SIMULATED ANNEALING FOR OPTIMISING SURGICAL SCHEDULING CONSIDERING DIFFERENT REAL-LIFE CONSTRAINTS FOR ELECTIVE PATIENTS

Masri Ayob [1], Dewan Mahmuda Zaman [2]
[1]Center for Artificial Intelligent (CAIT),
Faculty of Information Science & Technology,
Universiti Kebangsaan Malaysia (UKM), Malaysia
masri@ukm.edu.my
[2]Center for Artificial Intelligent (CAIT),
Faculty of Information Science & Technology,
Universiti Kebangsaan Malaysia (UKM), Malaysia
mahmudazaman0509@gmail.com

ABSTRACT - Surgical scheduling problem (SSP) deals with finding a good quality surgery schedule to minimise the maximum end time of the surgical operation, overtime, and optimised surgical resource utilisation. Some meta-heuristic approaches, such as Ant Colony Optimization, Genetic Algorithm, etc., are implemented for solving SSP. However, no work reported applying Simulated Annealing that considers all the surgery stages and the utilisation of resources. Therefore, our study aims to generate an optimised surgical schedule that minimises the end time of the post-operative phase and overtime schedule. We considered all the surgical resources and stages, and schedule the complete flow of daily surgery for elective patients and keep a balance of working time. To search for a good quality solution, we employed Simulated Annealing (SA) metaheuristic to solve five surgery test cases (on benchmark datasets) with a different number of surgeries and resource availability. To benchmark our method's performance, we compare it against the Ant Colony Optimization (ACO). The computational results illustrate that SA has superior performance over ACO, which reduces the end time and overtime. This demonstrates the effectiveness of SA in solving SSP.

Keywords: Surgical scheduling; Simulated Annealing; Operating room; Elective patients; Multi-stages

1. INTRODUCTION

To provide a good quality service, the importance of planning and scheduling health care increases significantly. Apart from that, the operating room's (OR) high productivity is crucial in improving the hospital's benefit. Good efficiency of OR is vital to provide essential service quality to patients [1]. Due to the increase in the ageing population, the need for surgical service is also growing very speedily in our society [2]. As a result, more than 60% of patients are admitted for surgical operations [3], which is a considerable percentage. The cost of the resources of the hospital is very high [4] and the OR sector accounts for more than 40% of a hospital's total revenues and expenses [5]. On top of that, lousy scheduling leads to overtime, postponement or cancellation, increased idle time and resource cost, etc.

Many studies on surgery scheduling problems have been reported so far, classified based on different decision levels, such as strategic, tactical, and operational. Our research focuses on the operational level that deals with daily scheduling. Several methods were applied to solve these kinds of problems like metaheuristics, simulation etc. Although this problem is tackled in many studies, in this study two sub-problems: surgery scheduling and resource allocation (surgeons, nurses, anesthetists etc.) are dealt simultaneously for three surgery stages. Usually, the complete surgery flow is combined by several activities and those are before surgery starting (pre-operative/surgery), during surgery (perioperative/surgery) and after surgery (post-operative/surgery). Figure 1 represents patient flow according to these three stages including their necessary human and material resources [6].

Pre-operative Stage: This is the initial stage of the surgery scheduling process which is also named the pre-surgery stage. Nurses and Preoperative Holding Units (PHU) beds are essential resources for this stage. It is assumed that most hospital nurses present all day long in the PHU stage and they prepare patients for the surgery and check

relevant documents of that patient [7].

Intra-operative Stage: This is the stage where surgeries occur. The necessary material resources are multiple OR and human resources are surgeons, nurses, and anaesthetists. Different numbers of surgeons, nurses and anaesthetists are involved with the surgery based on the surgery complication.

Post-operative Stage: This is the recovery stage where resources are the Post-anesthesia Care Unit (PACU) beds and an anaesthetist nurse who usually remains in PACU for the whole day in most hospitals. Patients with critical conditions are moved to intensive care units (ICU) for further treatment from here. Otherwise, they are released from PACU.
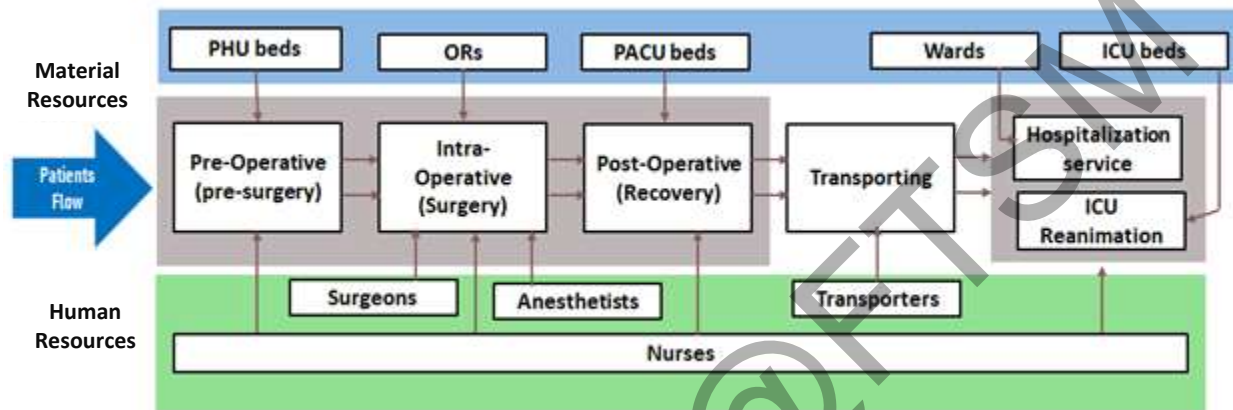

Fig. 1. Stages and different resources of a surgery scheduling process

In our study, we are considering multiple resources and multiple stages which is called "comprehensive operating room scheduling" where we worked on assigning patients to a specific OR and allocating related resources simultaneously. Simulated annealing metaheuristic which we proposed here to solve this complex problem and get an optimised schedule with minimised end time of stage-3. In addition, we tested our developed algorithm on real workday instances from the literature [6] and tried to improve the results.

2. SIMULATED ANNEALING FOR SURGICAL SCHEDULING

Simulated Annealing (SA) algorithm is an iterative random local search algorithm which is one of the most preferred approaches for solving optimisation problems. This algorithm was first introduced by [8], which was applied to optimisation problems. In combinatorial optimisation, this approach was successfully applied before. This approach is completed in two steps. The first step is to generate any random feasible solution, which can have a worse cost function. Step two is to generate random solutions and accept or reject them based on probability which depends on global defined temperature T. The temperature decreases slowly and improves the solution until the termination criteria are met. Algorithm 1 Represents simulated annealing. To find the optimal solution which has minimum make-span using simulated annealing, we need these elements:

Initial solution: Initial solution should be a randomly generated suitable solution which follows all the constraints. For our initial solution, we generate it by using First Come First Served. To complete a surgery successfully, surgery starts from the pre-surgery stage where resources are multiple PHU beds. After that the patients are moved to surgery stage and in this stage, resources are multiple OR, surgeons, anesthetists and nurses. Lastly, in the final stage which is the post-surgery stage, PACU beds are essential resources. So, a patient can be assigned for surgery when all these resources are available and suitable for that patient. To be more specific, if we want to assign a patient to an OR at time T, we need to ensure that:

- Required number of nurses are available
- Required number of anesthetists are available
- Surgeons are available with required specialty
- PHU bed is available at time T – PHU time
- OR is available at time T
- PACU bed is available at time T + surgery duration
- Among all the available resources, we select those resources to allocate for next which has minimum working time so far to provide the proper balance between resources.

Algorithm 1: Simulated Annealing

Generate an initial solution S_0
Set S_0 as best solution S^*
Set initial temperature T
While the termination condition does not meet Do: // when the temperature is 0 or the total number of iterations is executed
    Generate a neighborhood solution S_{new} of S_0 and compute current fitness
    Calculate δ = current_fitness – previous_fitness
    If $\delta <= 0$ Then:
        $S_0 = S_{new}$ //Accept neighborhood solution
        $S^* = S_{new}$ // Update best solution with current solution
    Else:
        Accept neighborhood solution with probability $\exp^{(-\delta/T)}$

    $T = \alpha * T$ (where $0<\alpha<1$)
End While

Generate neighbour: To generate a new neighbour, we use pairwise exchange where two surgeries are randomly selected from the schedule and exchange their places. We used this move because we can get a minimum change of the previous stage by using this move so that the solution improves its quality progressively.

Temperature and cooling schedule: An initial temperature is considered and reduced with each iteration and will continue until the temperature is zero. The probability of acceptance should be high during the beginning. It is essential for escaping from the local minimum. Here, for temperature decrease, we used a geometric schedule where the temperature is updated using the following formula:

$$T = \alpha * T \quad \text{where we considered } \alpha = 0.995$$

Acceptance criterion: Better and improved solutions are always accepted but for the worst move, the solution is accepted if the probability is $\exp^{(-\delta/T)} > r$ where r is a random number between 0 and 1.

3. RESULTS AND DISCUSSION

We experimented with our developed solution on the five test surgery cases that are different in surgery duration and their required OR resources which was previously solved using Ant Colony Optimization [6]. We tried to improve our result by 10,000 iterations. Table 1. Illustrates the comparison of ACO and SA for five different test cases with

- Makespan: End time of all surgeries to be scheduled by which efficiency of the schedule can be measured.
- Overtime: Time required to complete all the surgery after ending the regular work. Regular working time 8 hours and authorised overtime 2 hours considered.

- Coefficient of Variation (CV): Properly balanced utilisation of resources like OR, surgeons, anesthetists, and nurses

Table 1: Comparison between ACO and SA

Case No.	Method	Make-span	Overtime	Improvement of End Time (%)	CV of OR	CV of Nurse	CV of Anesthetist	CV of Surgeon Group -1	CV of Surgeon Group -2
1	ACO	341	0		0.08	0.55	0.13	0	0.2
	SA	293	0	14	0.11	0.21	0.18	0	0.34
2	ACO	574	94		0.06	0.45	0.37	0	0.07
	SA	502	22	12	0.02	0.13	0.18	0	0.28
3	ACO	464	0		0.08	0.45	0.42	0.26	0.26
	SA	391	0	15	0.06	0.201	0.21	0.22	0.22
4	ACO	489	9		0.09	0.46	0.18	0.08	0.15
	SA	410	0	16	0.04	0.19	0.107	0.27	0.23
5	ACO	789	42		0.09	0.44	0.31	0.21	0.08
	SA	502	22	36	0.04	0.24	0.107	0.13	0.13

4. CONCLUSION

We presented an operating room surgery scheduling problem in this study and applied simulated annealing meta-heuristic to optimise the complete scheduling flow with proper resource allocation and minimising the end time and overtime. Our approach is tested on the dataset which was previously worked with ACO and our result illustrates that the method we used has a superiority over ACO.

ACKNOWLEDGEMENT

REFERENCES

[1] Zhu, S., Fan, W., Yang, S., Pei, J., & Pardalos, P.M., (2019). Operating room planning and surgical case scheduling: a review of literature. *Journal of Combinatorial Optimization* 37, 575-805
[2] Etzioni, D. A., Liu, J. H., Maggard, M. A., & Ko, C. Y., (2003). The aging population and its impact on the surgery workforce. Annals of Surgery, 238(2), 170–177.
[3] Fügener, A., Schiffels, S., & Kolisch, R., (2017). Overutilisation and underutilisation of operating rooms: insights from behavioral health care operations management. *Health Care Manage Science*, 20(1):115–128
[4] Latorre-Núñez, G., Lüer-Villagra, A., Marianov, V., Obreque, C., Ramis, F., & Neriz, L., (2016). Scheduling operating rooms with consideration of all resources, post anesthesia beds and emergency surgeries. *Computers & Industrial Engineering 97. 248-257*.
[5] Denton, B., Viapiano, J., & Vogl, A. (2007). Optimisation of surgery sequencing and scheduling decisions under uncertainty. *Health Care Management Science*, 10(1), 13–24.
[6] Xiang, W., Yin, j., & Lim, G., (2015a). An ant colony optimisation approach for solving an operating room surgery scheduling problem. *Computers & Industrial Engineering 85, 335-345*.
[7] Belkhamsa, M., Jarboui, B., & Masmoudi, M., (2018). Two metaheuristics for solving no wait operating room surgery scheduling problem under various resource constraints *Computers & Industrial Engineering 126, 494-506*.
[8] Kirkpatrick, S., Gerlatt, C.D., & Vecchi, M.P., (1983). Optimisation by simulated annealing. *Science 220, 671–680*.