i.e. X_{ij}=1 if the $\mu_i > 0$, which means that the patient needs to be sent to postop stage, otherwise he/she is sent directly to the ward (if μ_i=0). The term $\sum_{k<j} \sum_{i \in I} \lambda_i b_{ik} Y_{ik}$ determines the number of patients in the postop stage transferred to day *j* from previous days, Y_{ik}=1 if the patient still needs to stay in the postop stage. Constraint (5) describes X_{ij}, a binary decision variable, which is equal 1, if μ_i>0. A patient is sent to the postop stage if his postop LoS is greater than zero, otherwise he will be directly sent to a bed in ward. Constraint (6) describes Y_{ik}, a binary decision variable, which is equal 1, if $\mu_i - (j - k) > 0$. If a patient in the postop stage still needs to spend more time in it, Y_{ik} is equal 1, otherwise he must be sent to a bed in ward (discharge from postop stage). Constraint (7) imposes that the daily number of OR blocks assigned to each group must fall between specified minimum and maximum values. Constraint (8) imposes that the number of OR blocks assigned to each group must be a positive integer. The BM model uses the deterministic mean LoS of the postop stage to determine the MSS. The BM model explicitly deals with the postop occupancy by considering arrival, discharge and current occupancy of postop stage. Here an assumption is that the ORs and postop resources are universal, which means they can be assigned to each surgery group.

4. Case study

To validate our BM model for OR block scheduling, we carry out three types of case studies. First, we solve the BM model to obtain the optimal MSS. Second, we construct a simulation model to test the robustness of MSSs generated by BM, PB and current MSS implementing in the studied hospital by Price et al. [26]. For the sake of simplicity, we name the hospital MSS in Price et al. [26] as "Base model". We introduce variations in μ_i and λ_i into the simulation model, in order to observe the number of blockings and daily occupancy of the postop stage generated by three models. Third, we test the process capabilities for three models, using statistical process control (SPC).

4.1 Optimal MSS

We use the data provided by Price et al. [26]. There are 16 ORs, 31 beds in the ICU and 3 surgery groups. Patients are clustered into groups based on similar case time and LoS. Table 1 shows the historical data. Patients in group 1 have short LoS and the case time is small for this group. Patients of group 2 have relatively longer LoS than group 1, and the case time is also longer for them. Finally, group 3 has the longest case time and also the longest LoS. Studies show that the case time is independently associated with increased LoS in postop stages [27]. The required, maximum and minimum OR blocks for each surgery group are determined from the historical data.

Table 1. Historical data of surgery groups [26]

Surgery group	Minimum blocks	Maximum blocks	Required blocks	ICU LoS	Total LoS	Patients per block
Group 1	1.0	5.0	11.1	0	1	2.5
Group 2	2.0	13.0	30.6	1	2	1.5
Group 3	3.0	15.0	33.2	2	3	1.25

Table 2 shows the MSS based on the optimum solution of BM model. Fig. 3 shows the graphical representation of the OR block schedule. It is possible to assign an OR block to a surgery group only for the morning or the afternoon, which is called "half-block". The MSS is constructed for a 5-week horizon, therefore the base unit of OR block is a tenth of a block over one week [26]. Notice that since the base unit of OR block is 0.1, the b_{ij} is scaled by a factor of 10 to maintain the integer nature of the problem; for example, the value 21 obtained from the BM model is equal to 2.1 blocks in the MSS. We coded the BM in GAMS 2013.

Table 2. The MSS obtained from BM model

Surgery group	Mon	Tues	Wed	Thu	Fri	Total
Group 1	2.1	1.0	3.0	2.0	3.0	11.1
Group 2	5.9	5.8	7.1	6.6	5.2	30.6
Group 3	7.9	8.2	5.9	6.2	3.0	31.2
Total	15.9	15.0	16.0	14.8	11.2	**72.9**

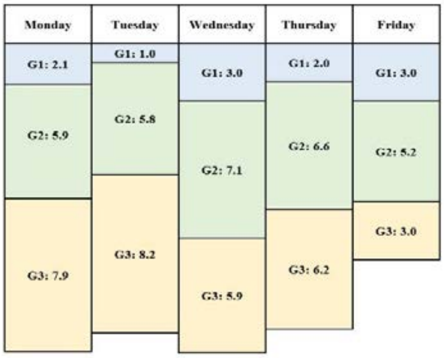


Fig. 2. A graphical representation of the MSS obtained from BM model
(Each entry is the number of OR blocks assigned to each surgery group)

4.2 Simulation

The BM model uses deterministic values for μ_i and λ_i, but in practice these parameters are random variables following known distributions. We construct a simulation model to test the robustness of the BM model under the presence of variations in ICU LoS and number of patients per block. Variation in number of patients per block is associated with variations in the case time and also the arrival of emergency cases. We compare the robustness of our BM model with the PB model and the Base model. A robust MSS can absorb the variations, and leads to fewer blockings.

First, we simulate the model for a long period of time to observe and collect the number of weekly blockings and daily occupancy of ICU. Second, we compare the performance of the BM model MSS with the MSS of PB model and the Base model in Price et al. [26]. In each OR block, a random number of cases was generated. In order to involve the disturbances from variations in case time and emergency arrivals, we considered $\pm 50\%$ variation in the number of patients per block (λ_i). For example, for group 2, equation (9) shows the uniform distribution of λ_2.

$$1.5 \times [0.50, 1.50] = [0.75, 2.75] = [1,3] \tag{9}$$

The ICU LoS for each case was randomly generated from a uniform distribution between 1/6 and 1/2 of the total LoS (see table 1). All random numbers were rounded to the nearest greater integer. The simulation was warmed up for 20 weeks to reach a steady state behavior; the model was then run for 52 weeks (one year) and results were averaged.

Table 3 shows the average and standard deviation of daily occupancy. Fig. 4 shows the average ICU occupancy generated by three models. BM model has a maximum occupancy of 25.30 which is far from the maximum capacity of ICU (31 beds), therefore, BM model can dampen the variations in number of patients and ICU LoS better than the PB and Base models. The maximum ICU occupancy of PB and Base models is 30.1 and 30.49 respectively, which occur on Tuesday. Their maximum ICU occupancy is remarkably close to the maximum capacity (31 beds), therefore a slight variation causes blocking in the periop process. Although the PB model has a lower occupancy on Wednesday (21.64) and Thursday (18.72) than those of BM model (24.41 and 22.68 respectively), on Tuesday and Thursday its ICU occupancy is close to the maximum capacity (30.49 and 29.92) respectively. This makes the PB model generate more blockings on Tuesday and Thursday, under the presence of variations. Besides, average ICU occupancy on Saturday is only 2.03 in BM model, which is desirable for OR managers because they need less weekend shifts. Fig. 5 shows the individual plot of blockings generated by three models. Since our BM model takes the current occupancy into consideration, and we have a more robust MSS to absorb variations, our BM model could generate fewer blockings comparing with the PB and Base models. It shows that BM is more robust under the presence of variations in the patients' arrival and ICU LoS.

In these models the total number of required OR blocks is fixed and is equal to 72.9, but the number of available OR blocks is 80 (5 day and 16 OR blocks on each). Using BM model, we can provide postop resources for more OR blocks, because BM evenly distributes the postop workload over the weekdays. Therefore, we can schedule for more patients using the unutilized OR blocks ($80 - 72.9 = 7.1$ OR blocks).

Table 3. The average and standard deviation of daily ICU occupancy

Model	**Average**							**Standard deviation**						
	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun
BM	19.65	25.30	24.41	22.68	16.53	2.03	0	3.89	4.21	4.29	3.96	2.97	1.18	0
PB	22.57	30.01	21.64	18.72	23.16	8.02	0	4.37	5.75	3.80	3.41	4.94	2.92	0
Base	21.23	30.49	27.32	29.92	30.24	9.56	0	3.98	4.73	4.42	4.47	4.93	2.90	0

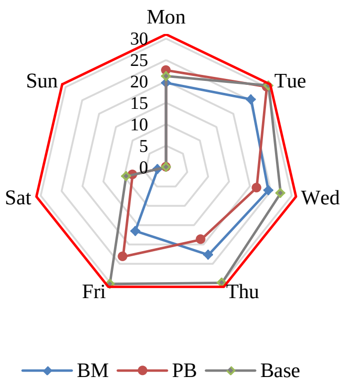


Fig. 4. The average ICU occupancy

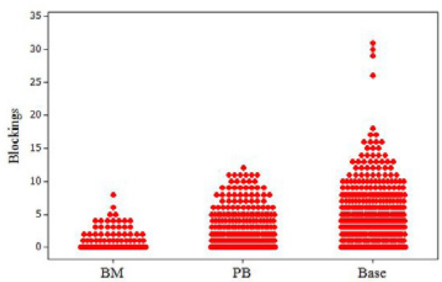
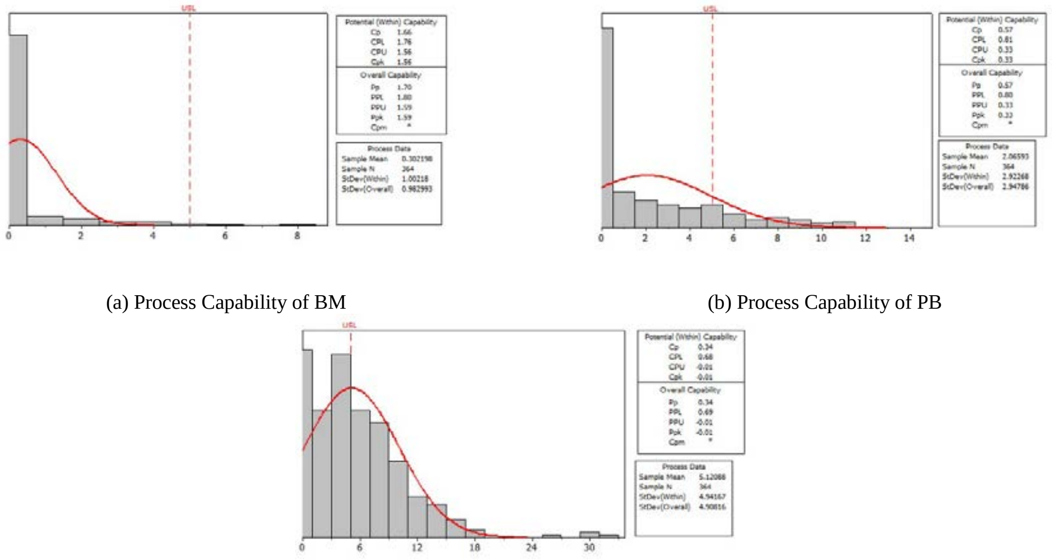


Fig. 5. Individual plot of blockings

4.3 Statistical Process Control (SPC)

To compare the robustness and stability of our BM model over the other two, we use SPC method to generate the process capability results for discussed models. Fig. 6 shows the process capability diagrams.



(a) Process Capability of BM

(b) Process Capability of PB

(c) Process Capability of Base

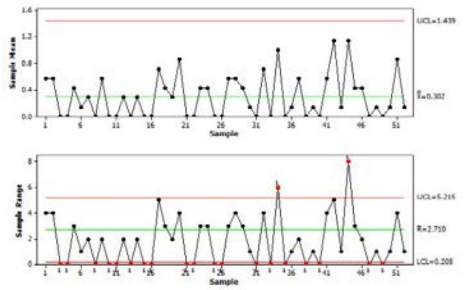
Fig. 6. Capability analysis of weekly blockings

Process capability c_p indicates if the outcomes of a process are within the control limits. With the fixed range of specification limits, which is $\mathrm{USL} - \mathrm{LSL}$, the larger the c_p, the less the variation in outcomes. Process capability index c_{pk} indicates if the outcomes are centred on the average performance. The larger the c_{pk}, the less likely that the outcomes will drop out of either LSL or USL. As shown in Fig. 6, the c_p is 1.66 for BM, 0.57 for PB, and 0.34 for the Base model. Therefore, the BM model generates the least variations in outcomes. The c_{pk} is 1.56 for BM and 0.33 for PB, and -0.01 for the Base model. Therefore, the blockings generated by the BM model are most centred within limits. Obviously, the average blockings generated by BM is more centred within the specification limits and with less variation, compared with those of the PB and the Base model. Table 4 shows the results of SPC and process capability analysis.

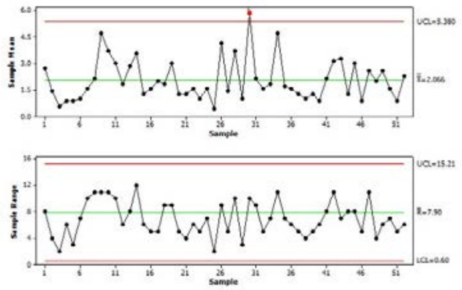
Table 4. SPC results

Model	C_p	C_{pk}	Max Blocking	Blocking Range Mean	Mean blocking	Improvement (comparing with Base)	Improvement (comparing with PB)
BM	1.66	1.56	8	2.71	0.30	94%	85%
PB	0.57	0.33	12	7.90	2.07	-	-
Base	0.34	-0.01	31	13.36	5.12	-	-

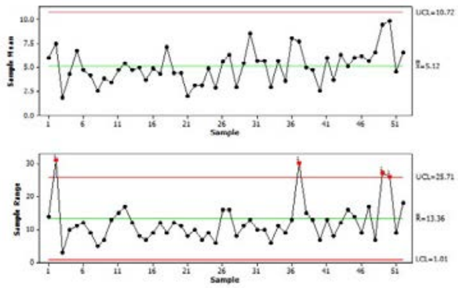
We generate the Xbar-R charts of average weekly blockings, as shown in Fig. 7. We simulate 52 weeks for a year. From the Fig. 7, we can obtain the weekly average blocking is 0.30 for BM, 2.07 for PB, and 5.12 for Base model. Besides, there are some weeks of BM model generating almost zero blocking. Compared with the Base model, the improvement on average blocking can be calculated by$(5.12 - 0.30)/5.12 \times 100 = 94\%$. Besides, compared with the PB model, the improvement of $(2.07 - 0.30)/2.07 \times 100 = 85\%$ can be achieved. The average range of variation of BM model is 2.71, less than 7.9 and 13.36 those of PB and Base model respectively. Therefore, the BM model generates the least average variations in blockings. These results from Xbar-R charts support those of *cp* and *cpk*. The 94% improvement on number of blockings indicates that potentially on average 250 additional cases could be served in one year, if the BM model is used for OR block scheduling. There would be an increase in the hospital net revenue from the additional cases. An estimate of this value can be calculated by multiplying the number of additional cases by net revenue per case, therefore there would be an annual increase of $250 \times \$15000 = 3.75$ million dollars in the hospital revenue. However, in practice, the availability of ORs, surgeons and staff are other factors that may limit the estimated increase in the hospital revenue.



a) BM



b) PB



c) Base

Fig. 7. Xbar-R charts of average weekly blocking

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5. Conclusion

Operating room (OR) scheduling is important, because ORs have the largest cost and revenue within a hospital, and the demand for surgical services is increasing. Therefore, hospitals must provide high quality care more effectively with limited resources by developing an efficient OR schedule. In most hospitals, when OR blocks are assigned to surgery groups, there is no specific mechanism to ensure the availability of downstream resources such as the beds in ICU and PACU. Because of the unavailability of downstream resources, patients cannot be sent from ORs to ICU or PACU, causing blocking between every two consecutive stages. This leads to many negative impacts on OR management, such as increased waiting time, length of stay (LoS), excessive overtime, and overnight shifts, etc. Therefore, when the MSS is constructed, it is necessary to consider the availability of downstream resources.

In this paper, we developed a BM model to reduce the number of blockings between two consecutive stages. To minimize blocking, the arrival, departure and current occupancy of the postop were taken into account. Our objective is to assign OR blocks to surgery groups in a way that the postop occupancy doesn't exceed the number of beds in the postop. Simulation results showed that the BM model outperformed the PB model proposed by Price et al. [26] and their studied hospital Base model as well. Moreover, using BM model, an improvement of 94% in reducing the number of blockings (over the Base model) can be achieved, which means that by using BM model potentially we can serve more patients. The SPC results showed that the BM model can dampen the variations in the case time and ICU LoS. Our work showed that considering downstream resources in OR department is important and our BM model can effectively improve the overall performance of the OR department. The BM model can be generalized to any two consecutive stages across the periop process. However, in practice, the availability of ORs, surgeons and staff are other factors that may limit the estimated improvement in the hospital revenue.

The managerial implication of this work is as follows. Taking the interaction of different stages into consideration, we should make sure in scheduling that upstream stages can feed downstream stages in time without overflowing, because overflow generates blockings between stages, which lowers the utilization of the whole process and slows down the patient flow across the process. Scheduling patient flow across the 3-stage periop process can be applied to work flow scheduling for the s-stage flow shop production in manufacturing, and also Smoothing patient flow in periop process can be applied to no-wait flow shop production.

Further work includes to maintain high OR utilization while reducing blockings. Also because there are other performance metrics such as Service rate (number of served patients), waiting list (patients waiting to receive services), cost, etc., a comprehensive work on these objectives and the possible trade-offs among them, is our current ongoing research.

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