An Optimization Model and Decision Support System of Operating Room Scheduling in a Teaching Hospital

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Department of Surgery (DOS) contributes to a major portion of hospital's expenditures and revenues. The costs come from resources which are involved in a surgery. These resources must be used optimally through proper scheduling. Recently, there are still many hospitals schedule the operating rooms manually which will take relatively longer time. Whereas the scheduling of the operating room can be done through developing a mathematical model. We consider several aspects in the model of this research, including the number of operating rooms, working hours, the available number of anesthetic machines, and utilization of each room. We propose a mixed integer linear programming (MILP) model to solve the operating room scheduling problem and based on the model, a decision support system (DSS) is developed to allow the hospital generates a better schedule with a shorter time. The results of sensitivity shows that the model is sensitive to the changes of surgery duration and the available number of anesthetic machines.

Keywords: Decision support system; Mixed Integer Linear Programming; Operating rooms; Scheduling

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1. Introduction

Department of Surgery (DOS) has been estimated to contribute more than 40% of the hospital's revenues and also the same proportion of their total expenses. It makes the DOS becomes hospital's biggest cost center as well as its most prominent income source [1]. The amount of surgery costs incurred in hospitals occurs due to the large number of resources used to carry out the surgeries, including staff (e.g., anesthesiologists, surgeons, and nurses), equipment and other supporting facilities.

The allocation of resources must be done efficiently and considered at every stage of the process so that the available resources can be used optimally to minimize additional costs due to overtime. Operating room (OR) scheduling is a challenging task, due to the uncertainty of the surgery duration [2]. If the OR manager reserves lesser time than the actual duration, then the next surgery cannot be started until the previous surgery is finished. This causes the next surgery will be delayed. This delay will cause the OR to operate beyond the regular time and result in additional costs in term of overtime. On the other hand, if the OR manager reserves surgery time more than the actual duration, then the OR will be idle until the next patient's schedule.

Currently, most of the OR scheduling is done manually, even though the development of mathematical model and Decision Support System (DSS) based on the model can increase the efficiency in the OR scheduling. In this research, the OR scheduling is carried out using an open strategy and blocking method. In the open strategy scheduling, the ORs of a hospital are opened to be scheduled for any types of surgical specialty. Hence, any patients can be treated in all available ORs. On the other hand, blocking method allocates specifically an OR to a certain surgical specialty [3].

The use of optimization models for scheduling requires a knowledge about how to program and run the model to produce optimal solutions using a certain software. One way to overcome this issue is to develop a DSS to facilitate the scheduling process. A DSS is designed to be used easily by people who do not have a high basic computer operating ability [4]. The use of a DSS in the hospital scheduling can help reduce the complexity of data processing from the optimization model [5]. A DSS requires a platform that is able to integrate all its components and one of the platforms that supports the development of DSS is Microsoft Office Excel [6].

Microsoft Office Excel has some features for developing graphical interfaces using Visual Basic for Applications (VBA), storing data in databases, and completing optimization models using the add-in Solver [7]. In this study, we propose an operating room scheduling optimization model with the aim of minimizing the use of the operating room during overtime and first period with limited available resources and develop a DSS for the OR scheduling.

1.1. Literature Review

The optimization has been used in many centuries to solve many problems, mainly in the fields of science, technology, engineering, and mathematics. Currently, the application of optimization is not limited to those fields, but has been spread to be used to solve some other other fields such as financial management, economics, life sciences, genetics, population studies and several others [8]. A general review on operating room optimization model has been conducted by Marques [9] which focused on maximizing the use of the operating room using linear integer programming.

The research allows an OR to be used more efficiently and reduces waiting lists for further operations. The scope of the work covers a real case of elective surgery. The model was then tested using real data which obtained from the hospital's record. The analysis showed that the proposed plan assigns an OR in more periods of overtime hours. However, this can easily be overcome by using a more accurate estimates for surgery duration. Jeang [10] developed a model with the aim of minimizing overtime and idle time of OR to achieve the effective utilization of the OR. The constraints imposed to the model included the availability of operating rooms, the availability of doctor's time and the number of operations in the planned period. Saadouli [11] developed an OR scheduling model using MILP with the aim of minimizing patient waiting time, by taking into account the average duration of surgery as well as the distribution of workload for each surgical team. Abedini [12] developed an integer programming model to solve the scheduling problem of ORs at Shomal hospital in Amol, Iran.

The hospital is a private hospital, and its surgical department has a policy to reduce the costs of operating rooms, the time between surgeries, and generally to reduce the total costs of surgeries. The model was solved using CPLEX 12.9, and a set of real data from the hospital is used to test the model. Hamid [13] investigated an integrated OR and surgical member scheduling by considering the limitation of human resources, equipment, and lunch break necessity. A mathematical model was developed to solve the problem. According to the result, the model is considered to be superior than manual scheduling both in the quality of the solution and computation time.

In the development of DSS for OR scheduling, Dios [14] developed a DSS that provided a number of optimization procedures to support decisions regarding the date and operating room assignment of patients in the waiting list. The DSS was designed using Microsoft C# and Visual Studio as the Integrated Development Environment (IDE) and mySQL as the database system management. Zanda [5] designed a DSS to determine a long-term schedule for nurses.

The objective function of the scheduling satisfies three main requirements: minimizing the shortage of nurses; minimizing the difference between the scheduled and expected nurse working hours; and giving priority to scheduling where free days are applied sequentially. To find the optimal solution of the model, the research used the CPLEX solver. Clavel [14] proposed and evaluated a DSS to assist medical staff in automatic scheduling of elective surgery patients to improve the work efficiency of the medical team. A CIPLAN application was developed in the research based on Java programming language and its database was developed using SQL. Güler & Geçici [15] developed an optimization model to minimize the potential for doctors to be exposed to COVID-19 by balancing the workload while maintaining the quality of health services provided for each department. The mathematical model was then solved using the Gurobi solver. The model was then implemented into a DSS in which Microsoft Excel was used as the application interface and data storage.

2. Problem Definition and Mathematical Model

2.1. Problem Definition

Department of Surgery (DOS) in a teaching hospital handles all surgery in elective cases and emergency cases. The DOS has 5 operating rooms that can be used for any types of surgical specialty. The working hours start from 07:30 until 15:30. The surgery which is performed beyond the working hours is known as overtime. In actual conditions, there are 3 anesthetic machines available to be used interchangeably. To simplify the scheduling process, a slot in this research is defined based on the average duration of historical data. A slot represents the room and period of the surgery within 60 minutes of time.

Table 1 shows the allocation of slots based on the period and operating room. The regular working hours comprise of Periods 1-8, while the rests of the periods are the overtimes. In this research, the surgery in the overtime period will be minimized because it will incur higher costs than the regular time. On the other hand, there is often a delay of the surgery in the morning period (Period 1 in Table 1), so the surgery in this period will also be minimized. Assigning a surgery in the morning period is better than the overtime because it incurs lower costs.

2.2. Mathematical Model

We first provide the notations of the parameters and the decision variables used in the MILP model as shown in Table 2.

2.2.1. Objective Function

The objective function of the MILP model is shown in Eq. (1).

$$\text{Min } Z = w\left(\sum_{i\in I}\sum_{j\in O}\sum_{k\in K} X_{ijk} + \sum_{i\in I}\sum_{j\in J=1}\sum_{k\in K} X_{ijk}\right) \quad (1)$$

The objective function in Eq. (1) minimizes the slot allocation in the overtime period and morning period. A weight is given on each period based on the priority of its period. Periods 2-8 are given a weight of 1, while the morning period is given a weight of 2. Period 9-11 in the overtime period is given the weight of 3, 4, and 5 respectively.

2.2.2. Constraints

In this section we formulate the constraints of the MILP model.

1. Eq. (2) expresses the estimated slot requirement for each patient.

$$\sum_{j\in J,O} X_{ijk} = r_i; \forall i \in I \quad (2)$$

2. Eq. (3) allocates slots sequentially for patients who require more than one slot.

$$X_{i(j+r_i)k} \leq X_{i(j+1)k} \leq X_{i(j)k} \quad (3)$$

3. Eq. (4) ensures that each slot can be assigned to only one patient.

$$\sum_{i\in I}\sum_{j\in J,0}\sum_{k\in K} X_{ijk} \leq 1; \forall j \in J, O \text{ and } \forall k \in K \quad (4)$$

4. Eq. (5) ensures each surgeon should not be placed in the same period.

$$\sum_{i\in D}\sum_{j\in J,O}\sum_{k\in K} X_{ijk} \leq 1; \forall j \in J \quad (5)$$

5. Eq. (6) ensures the number of surgery at each period should not exceed the number of available anesthetic machines (M).

$$\sum_{i\in I}\sum_{j\in J,O}\sum_{k\in K} X_{ijk} \leq M; \forall j \in J \quad (6)$$

6. Eq. (7) calculates the difference of operating room utilization

$$\sum_{i\in I}\sum_{j\in J,0} X_{ijk_1} - \sum_{i\in I}\sum_{j\in J,O} X_{ijk_n} \geq 1; \forall k \in K \quad (7)$$

7. Eqs. (8) to (13) define surgical specialty for each room. Room 1 is dedicated to otorhinolaryngology and general surgery. Room 2 is dedicated for urological surgery, Room 3 is for orthopedic and neurological surgery, and Room 4 is for gynecologic and general surgery. Lastly, Room 5 is for general surgery.

OTORHINOLARYNGOLOGY

$$\sum_{i\in I}\sum_{j\in J,0}\sum_{k=2}^{5} X_{ijk} = 0 \quad (8)$$

UROLOGIST

$$\sum_{i\in I}\sum_{j\in J,0} X_{ij1} + \sum_{i\in I}\sum_{j\in J,0}\sum_{k=3}^{5} X_{ijk} = 0 \quad (9)$$

ORTHOPEDIC

$$\sum_{i\in I}\sum_{j\in J,O}\sum_{k=1}^{2} X_{ijk} + \sum_{i\in I}\sum_{j\in J,O}\sum_{k=4}^{5} X_{ijk} = 0 \quad (10)$$

NEUROLOGIST

$$\sum_{i\in I}\sum_{j\in J,O}\sum_{k=1}^{2} X_{ijk} + \sum_{i\in I}\sum_{j\in J,0}\sum_{k=4}^{5} X_{ijk} = 0 \quad (11)$$

GYNAECOLOGIST

$$\sum_{i\in I}\sum_{j\in J,0}\sum_{k=1}^{3} X_{ijk} + \sum_{i\in I}\sum_{j\in J,0} X_{ij5} = 0 \quad (12)$$

GENERAL

$$\sum_{i\in I}\sum_{j\in J,O}\sum_{k=2}^{3} X_{ijk} = 0 \quad (13)$$

Table 1. Slot Allocation

Period	Time	Room 1	Room 2	Room 3	Room 4	Room 5
1	7.30 - 8.30	slot 1	slot 1	slot 1	slot 1	slot 1
2	8.30 - 9.30	slot 2	slot 2	slot 2	slot 2	slot 2
3	9.30 - 10.30	slot 3	slot 3	slot 3	slot 3	slot 3
4	10.30 - 11.30	slot 4	slot 4	slot 4	slot 4	slot 4
5	11.30 - 12.30	slot 5	slot 5	slot 5	slot 5	slot 5
6	12.30 - 13.30	slot 6	slot 6	slot 6	slot 6	slot 6
7	13.30 - 14.30	slot 7	slot 7	slot 7	slot 7	slot 7
8	14.30 - 15.30	slot 8	slot 8	slot 8	slot 8	slot 8
9	15.30 - 16.30	slot 9	slot 9	slot 9	slot 9	slot 9
10	16.30 - 17.30	slot 10	slot 10	slot 10	slot 10	slot 10
11	17.30 - 18.30	slot 11	slot 11	slot 11	slot 11	slot 11

Table 2. Parameters and Decision Variable

	Parameters
i	:Index of patient : $\{1,\ldots,\lvert I\rvert\}$: Set of all patient : $\{d_1,\ldots,\lvert D_n\rvert\}$: Set of patient i treat by surgeon d
j	:Index of period $\{1,\ldots,\lvert J\rvert\}$: Set of regular periods $\{j+1,\ldots,\lvert O\rvert\}$: Set of overtime periods
k	:Index of operating room : $\{1,\ldots,\lvert K\rvert\}$:Set of operating room
d	:Index of surgeon
r_i	:Number of slot required by patient i
M	:The number of available anaesthetic machines
w	:Weight of each period
	Decision Variable
X_{ijk}	: Patient i allocate to period j at room k : 1, if patient i allocate to period j at room k and 0, otherwise

To show the implementation of our model in the OR scheduling, a case study is given based on the historical data in the teaching hospital. There are 13 patients who will be scheduled for surgery in the next day. The scheduling needs 18 slots. There are five ORs are available for the scheduling. Room 5 cannot be used in the time of this research due to the maintenance. The number of anesthetic machines that can be used is 3. The optimal solution of the case study is solved using LINGO 18.0 and the result is shown in Table 3.

Table 3 shows there is no surgery in the overtime or in the morning period. Each slot is filled by only one patient and each patient is treated by the same doctor who are not scheduled in the same period. For example, in periods 2 (08.30-09.30) and 3 (09.30-10.30) there is a surgery schedule for patient 6 which is handled by doctor C.

Table 3 also shows that the number of surgeries in a period does not exceed the number of anesthetic machines. We can also see that the model relatively allocated the equal number of patients to each room. The number of slots used by each room is also relatively the same. For example, Room 1 and Room 3 used four slots, while for Room 2 and 4, used five slots. Moreover, patients who have surgery for more than one period are scheduled in consecutive period. Hence, the resulted schedule indicates that all the constraints have been satisfied.

3. DSS Implementation

In this part of the study, we developed a DSS to generate the OR schedules. The DSS is a model-driven DSS, which uses an optimization model to obtain the optimal scheduling solution. The DSS consists of 3 main components, namely user interface, data management, and model management [16]. In Fig. 1, we provide the schematic diagram of our designed DSS's component.

The user interface component consists of 2 parts, namely input and output. Input is used to insert the patient data which have to be scheduled and setting the parameters. Meanwhile, the output is used to display the scheduling results based on the optimal solution obtained from the model. The user interface is developed in Microsoft Excel with the help of Visual Basic for Application (VBA). VBA serves to create command codes in Microsoft Excel in the

Table 3. Operating Room Schedule

Period	Time	Room 1		Room 2		Room 3		Room 4		Room 5	
		Patient	Doctor	Patient	Doctor	Patient	Doctor	Patient	Doctor	Patient	Doctor
1	07.30 - 08.30	-	-	-	-	-	-	-	-	-	-
2	08.30 - 09.30	6	C	3	A	10	F	-	-	-	-
3	09.30 - 10.30	6	C	-	-	10	F	8	E	-	-
4	10.30 - 11.30	-	-	5	B	-	-	13	F	-	-
5	11.30 - 12.30	1	A	7	D	-	-	13	F	-	-
6	12.30 - 13.30	1	A	12	C	9	B	-	-	-	-
7	13.30 - 14.30	-	-	12	C	11	F	4	B	-	-
8	14.30 - 15.30	-	-	-	-	-	-	2	A	-	-
9	15.30 - 16.30	-	-	-	-	-	-	-	-	-	-
10	16.30 - 17.30	-	-	-	-	-	-	-	-	-	-
11	17.30 - 18.30	-	-	-	-	-	-	-	-	-	-

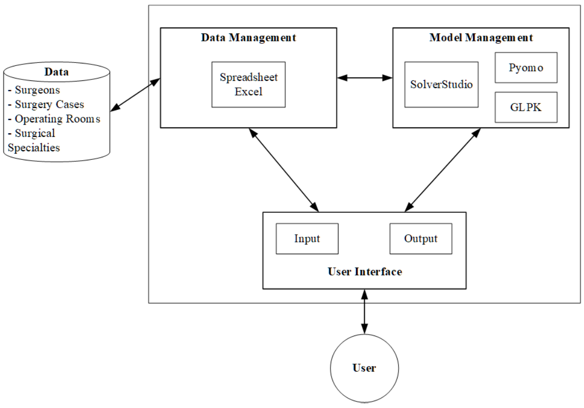

Fig. 1. Schematic diagram of our designed DSS's components

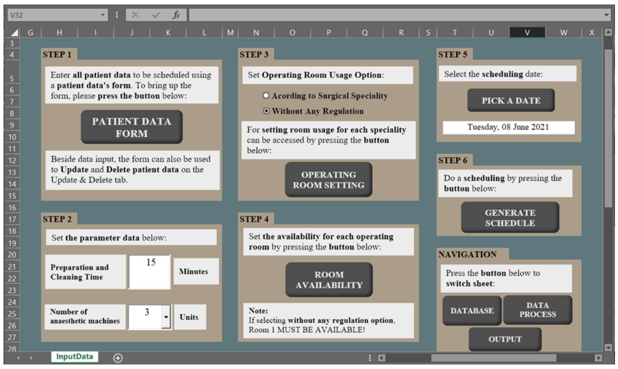

Fig. 2. Input section of the DSS

form of macro programming language.

Then, these codes are integrated into interactive buttons to make it easier for users to operate the DSS. The data management component manages all data, both from input and database. The data in the database include surgeries, surgery cases, operating rooms, and surgical specialty. The Database Management System (DBMS) is developed using Microsoft Excel.

The model management component consists of several applications to run the optimization model. Solver Studio is an additional application (add-ins) of Microsoft Excel and will be used to integrate the Microsoft Excel with the modelling language, so that the process of finding solutions becomes easier and integrated into one Excel application [17]. For the modelling language, we used Pyomo to run the mathematical model scripts and determine the solution [18].

The input section of the DSS in Fig. 2 contains the steps to operate the DSS and interactive buttons that are useful for insert the patient data and set the parameters. There are 6 steps to operate the DSS, starting from input the patient's data (patient's name, surgeon, surgery case, and estimation time); setting parameters (number of anesthetic machines and preparation and cleaning time); selecting room rule options (with or without surgical specialty), setting operating rooms availability, selecting scheduling date, and lastly generate a schedule based on the predetermined data and conditions.

The output section of the DSS contains the results of the scheduling from the data and parameters that have been set. The resulted schedule is displayed in a tabular form, where each patient will be placed in a certain room and in certain periods. The output displayed the patient's name, surgical case, and surgeon. There is a print button where the users can print the resulted scheduling.

Besides input and output, the DSS also contains database sheet and data process sheet. Database sheet is used to store the data, which are required by the DSS. The database includes data of surgeons, surgery cases, surgical specialty, and operating rooms. Surgeon's data includes surgeon ID, surgeon name, and surgeon specialty. Surgery cases data includes the name of surgery and its estimated time in minutes. Surgical specialty data include operating room arrangement for each surgical specialty, while the operating rooms data consist of the operating room combination usage along with its combination code. The data process sheet contains all the data components used to run the model and store the data variables from the model. The syntax of the optimization model for the Pyomo is also stored in this sheet. The procedure for using the DSS is shown in Fig. 3.

Here, we exemplify the application of the DSS in the OR scheduling based on a case in a teaching hospital. There are 13 patients who will be scheduled for the surgery. The patient data is shown in Table 4. The parameters and constraints for the scheduling are: a) preparation and cleaning time are estimated by 15 minutes; b) 3 units of anesthetic machines are available; c) there are no specialty of the room usage; and d) Room 1, Room 2, Room 3, and Room 4 are available. The scheduling results are shown in Fig. 4. The designed DSS provides convenience for users in scheduling the operating room. The scheduling process using the designed DSS can be done in less than one minute. It is very efficient and effective compared to manual scheduling.

3.1. Sensitivity analysis

Sensitivity analysis is performed to determine the effects of certain important parameters to the decision variables and objective function of the model. We develop 4 scenarios in this analysis. In the Scenario 1, we changed the number of available operating rooms from 4 into 3. This scenario is important to determine the effects of the room unavailability due to some reasons such as disruptions, constructions, equipment installations, or any other reasons. From Table 5, the reduction of operating room by 1 still resulted a schedule with no patient allocation on the first and overtime periods.

Hence, reducing the operating room by 1 is insensitive to the model. In Scenario 2, we adjust the duration of surgery to anticipate a situation where a surgery takes a longer time then the normal time. It represents the condition in which a surgery has a high level of difficulty. In this scenario, we added several patients who need 4 slots in their surgeries. The existence of longer surgery duration causes one allocation of Period 1.

This result conforms to the penalty of Period 1 allocation, which has lower penalty than the allocation to overtime periods. In Scenario 3, the available anesthetic machines are changed from three to two. This situation simulates the real condition in anticipation of machine unavailability due to maintenance or breakdown. The scenario causes two allocations at the morning and overtime periods. Hence, the number of anesthetic machines is sensitive to the model.

The last scenario is developed for the specialty scheduling. In this scenario, we added one room for the general surgery. This simulates the current condition in the hospital where the number of general surgery case is higher than the other cases. This scenario resulted the same optimization results as for actual condition and Scenario 1. Table 5 shows the comparison between the four scenarios with the actual conditions.

We have calculated the hours used in each operating room based on scheduling results from the DSS in Fig. 4. The calculations include the idle time and utilization of each room. Fig. 5 illustrated the Gantt chart of the OR schedule. In addition, we also calculate the percentage of the utilization of each room as shown in Table 6. From the table, Scenario 1 gives the scheduling in which the patients are distributed evenly to each room. In Scenario 2, the longer operating time will make the utilization of the rooms slightly higher. In Scenario 3, reducing the number of available anesthetic machines gives the same average utilization compared to the actual condition. While Scenario 4 gives the same utilization of Room 1, 4, and 5. Those rooms are dedicated to the general surgery as the most number of cases found in the hospital.

4. Conclusions

In this research, a MILP model is proposed to solve a real OR scheduling problem. The objective function of the model is to minimize patient allocation in the overtime and first period. The results of the optimization showed that the optimal schedule indicates that all the constraints of the model have been satisfied.

We examined the model with four scenarios of sensitivity analysis to simulate four conditions. The model was not sensitive to the reduction and addition of the operating room. When a surgery needs longer time duration than the average, then the model still can cope the situation by allocate only one time in Period 1. While the reduction of anesthetic machine made the model to allocate the schedule into two time slots both in Period 1 and overtime. From all scenarios, the utilization in each room is balanced which shows that the model is relatively robust to the changes of variables.

Based on the model, we developed a DSS using Microsoft Office Excel, Solver Studio and Pyomo. The DSS is able to generate schedules for the OR within less than one minute. The patients and the usage of each operating room are distributed evenly and satisfy all the constraints of the model. The DSS allows the user to schedule the operating room easily and gives higher effectiveness and

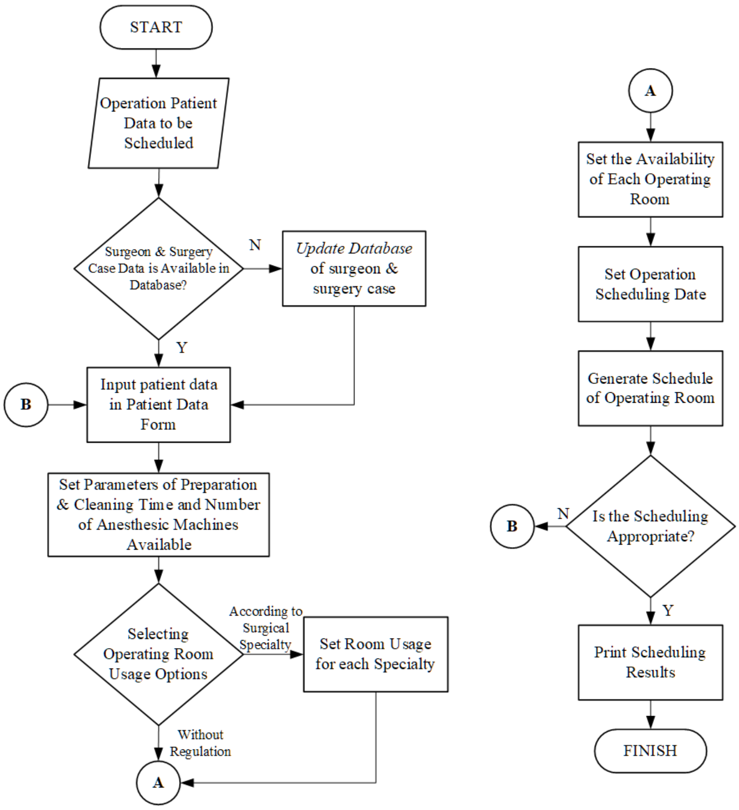

Fig. 3. Procedure for using the DSS

Table 4. Patient data

No.	Patient Name	Surgery Case	Doctor	Estimation Time (Minute)
1	Patient 1	Mastectomy	A	60
2	Patient 2	Excision	A	30
3	Patient 3	Excision	A	30
4	Patient 4	Debridement	B	30
5	Patient 5	Multiple Excision	B	30
6	Patient 6	URS (S) Lithotripsy	C	60
7	Patient 7	Septoplasty + Conchotomy	D	30
8	Patient 8	CDL Installation	E	15
9	Patient 9	Hernia Repair (Mesh)	B	30
10	Patient 10	BG + ORIF + Debridement	F	60
11	Patient 11	Plaster cast Installation	F	15
12	Patient 12	TURP	C	60
13	Patient 13	HA + Cemented	F	60

Table 5. Sensitivity Analysis

Period	Actual Condition	Scenario 1	Scenario 2	Scenario 3	Scenario 4
1	0	0	1	2	0
2-8	18	18	20	14	18
9	0	0	0	2	0
10	0	0	0	0	0
11	0	0	0	0	0

Table 6. Calculation Utilization

Condition	Room 1	Room 2	Room 3	Room 4	Room 5
Actual	50%	62,5%	50%	62,5%	-
Scenario 1	75%	75%	75%	-	-
Scenario 2	62,5%	62,5%	75%	62,5%	-
Scenario 3	50%	62,5%	62,5%	50%	-
Scenario 4	50%	37,5%	37,5%	50%	50%

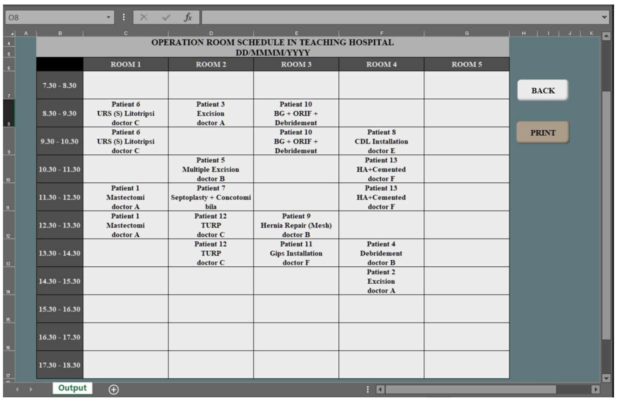

Fig. 4. Scheduling results using the DSS

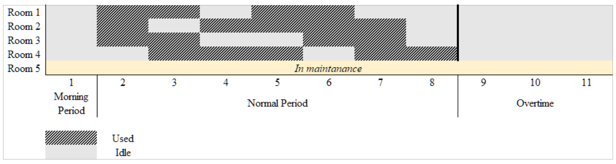

Fig. 5. Gantt Chart of Idle and Used Time

efficiency compared to the manual scheduling. For further research, the model could be enriched by involving nurse assignment in the surgery and including the schedule of the preoperative and postoperative room.

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