การจัดตารางห้องผ่าตัดภายใต้จำนวนเตียง ICU ที่จำกัด

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บทคัดย่อ

ผู้ป่วยของโรงพยาบาลรัฐในหลายประเทศทั่วโลกต้องเผชิญกับการรอคอยการผ่าตัดรักษาเป็นระยะเวลานาน เนื่องจากการขาดแคลนห้องผ่าตัดและทรัพยากรการดูแลรักษาหลังผ่าตัดของโรงพยาบาลรัฐ ยิ่งไปกว่านั้นการเพิ่มจำนวนห้องผ่าตัดหรือทรัพยากรต่างๆที่เกี่ยวข้องยังเป็นไปได้ยากเพราะทรัพยากรที่ต้องใช้มีราคาสูง แต่งบประมาณของโรงพยาบาลกลับมีอย่างจำกัด จากการศึกษาพบว่าการจัดตารางห้องผ่าตัดอย่างเหมาะสมสามารถเพิ่มจำนวนผู้เข้ารับการรักษาได้และยังสามารถเพิ่มอัตราการใช้ประโยชน์ของห้องผ่าตัดอีกด้วย ดังนั้นงานวิจัยนี้จึงได้พัฒนาแบบจำลองเชิงเส้นเพื่อเพิ่มจำนวนผู้ที่สามารถเข้ารับการผ่าตัดรักษาต่อวันภายใต้จำนวนเตียงในแผนกผู้ป่วยหนัก (ICU) ที่จำกัด โดยงานวิจัยนี้ได้ทำการจัดตารางผู้ป่วยคนใดสามารถผ่าตัดได้วันไหน ที่ห้องผ่าตัดใด ที่คาบเวลาใด ผู้วิจัยได้ทำการสร้างชุดทดลองขึ้นมา 10 ชุด เพื่อทำการทดสอบแบบจำลองและใช้ซอฟแวร์ในการหาคำตอบภายในระยะเวลา 3 ชั่วโมง ผลที่ได้รับพบว่าแบบจำลองนี้เหมาะกับชุดทดลองขนาดเล็กและกลางเท่านั้น ส่วนชุดทดลองขนาดใหญ่ไม่สามารถหาคำตอบที่เหมาะสมที่สุดได้ภายในระยะเวลาที่กำหนด แต่อย่างไรก็ตามคำตอบที่ได้จากชุดทดลองขนาดใหญ่ยังคงมีการลู่เข้าใกล้ค่าที่เหมาะสมที่สุดอย่างมาก

คำสำคัญ: การหาค่าเหมาะสมที่สุด การจัดตารางห้องผ่าตัด เตียงแผนกผู้ป่วยหนัก แบบจำลองเชิงเส้น

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OPERATING ROOM SCHEDULING UNDER LIMITED ICU BEDS

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Abstract

Many patients in public hospitals around the world have to wait for a long time for their operations due to Operating Room (OR) and/or downstream resources scarceness. Moreover, increasing the number of ORs or related resources is difficult because of expensive OR costs and limited budget in hospitals. From our knowledge, a well OR schedule can raise number of patient throughputs and maximize the OR utilization so, we developed a binary programming model which aims to maximize the number of patients that can be included in the OR schedule under the limited number of ICU beds. Our OR schedule specifies which patient will be operated, OR, day, and period. Then, ten instance sets were generated from real data to test the model and solved by an optimization software. The results showed that, for small and medium instances, our model can guarantee the optimal solutions under 3-hours limited time, while the large instances cannot. However, there are small gap percentages for non-optimal solutions.

Keywords: optimization, OR scheduling, ICU beds, linear programming

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1. Introduction

The incomes of operating rooms are two – thirds of hospital while the expenditures are 40 – 60% [1-2]. Furthermore, ORs are significantly related to many stakeholders, downstream resources, and activities in hospitals such as nurses in OR and Post – Anaesthesia Care Unit (PACU), surgeons, available ward/PACU/ICU beds, etc. [3].

Public hospitals inherently have high volume of patients in waiting list while many resources are shortage and hard to increase [4-7]. Waiting list is a formal record of the number of non-emergency surgical patients who have the appointment for treatment [6]. There has a strong relationship between waited duration and pain or disability including worsening condition of patient illness that might increase the total costs of treatment for both preoperative and postoperative. The key of waiting list management is to understand the relationship between demand and supply clearly. The variability of inappropriate OR scheduling is a cause of long surgical waiting times, but it can be managed by the advantage of exact or heuristic algorithms [8].

This research recognized that long waiting times problem is an important issue in Thailand. We aimed to study OR management and develop a model based on Thailand public hospitals characteristics to decrease surgical waiting times, level hospital resources, and to represent the impact of OR scheduling on downstream resources. We propose a binary programming model to maximize case throughput and balancing ICU beds by modified Abedini et al. [9] model. They proposed a non-linear integer programming for balancing the number of ICU beds occupied as their objective called Blocking Minimization (BM). Their model has a great performance which can eliminate the blocking between stages by including the number of ICU patients from three stages: patient from upstream, patient from previous day and still need to stay in ICU, and patient from previous day but ready to leave. The model can obviously investigate ICU patient flows from their model which can be benefit for ICU bed management in hospitals.

The rest of the paper is organized in the following way. Necessary background is described in section 2. Section 3 contains a review of related literature while Section 4 gives a detailed description of the problem of allocating and scheduling operations to ORs. A binary model is presented in Section 5. The results for the developed model are presented in Section 6. Finally, the main conclusions of the paper can be found in Section 7.

2. Background

2.1 Patient classification [10]

Gür and Eren [10] categorized patients in OR planning and scheduling into two main groups:

2.1.1 Elective patients are the major group in hospital because they occur frequently. The patients will be put in a waiting list because they are not necessary to operate promptly but,

2.1.2 Non – elective patients have high variability because they can unexpectedly show up at any time and need to be treated immediately such as emergency patients.

2.2 OR planning strategy [2-6]

There are divided into three groups:

2.2.1 Open Planning Strategy is a flexible and high utilization rate strategy that allow surgeons to arbitrarily reserve all available time blocks. The surgeons can appoint until the surgery day.

2.2.2 Block Planning Strategy is commonly applied in hospitals. All time blocks of OR capacities are pre-allocated to particular surgeons, surgical groups, or wards. It is usually concerned as a cyclic scheduling called Master Surgical Scheduling (MSS) and fill – up the assigned time blocks by cases.

2.2.3 Modified Planning Strategy combine the advantages of block planning strategy and open planning strategy.

2.3 Decision levels of OR management [2],[11]

The level of OR scheduling decision is categorized in three levels as follow:

2.3.1 Strategic level is a long-term planning including capacity planning problem, capacity allocation problem, and case – mix problem (CMP) which is based on information and forecast.

2.3.2 Tactical level is a cyclic scheduling based on medium plan horizon usually constructed for monthly or quarterly. Main aim is to produce or improve Master Surgical Scheduling (MSS) for managing only the elective patients. The MSS construction is affected by the number of ORs, the available operating time and the capacities of pre-operative and post-operative such as the number of available beds. An improvement of MSS efficiency relates to the increasing resource performances such as beds in ward and ICU.

2.3.3 Operational level focused on short-term decision planning of elective case on daily basis. Surgical cases in a waiting list are scheduled to specific OR, day, and starting time. There are two steps of OR planning in this decision level: advance scheduling assigning an OR and a day to each surgery and allocation scheduling considering the certain start time of each case, sequencing it and allocation of the resources.

3. Literature Review

From recent literature reviews on OR scheduling, see [1] and [10], we focus on articles that combine OR scheduling with ICU beds management.

Many researches focus on hospital's cost and/or patient's cost. Min and Yih [12] consider OR scheduling on operational level for elective patients with the uncertainty of surgery durations and the available of ICU units. The schedule focuses on minimizing the patient total costs and overtime costs and solved their model numerical experiments. Tànfani and Testi [13] propose a 0-1 programming model and a heuristic algorithm for MSS problem including schedule patients to be operated on a day. To maximize overall societal benefit, minimizing a cost function based on a priority score, waiting time, and urgency status of patients are the objective of the model. Fügener et al. [14] propose a stochastic analytical approach to solve an MSS problem. They define downstream costs resulting from the MSS and propose exact and heuristic algorithms to minimize these costs. Al-Refaie et al. [15] propose a multi-period scheduling in ORs and ICUs and sequence patients in the ORs to improve patient satisfaction, resource utilization, and decrease hospital costs. Jebali and Diabat [16] proposed a two-stage chance-constrained stochastic programming to minimize total patient costs, OR costs, and ICU overutilization costs.

Bed management can be considered as in term of expected bed occupancy. Beliën et al. [3] is the first researcher who introduced mixed integer programming and simulated annealing (SA) which consider the expected bed occupancy over a planning horizon as an objective of an MSS. Penn et al. [17] also consider to reduce the maximum number of beds required. Multiple criteria mixed-integer linear programming model which taking account of a range of important factors is used to assist hospitals to produce new an MSS quickly. Price et al. [18] founded ICU beds are the source of bottleneck, so a model of minimizing overcapacity in the ICU was proposed. Data has gathered from the historical block schedule. Integer programming was used to solve the problem and can generate a practical and implementable time block schedule using rules of thumb which have a large impact to reduce the number of boarders.

Banditori et al. [19] considered the patient suffer more than the aforementioned researches. To have OR utilization and decrease patient waiting times, they generate an MSS which aim to maximize the patient throughput while cases' due dates were taken into account. They combined optimization-simulation approach to trade-off robustness and efficiency.

From our knowledge, previous researches aim to reduce patient waiting times and to balance ICU beds. They consider it as costs function or penalty function within only single OR decision level. We propose a binary programming that integrated decision level of OR management between tactical level and advance scheduling in operational level which aim to reduce waiting times of surgical patient whereas the ICU beds are not overutilized. Our occupied ICU's bed calculation is based on approach of Abedini et al. [9]. They proposed an integer programming which was modified from Price et al. [18]. The diverse of LOS of each case has directly impact to the calculation of discharged case from ICU likewise some cases from duplicate ward are not necessary to recover in ICU which is obviously different from the original model. Along with our model makes the decisions based on waiting list of each ward that indicate the current demand of each ward similar with real scheduling of public hospitals in Thailand. The results indicated that BM model could effectively reduce the variations in the case durations and patient arrivals.

4. Problem Description

A few patients experienced waiting as an opportunity to live full lives in spite of torment and inability. Thus, in many countries, the waiting list management is a main problem in health care services which aims to decrease the patient waiting times. It has severely a negative impact on patient treatment. Duration of wait and health-related quality can raise the severity of uncertainty both during and post-surgery such as the increasing of postoperative adverse event, diminishing probability of full recovery. Additionally, the waiting times constantly stimulate stressful and anxiety of patients [5, 20].

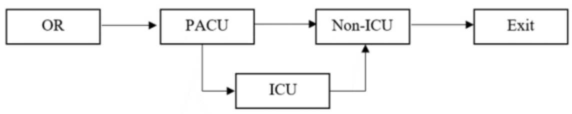

Figure 1 The patient's path by Price et al. [18]

From Figure 1, after a patient has finished from OR, the patient is then transferred to PACU for recovering from anaesthesia and examine side effects. Then, they might be transfer to Non-ICU such as wards but for some case the patients are necessary to recovery in ICU depends on length of stays (LOSs) before moved to Non-ICU.

One of the causes of waiting time is the imbalance between rising demand and the supply in health care services which was a debate around proportioning and priorities in most European nations [21]. If the patient cannot be transferred to ICU due to no available bed, the patient has to stay in PACU until any beds become available. Blocking between ICU and PACU can be a cause of surgical postpone, OR overutilization, and staff overtime because no PACU bed is available due to occupied by ICU's patients, who cannot be moved to ICU. Then, the patient has to stay in OR for waiting available bed and surgical team cannot perform any case until the previous patient is left the OR [18].

Public hospitals in Thailand also have numerous patients on waiting list which directly affected to waiting time. We interviewed some surgeons from large hospitals in Thailand whereas they described that hospitals have long patient waiting lists and have scarceness for some resources such as surgical equipment, ICU beds. The difference of patient costs between public hospitals and private hospitals is the main cause of long waiting list problem and resource shortages. It forces all of patients who cannot affordable for private hospitals to wait for the cure. OR scheduling in Thailand is usually allocate based on the number of patients on the waiting lists of each ward by surgical nurses, for example Orthopaedics receive all periods of OR 1 on Monday, then, patients are filled in. It indicates hospitals in Thailand also generate their MSS which detailed day, OR as major information and time block in some hospital from the waiting list of each ward. And, we can state that the scheduler knows the ICU bed requirement because surgeon must reserve an ICU bed for his/her patient, if they are imperative to recovery in ICU. These are our information appearing in public hospitals in Thailand.

5. Mathematical model

In our model, we assume all operating rooms are not unique and some ORs are reserved for emergency patients. Surgeons, surgical teams and cases are independent. Surgeons and surgical teams can operate any unoccupied cases within identical ward.

A prevalent objective to define the OR utilization is patient throughput because it can relate to financial hospital and patient waiting list whereas shown in a formulation named "Little's Law". The average number of works in process in the system L equals the average arrivals λ multiplied by the average cycle time W [22].

$$L=\lambda W \tag{a}$$

The definition (a) can be translated in term of OR planning by considering L as the number of patients in waiting list, λ as the patient's throughput, and W as summation of waiting time. The summation of waiting time can be reduced by decreasing number of patients in waiting list or increase throughput. Thus, increment throughput by utilized current resources is a satisfactory arrangement to bargain with patient preference and expanding hospitals financial gaining.

$$\text{Maximize} \sum_{i \in W} \sum_{j \in D} \sum_{k \in OR} \sum_{m \in C} y_{ijkm} \tag{1}$$

$$\sum_{i \in W} \sum_{p \in P} x_{ijkp} \leq TB_{jk}, \qquad \forall j, \forall k, \tag{2}$$

$$\sum_{j \in D} \sum_{k \in OR} \sum_{p \in P} x_{ijkp} \leq D_i, \qquad \forall i, \tag{3}$$

$$\sum_{i \in W} x_{ijkp} \leq 1, \quad \forall j, \forall k, \forall p, \quad (4)$$

$$\sum_{j \in D} \sum_{k \in OR} \sum_{m \in C} \rho_{im} y_{ijkm} \leq \varphi_i, \quad \forall i, \quad (5)$$

$$SC_{jm}^{ad} = \sum_{i \in W} \sum_{k \in OR} \rho_{im} y_{ijkm}, \quad \forall j, \forall m, \quad (6)$$

$$SC_{jm}^{dis} = SC_{dm}^{ad}, \quad d>0, d=j-LOS_m, \forall j, \forall m, \quad (7.1)$$

$$SC_{jm}^{dis} = 0, \quad d \leq 0, d=j-LOS_m, \forall j, \forall m, \quad (7.2)$$

$$SC_{jm}^{stay} = SC_{bm}^{stay} + SC_{jm}^{ad} - SC_{jm}^{dis}, \quad b>0, b=j-1, \forall j, \forall m, \quad (8.1)$$

$$SC_{jm}^{stay} = SC_{jm}^{ad}, \quad b \leq 0, b=j-1, \forall j, \forall m, \quad (8.2)$$

$$\sum_{m \in C} SC_{jm}^{stay} \leq B, \quad \forall j, \quad (9)$$

$$\sum_{j \in D} \sum_{k \in OR} y_{ijkm} \leq 1, \quad \forall i, \forall m, \quad (10)$$

$$\omega \sum_{p \in P} x_{ijkp} \geq \sum_{m \in C_i} dur_{im} y_{ijkm}, \quad \forall i, \forall j, \forall k, \quad (11)$$

$$\sum_{j \in D} \sum_{k \in OR} \sum_{m \in C_i} y_{ijkm} \leq \delta_i, \quad \forall i, \quad (12)$$

$$x_{ijkp}, y_{ijkm}, SC_{jm}^{ad}, SC_{jm}^{dis}, SC_{jm}^{stay} \in \{0,1\}, \quad \forall i, \forall j, \forall k, \forall p, \forall m. \quad (13)$$

All the indices, variables and parameters used in the research are listed below:

Indices

i Index of ward, $i \in W$

j Index of day during the planning horizon, $j \in D$

k Index of OR, $k \in OR$

p Index of period, $p \in P$

m Index of case during the planning horizon, $m \in C$ (A case has a patient which is operated by only an operation)

Input Parameters

C_i Subset of cases from ward i where $C_i \subset C$

δ_i Number of cases of ward i where $\delta_i = |C_i|$

TB_{jk} Maximum periods of each OR on day j

D_i Number of required periods of ward i for clearing all of patient on this planning horizon waiting list

ρ_{im} ICU requirement where $= \begin{cases} 1, & \text{if case } m \text{ of ward } i \text{ needs to recover in ICU} \\ 0, & \text{Otherwise} \end{cases}$

B The maximum capacity of ICU beds

φ_i Number of cases m of ward i requires to recover in ICU where $\varphi_i \leq |C_i|$

LOS_m Number of nights that case m needs to recover in ICU

dur_{im} Duration in minutes unit required to operate case m of ward i

ω Duration of period in minute unit (ω=240 minutes in our problems)

Decision Variables

$$SC_{jm}^{ad} = \begin{cases} 1, & \text{if case } m \text{ is chosen to be admitted to ICU on day } j \\ 0, & \text{Otherwise} \end{cases}$$

$$SC_{jm}^{dis} = \begin{cases} 1, & \text{if case } m \text{ is chosen to be discharged from ICU on day } j \\ 0, & \text{Otherwise} \end{cases}$$

$$SC_{jm}^{stay} = \begin{cases} 1, & \text{if case } m \text{ is chosen to be stayed at ICU on day } j \\ 0, & \text{Otherwise} \end{cases}$$

$$x_{ijkp} = \begin{cases} 1, & \text{Period } p \text{ of OR } k \text{ on day } j \text{ is chosen to be assigned to ward } i \\ 0, & \text{Otherwise} \end{cases}$$

$$y_{ijkm} = \begin{cases} 1, & \text{Case } m \text{ of ward } i \text{ is chosen to operate in OR } k \text{ on day } j \\ 0, & \text{Otherwise} \end{cases}$$

Equation (1) is the objective function which maximize the assigned cases of every day during planning horizon. Constraint (2) imposes the assigned periods cannot exceed the maximum period of each OR on a day which is stable during planning horizon. Our demand calculates from all surgical duration of case on each ward waiting list, so constraint (3) imposes the assigned periods cannot exceed the demand of each ward. Constraint (4) imposes one period of an OR on each day can be occupied by only one ward. Constraint (5) imposed ICU cases of each ward assigned on a day cannot exceed the ICU cases on waiting list of each ward. Constraint (6) recursively defines cases which has to be transferred to ICU for recovering on a day. In our model, even though an OR is available, but if a patient needs to recovery in ICU after his/her surgery but there is no available bed in ICU, then the patient cannot be operated until ICU becomes available. Constraint (7.1) and constraint (7.2) recursively defines cases can be discharged form ICU on a day. The ICU patient who has full LOS recovery in ICU will be discharged from ICU before the first cases of each day start. For example, if a patient has to be admitted on day 1 within LOS 3 days, the patient will be discharged on day 4 for this model as shown on Figure 2.

Day1		Day2		Day3		Day4	
7.00-8.00		7.00-8.00		7.00-8.00		7.00-8.00	
	Current LOS = 1		Current LOS = 2		Current LOS = 3		
					Discharge day 4		

Figure 2 Example of LOS counting in ICU

Constraint (8.1) and constraint (8.2) recursively defines cases still stay in ICU during each day. Constraint (9) imposes all of case stay on each day cannot exceed the capacity of ICU beds. Constraint (10) imposes each case can be assigned only once. Constraint (11) imposes the cases of each ward can be assigned to the periods which occupied by their ward and the periods are advantage to operate the case (One period has 4 hours and it has two periods per day, so one period has 240 minutes). Constraint (12) imposes all of assigned case of each ward cannot exceed the maximum number of cases of the ward. Constraint (13) imposes the assigned periods, the assigned cases, cases admitted, cases discharged, and cases stayed on each day are binary.

6. Experimental setup and testing

Our case duration parameter estimated from Neyshabouri and Berg [23] plus setup time 30 minutes which stated by Batun [24]. Case durations (μ_d^s), standard deviation (σ_d^s), and percentage of surgeries of 9 wards: Ear, Nose, and Throat (ENT), Obstetrics and Gynecology (OBGYN), Orthopedic (ORTHO), Neurosurgery (NEURO), General surgery (GEN), Ophthalmology (OPHTH), Vascular, Cardiac, and Urology represented in Figure 3 are the information from Neyshabouri and Berg [23].

We adopted three of nine surgeries that occupied more than 67% of surgical requirement and referred Orthopedic as ward 1, General surgery as ward 2, and Ear, Nose, and Throat as ward 3.

Ward	μ_d^s (minutes)	σ_d^s (minutes)	Percentage (% of surgeries)
ORTHO	107	44	23.26
GEN	93	49	22.12
ENT	74	37	21.34
OBGYN	86	40	9.26
Vascular	120	61	8.2
Urology	64	52	5.36
NEURO	160	77	5.04
OPHTH	38	19	2.98
Cardiac	240	103	2.44

Figure 3 Data of surgical duration from Neyshabouri and Berg [23] for generating the instance sets

Uniform integer distribution $U_{int}(1,4)$ is used as LOSs in Neyshabouri and Berg [23]. Although they are distant from the reality, the proposed for creating data allows us to understand its behavior on our model. From our information, LOS is depended on their operation types so, there are different LOS for each case in a ward. Although, the data of Neyshabouri and Berg [23] was reality but, there still have some differences among hospitals in the world and might have gaps of medical knowledges and technologies between 2015 and 2021. Moreover, surgery durations are depended on many factors such as surgeon team's experience, patient illnesses, and equipment.

To face the reality, the scarceness is raised on purpose by defining the number of ORs and ICU beds that cannot serve all patients on waiting list for each set of instances as shown on Table 1. Cases and periods can be assigned to OR only opened day, but cases can be discharged from ICU every day. For your information, constraint (5) and constraint (12) are redundant for this problem, but it will be benefit for further study.

Table 1 OR and ICU bed parameters for each of instance sets

	Small	Medium	Large
OR: $\lvert OR \rvert$ (rooms)	1	2	4
ICU Bed: B (beds)	3	7	10
Opened Day (TB_j>0)	3	5	5
Day: $\lvert D \rvert$ (days)	5	7	7

Our model coded in IBM ILOG CPLEX Optimization Studio12.4 and we executed our experiments on Intel® Core™ i7-1065G7 CPU @ 1.30 GHz 1.50 GHz RAM 16.0 under window 10. We impose a 3-hour time limit on the algorithm.

The results of the experiment on Table 2 represented there have high computational performance for small instance sets both computational time and result quality. For medium sizes, the model can guarantee the optimal solutions three out of four instance sets. Finally, only one out of three instance sets that can be guaranteed the optimal solution.

Table 2 Maximum case throughput and computational performance

	$\lvert C \rvert$	y_{ijkm}	time (sec.)	Status	% Gap
Small Instance Sets	10	9	3.01	Optimal	-
	20	11	4.11	Optimal	-
	30	13	3.53	Optimal	-
Medium Instance Sets	40	36	4.61	Optimal	-
	50	43	1307.58	Optimal	-
	60	41	44.16	Optimal	-
	70	51	10800.00	Non-Optimal	1.58 %
Large Instance Sets	80	73	5.35	Optimal	-
	100	83	10800.00	Non-Optimal	2.16 %
	150	89	10800.00	Non-Optimal	1.70 %

Our model has advantages for OR management which can define day, OR, and period for a case with decreasing waiting times and balancing ICU bed utilization. But it is impractical in reality, since large instance sets need more than 3-hours computation times for optimal solution. The results indicate that the computational times are not increased only by number of cases on waiting lists, for example computational time of 60-cases instance on waiting list is less than 50-cases instance. Also, in large instance sets, gap percentage of instance size 150 case has smaller than instance size 100 case that shown 150-cases instance is more convergent to optimal than 100-case instance. It might be raised by the calculation beginning point of instance is not distance from the optimal point.

7. Conclusion

This research formulated an MSS combining with advance scheduling as a binary programming to manage long waiting time problem where the scheduling decisions are assigned periods of ORs on each day to ward and case scheduling. Number of ORs and ICU beds are considered as main resources in our model under the objective that to maximize the total case throughput.

Our model can overcome the limitations of Abedini et al. [9] that can serve for the various LOS and case duration in the same ward and make the decision based on current demand, whereas the previous model used the historical data to decide and considered their LOSs are homogeneous in a ward. Moreover, our model is including the operational level of OR decision making which can indicate room and period for a ward. Due to restrict of ICU resources, our model cannot accept overutilize in ICU every day, but it was allowed on Abedini et al. [9].

To test the model, we generated ten sets of different case size as instance sets. The results indicated our model is suitable for small size and medium size problems, but for large problems, the model is not able to guarantee the optimal within 3-hours limited time. However, the problems which cannot be guaranteed the optimal solution have small percentage of gap. In our opinion, it might be reached to optimal solution within more computational times. Finally, although our model is effective for OR management, it is still impractical in reality due to long computation time for large size problems.

In our further work, in reality, OR scheduling is extremely complex as follow: a case is occupied by a surgeon and his/her team, so they cannot concurrently operate or have two consecutive operations. And, patient severity parameter should include in the future. To manage the computational time, developing a meta-heuristic which can serve the OR uncertainties is a better way to manage the large and medium size problems and testing with the real data of waiting list from a Thai hospital is essential to prove the advantages of our model.

8. References

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