Challenges and solutions for the integrated recovery room planning and scheduling problem during COVID-19 pandemic

This paper presents an efficient solution for the integrated recovery room planning and scheduling problem (IRRPSP) during COVID-19 pandemic. The complexity of this problem arises from the following causes:

- this problem combines the assignment of patients to recovery rooms and the scheduling of caregivers over a short-term planning horizon
- there are both hard and soft constraints e.g. the maximum capacity of recovery rooms, the maximum daily load of caregivers, the treatment deadlines

Former approaches to patient assignment and scheduling

Using DSS (decision support system) - in 2020, Guler MG et al. developed in [1] a DSS which addressed the shift scheduling problem of physicians during COVID-19 pandemic. The solution proposed was a mixed integer programming which was solved using Gurobi software. The main limitation of this approach is to not solve the problem using heuristic or metaheuristic algorithms which results in impossibility to solve if the number of patients blows up.

Using a branch-and-price-and-cut algorithm based on a constraint programming model - in 2016, Hasemi Doulabi SH et al. developed this solution in [2]; to improve the efficiency, they also developed a set of dominance rules and a fast infeasibility-detection solution using multidimensional knapsack problem.

Using NSGA-II (Non-dominated sorting genetic algorithm II) and MOPSO (Multiple Objective Particle Swarm Optimization) metaheuristics - in 2019, Hamid M et al. developed in [3] a solution which addressed the scheduling problem of inpatient surgeries to improve the impact on the quality and safety of surgery. To model the problem, the authors proposed a comprehensive multi- objective programming model that aims to ensure three objectives, which are the minimization of the total cost, the maximization of the patients’ satisfaction, and the maximization of the aggregation of compatibilities of the surgical teams.

Using 3 solving methods in [4] which are (i) a Tabu Search metaheuristic (TS), (ii) a fastest ascent local search, and (iii) the sample average approximation method, to solve the problem of operating room planning problem while incorporating uncertainty in surgery durations.The experimental study shows that the TS metaheuristic provides effective solutions within reasonable computation times.

Current approach

The studied problem aims essentially to optimize two goals which are (i) the assignment of patients to recovery rooms and (ii) the scheduling of nurses to patients. There are 4 main types of cases considered: asymptomatic, middle to moderate, severe cases and critical patients. The problem can be summarized as follows: a set of **p** patients to be scheduled in **k** recovery rooms given an available rooms' capacity **c**. Two types of resources are considered: **recovery beds (RB)** and **respiratory machines (RM)**. These types of resources are used mainly by two types of recovery room schedules which are considered in the hospitals. The first type treats the severe patients without considering the critical cases; thus, rooms contain only recovery beds and are designed as **Recovery Beds Rooms (RBR)**. The other one treats the critical cases using special respiratory machines and this type of room is designed as **Recovery Respiratory Rooms (RRR)**. After assigning patients to rooms, the set of caregivers must be scheduled based on the type of required care. In this respect, only skilled caregivers may serve patients of RRR, which are NRRR, and other nurses can satisfy tasks of patients in RBR, which are NRBR.

The proposed solution follows 3 levels:

- **First level: Assignment of patients to recovery rooms**
  Sweeping Algorithm → Pre-assignment of patients (Pre-schedule - Initial Solution) → Local Neighborhood Search Algorithm → Optimal Assignment of patients to rooms
- **Second level: Assignment of nurses to patients**
  Random Initial Solution → Pre-assignment of nurses to patients (Pre-schedule) → Tabu Search Metaheuristic → Optimal assignment of nurses to patients
- **Third level: Overall solution implementation**
  2 branches: Heuristic approach → Balanced workload and second one is Greedy Algorithm → Minimize Overtime; both meet each other at the Near-optimal solution

Benchmark instances

They used real data provided by the Department of Respiratory and Chest Disorders of the King Abdulaziz Hospital, Jeddah, KSA, to produce realistic instances that would be used to test their modeling and solving approach. A configurable number of recovery rooms with respiratory machines, a variable number of recovery rooms with recovery beds, 2500 patients, 30 nurses, and the provided data instances all include all the pertinent information.

They created two distinct benchmarks from this data, each with four instances. The first benchmark B1 is made up of patients in critical condition, whereas the second benchmark B2 is made up of patients in severe condition. There are a variable number of rooms with recovery beds (RB) and a variable number of rooms with breathing equipment in the collection of instances (RM). All data instances, however, have the same number of carers, N = 30.

Table 2 Characteristics of the benchmark set B1

From: Challenges and solutions for the integrated recovery room planning and scheduling problem during COVID-19 pandemic

ID	NCP	NSP	nRRR	nRBR	NRM	NRB	NRRR	NRBR
1	177	354	13	25	182	350	10	20
2	204	408	13	25	182	350	10	20
3	229	458	15	29	210	406	10	20
4	240	479	15	29	210	406	10	20

Table 3 Characteristics of the benchmark set B2

From: Challenges and solutions for the integrated recovery room planning and scheduling problem during COVID-19 pandemic

ID	NCP	NSP	nRRR	nRBR	NRM	NRB	NRRR	NRBR
5	267	533	19	38	266	532	10	20
6	340	679	22	44	312	622	10	20
7	415	829	26	51	358	716	10	20
8	479	958	30	60	420	839	10	20

Legend

- B1 and B2 refer to the first and second generated benchmarks.
- ID: the number of data instances.
- NCP: number of critical state patients.
- NSP: number of severe state patients.
- nRRR: number of recovery respiratory rooms.
- nRBR: number of recovery beds rooms.
- NRM: number of respiratory machines.
- NRB: number of recovery beds.
- NRRR: nurse that serves patients of RRR.
- NRBR: nurse that serves patients of RBR.

References

[1] Guler MG, Gecici E (2020) A decision support system for scheduling the shifts of physicians during covid-19 pandemic. Comput Industrial Eng 150:106874

[2] Hashemi Doulabi SH, Rousseau LM, Peasant G (2016) A constraint programming based branch-and-price-and-cut approach for operating room planning and scheduling. INFORMS J Comput 28(3):432–448

[3] Hamid M, Nasiri MM, Werner F, Sheikh Ahmadi F, Zhalechian M (2019) Operating room scheduling by considering the decision making styles of surgical team members: a comprehensive approach. Comput Oper Res 108:166–181

[4] Eun J, Kim SP, Yih Y, Tiwari V (2019) Scheduling elective surgery patients considering time-dependent health urgency: Modeling and solution approaches. Omega 86:137–153