SUSTAINABLE ENHANCEMENT OF HEALTHCARE DELIVERY: A COMPREHENSIVE PARADIGM FOR OPTIMIZING ELECTIVE SURGERY RESOURCES

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ABSTRACT

This study introduces a novel, comprehensive surgery scheduling model for elective surgeries, aiming to enhance coordination among preoperative, operating room, and postoperative units. The model encompasses three objectives to achieve a trade-off among stakeholders' priorities: firstly, minimizing idle time and overtime in Operating Rooms (ORs); secondly, maximizing the interval between two consecutive patients in the operating room to facilitate stakeholder satisfaction; and thirdly, maximizing the number of scheduled patients from the waiting list throughout the scheduling horizon. Given the problem's NP-hard nature, a new meta-heuristic approach (NSGA-SA), the hybrid of Non-dominated Sorting Genetic Algorithm (NSGA-II) with Simulated Annealing (SA), is employed for problem solving. Following parameter setting of the solution approaches, multiple numerical experiments are conducted. The exact results obtained through the General Algebraic Modeling System (GAMS) are compared with the outcomes of the outlined meta-heuristic approach, demonstrating the effective performance of the proposed method.

Keywords: Surgery Scheduling, Meta-heuristic Optimization, Stakeholder Priorities, NP-hard Problem

1 INTRODUCTION

The increasing need for elective surgeries due to an aging populace and medical advancements necessitates resource optimization in hospitals for better healthcare. In public healthcare systems, strategic allocation of taxpayer funds is crucial to match demand and capacity for elective services. Focusing only on maximizing operating room usage may cause surgery cancellations and stakeholder dissatisfaction.

This research introduces a thorough surgical scheduling model for elective patients, accounting for resource allocation across all stages, including postoperative care. The main goal is to cut down idle time and overtime costs related to operating room usage, catering to hospital management needs. Secondary goals include reducing surgery cancellations and providing surgical teams with ample time via extended time buffers. This model aspires to meet both hospital managers' and patients' expectations by maximizing scheduled surgeries and minimizing cancellations.

This research's significance lies in its potential to boost hospital sustainability within the surgical domain, surpassing previous studies by considering stakeholder expectations and innovative factors like time buffers. This approach seeks a balance between financial limitations and community satisfaction, which is crucial for contemporary healthcare institutions.

Addressing this complex issue, a multi-objective, multi-stage surgery scheduling method is proposed. Given the problem's intricacy, heuristic and meta-heuristic techniques like HNSGA and HNSGA-SA are employed to solve the suggested mathematical model efficiently. These methods are crucial in tackling real-world situations while maintaining practical CPU times, as surgery scheduling is a challenging problem recognized as a flexible flow-shop scheduling problem in academic domains.

2 LITERATURE REVIEW

The literature on multi-stage integrated operational scheduling of Operating Rooms (ORs) and robust optimization is reviewed in this section. Comprehensive reviews on OR planning and scheduling are detailed by Cardoen et al. [1], Guerriero and Guido [2], Zhu et al. [3]. The surgical process involves several stages where specific human resources and equipment needs (e.g., beds) significantly interact Hans et al.[4], Lamiri et al. [5], Van Houdenhoven et al. [6], Wullink et al. [7]. However, most research on hospital and OR scheduling overlooks the entire process, focusing primarily on OR resources and capacity.

Weinbroum et al. [8] underscored the processes importance, showing that 17% of OR idle time is due to Preoperative Holding Unit (PHU) unavailability, while another 15% relates to recovery room or Intensive Care Unit (ICU) availability. Notwithstanding, some studies consider other resources, but focus primarily on preoperative/OR resources and capacity Mulholland et al.[9], van Oostrum et al. [10], Vissers [11], Zhang et al. [12], or both OR and postoperative Neyshabouri and Berg [13], Shehadeh and Padman [14].

Few models consider both the Operating Room and the complete surgical process, including preoperative, Operating Room, and postoperative stages as a single system Belkhamsa et al.[15], Moosavi and Ebrahimnejad [16], Vali-Siar et al.[17]. For instance, Belkhamsa et al.[15] examined daily OR scheduling considering resource constraints in all stages to minimize OR idle time and maximum postoperative stage end time.

Vali-Siar et al.[17] used mixed-integer linear programming for an integrated operational surgery scheduling approach accounting for upstream and downstream resources. Their model aimed to minimize surgery tardiness, reduce overtime and idle time, and address time uncertainties while neglecting to consider all stakeholder viewpoints. Our proposed model, like Vali-Siar et al.[17], focuses on a comprehensive system approach, aiming to address current challenges in balancing system-wide resource utilization within the hospital and making a trade-off between stakeholder preferences for sustainable surgery.

Several criteria are utilized to gauge OR planning and scheduling performance. Eight main performance measures include patient waiting times, total operated patients, surgery postponement or cancellations, total completion time, resource utilization, overtime, and idle time. These performance criteria are explained in OR scheduling literature reviews Cardoen et al. [1], Guerriero and Guido [2], Zhu et al. [3].

Given the performance criteria range, diverse parties are involved in the surgical process. Patients prioritize completed surgeries and low waiting times, hospitals aim to improve resource utilization and minimize overtime and idle time, while surgical teams require time management. To satisfy multiple stakeholders, we consider multi-criteria models addressing multiple objective functions as many studies often multiple criteria. For example, Vali-Siar et al. [17] developed a model to minimize idle time and overtime (hospital criterion) and surgery tardiness (patient criterion) but overlooked the surgical team's preferences.

This research introduces a multi-objective, multi-period OR planning and scheduling model to address research gaps and increase solution relevancy. The goals include reducing overtime and idle time, increasing time buffers, and boosting scheduled patients. The study strives for surgical sustainability by balancing stakeholder preferences, both financial and social aspects.

3 PROBLEM DESRIPTION

Patients undergoing the surgical process pass three stages. Initially, upon ward admission, they're assigned a bed; a nurse prepares them for surgery, assesses their health, and updates records. They are then moved to the PHU, prepped for surgery, and allocated a specific operating room manned by specialized personnel, including the designated surgeon, various nurses, and anesthesiologists. Post-surgery, patients are transferred to the recovery unit, requiring a bed and nurse anesthetist for post-anesthesia care. If intensive care is required, they are moved to the ICU with allocated beds. Finally, surgeons' post-surgical assessment allows patients to be discharged.

3.1.1 Mathematical formulation

The following notations are used to represent the model:

Indices		Sets
p, p'	Index for elective patient	$p,p' = \{1,2,3,\ldots,P\}$
o	Index for operating room	$o = \{1,2,3,\ldots,O\}$
t	Index for time slot	$t = \{1,2,3,\ldots,T\}$
d	Index for day	$d = \{1,2,3,\ldots,D\}$
k	Index for surgery type	$k = \{1,2,3,\ldots,K\}$
j	Index for the stages of surgery process, PHU (j = 1); Operating room (j = 2); Recovery room (j = 3)	$j = \{1,2,3\}$
i	Index for the ward before surgery (i = 1); ICU (i = 2); and the ward after surgery (i = 3)	$i = \{1,2,3\}$

Parameters

S_{pk}	Binary variable; 1 if patient p goes under surgery type k; 0, otherwise.
∂_{kotd}	Binary variable; 1 Surgery type k can operate in operating room o on day d in time slot t; 0, otherwise
t_{int}	Time intervals
DU_{pj}	Duration of stage j for patient p

LOS_{pi}	Length of stay for elective patient p in the ward before surgery (i=1), ICU (i=2) and the ward after surgery (i=3)
LOS_{ei}	Length of stay for emergency case in the ward before surgery (i = 1), ICU (i=2) and the ward after surgery (i=3)
LT_o	The last time slot in the regular opening hours of operating room o (which is not considered as overtime)
KT_o	The last time slot in the opening hours of operating room o (LTo plus maximum allowed overtime hours)
C_o^{OVT}	Cost of overtime for operating room o per minute
C_o^{IDT}	Cost of idle time for operating room o per minute
$\varepsilon_{d_x}^{ICU}$	Occupied beds in ICU from the previous period in the day dx
$\varepsilon_{d_x}^{ward}$	Occupied beds in ward from the previous period in the day dx
γ_k^1	Required number of scrub nurses for each surgery regarding surgery type
γ_k^2	Required number of circulating nurses for each surgery regarding surgery type
γ_k^3	Required number of anaesthetist nurses for each surgery regarding surgery type
N_{td}^{sc}	Total number of scrub nurses available at time t on day d
N_{td}^{c}	Total number of circulating nurses available at time t on day d
N_{td}^{an}	Total number of nurse anaesthetist available at time t on day d
N_{td}^{anest}	Total number of anaesthesiologists available at time t on day d
B^{ICU}	Total number of beds in ICU
B_k^{ward}	Total number of beds in ward for surgery type k
Cl_o	Cleaning time of operating room o after each surgery

Decision Variables

x_{potd}	Binary variable; 1, if patient p is assigned to operating room o in time slot t of day d; 0, otherwise.
y_{pjtd}	Binary variable; 1, if patient p is assigned to stage j in time slot t of day d; 0, otherwise.
ovt_{od}	Overtime of operating room o in day d.
idt_{od}	Idle time of operating room o in day d
st_{pj}	Start time of phase j for patient p
ft_{pj}	Finish time of phase j for patient p
$tb_{pp'od}$	Time buffer for two consecutive patients p and p′ in operating room o on day d
δ_{pd_xi}	Binary variable; 1, if elective patient p stay in the ward before surgery (i=1), ICU (i=2) and ward (i=3) after surgery on the day dx ;0, otherwise.
q_{pod}	Binary variable; 1, if a patient p assigned to operating room o on day d; 0, otherwise.
$qs_{pp'od}$	Binary variable; 1, if two consecutive patient p and p′ are assigned to operating room o on day d; 0, otherwise.
z_{pjd}	Binary variable; 1, if the emergency case is assigned to operating room o on day d; 0, otherwise

The mathematical model is comprised of three objectives, which are as follows.

$$Min\ f_1 = t_{int}\Big(\sum_o \sum_d C_o^{OVT}.ovt_{od} + C_o^{IDT}.idt_{od}\Big) \tag{1}$$

$$Max f_2 = \sum_p \sum_{p'} \sum_o \sum_d tb_{pp'od} \tag{2}$$

$$Max f_3 = \sum_p \sum_o \sum_d q_{pod} \tag{3}$$

The first objective function (1) minimises the overtime and idle time costs for the operating room. The second objective function (2) maximises the time buffer between two consecutive patients in operating rooms. The third (3) maximises the number of patients scheduled during each planning horizon.

$$\sum_{p} x_{potd} \leq 1 \qquad \forall\, o,t,d \qquad (4)$$

$$\sum_{o}\sum_{d} q_{pod} \leq 1 \qquad \forall\, p \qquad (5)$$

Constraint (4) ensures that only one patient (either emergency arrival or elective) can be scheduled in a single OR at any one time. Constraint (5) states that each patient can have surgery in one operating room and one day over the planning horizon. It means each patient is scheduled for surgery only once.

$$\sum_{t} x_{potd} \geq q_{pod} \qquad \forall\, p,o,d \qquad (6)$$

$$\sum_{p}\sum_{o}\sum_{t>KT_o}\sum_{d} x_{potd} = 0 \qquad (7)$$

$$x_{potd}.S_{pk} \leq \partial_{kotd} \qquad \forall\, p,o,d,t,k \qquad (8)$$

Constraint (6) shows the relation between xpotd and qpod. Constraint (7) outlines that surgery cannot be performed outside the allocated time slots for activity in the ORs. Constraint (8) ensures that elective patients can only be assigned to the OR correspondingly assigned to that surgery type.

$$\sum_{o} x_{potd} = y_{p2td} \qquad \forall\, p,t,d \qquad (9)$$

Constraint (9) determines the relationship of two decision variables xpotd and ypjtd.

$$st_{pj} \leq t.y_{pjtd} + M.(1 - y_{pjtd}) \qquad \forall\, o,t,d \qquad (10)$$

$$st_{pj} \leq M \sum_{t}\sum_{d} y_{pjtd} \qquad \forall\, p,j \qquad (11)$$

$$ft_{pj} \geq (t+1) - M(1 - y_{pjtd}) \qquad \forall\, p,j,t,d \qquad (12)$$

$$ft_{pj} \leq M \sum_{t}\sum_{d} y_{pjtd} \qquad \forall\, p,j \qquad (13)$$

$$ft_{pj} - st_{pj} \leq \sum_{t} y_{pjtd} + M(1 - z_{pjd}) \qquad \forall\, p,j,d \qquad (14)$$

Constraints (10) and (11) provide the starting time for the separate stages; the finish times are provided by constraints (12) and (13). Constraint (14) defines the duration for the stage as the difference between the start and finish times; interventions cannot occur unless they are inside the specified hours, given by st_{pj} and ft_{pj}.

$$\sum_{t} y_{pjtd} = DU_{pj}.z_{pjd} \qquad \forall\, p,j,d \qquad (15)$$

$$\sum_{d} z_{pjd} \leq 1 \qquad \forall\, p,j \qquad (16)$$

Constraint (16) expresses that each patient p is to be scheduled over consecutive time slots. Constraint (17) ensures patients are assigned to a stage only once during the scheduling period.

$$\sum_{p}\sum_{o}\sum_{k} \gamma_k^1 \cdot x_{potd} \cdot S_{pk} \leq N_{td}^{sc} \qquad (17)$$

$$\sum_{p}\sum_{o}\sum_{k} \gamma_k^2 \cdot x_{potd} \cdot S_{pk} \leq N_{td}^{c} \qquad \forall t,d \qquad (18)$$

$$\sum_{p}\sum_{o}\sum_{k} \gamma_k^3 \cdot x_{potd} \cdot S_{pk} \leq N_{td}^{an} \qquad \forall t,d \qquad (19)$$

$$\sum_{p}\sum_{o} x_{potd} \leq N_{td}^{\text{anes}} \qquad \forall t,d \qquad (20)$$

Constraints (17) to (20) provide the limitations to the availability of nurses and anesthesiologists.

$$\sum_{d_x=d-LOS_{p1}}^{d-1} \delta_{pd_x1} = LOS_{p1} \cdot z_{p2d} - LOS_{p1} \geq 0 \qquad \forall p,d:d \qquad (21)$$

$$\sum_{d_x=d}^{d+\text{LOS}_{p2}-1} \delta_{pd_x2} = LOS_{p2}.z_{p2d} \qquad \forall p,d:d \leq D-LOS_{p2}+1 \qquad (22)$$

$$\sum_{d_x=d+LOS_{p2}}^{d+\text{LOS}_{p2}+\text{LOS}_{p3}-1} \delta_{pd_x3} = \text{LOS}_{p3} \cdot z_{p2d} \qquad \forall p,d:d \leq D-LOS_{p2}-LOS_{p3}+1 \qquad (23)$$

Constraint (21) determines the days an elective patient stays in the ward before surgery. Constraints (22) and (23) determine the days following surgery that an elective patient may stay on the ward and the ICU.

$$\sum_{p} \delta_{pd_x2} + \varepsilon_{d_x}^{ICU} + \sum_{d_x} \delta_{ed_x2} \leq B^{ICU} \qquad \forall d_x \qquad (24)$$

$$\sum_{p} \left(\delta_{pd_x1} \cdot S_{pk} + \delta_{pd_x3} \cdot S_{pk}\right) + \varepsilon_{d_x}^{\text{ward}} + \sum_{d_x} \delta_{ed_x3} \leq B_k^{\text{ward}} \qquad \forall d_x,k \qquad (25)$$

Constraints (24) and (25) address capacity in the ICU and ward for each speciality, carrying over patients from past planning horizons who are still in the units.
Constraints (26) to (33) calculate the time buffers between two consecutive patients.

$$tb_{pp'od} - tb_{p'pod} \leq st_{p',2} - ft_{p,2} + M * \left(2 - q_{pod} - q_{p'od}\right) \qquad \forall o,d,p,p':p<p' \qquad (26)$$

$$tb_{pp'od} - tb_{p'pod} + M * \left(2 - q_{pod} - q_{p'od}\right) \geq st_{p',2} - ft_{p,2} \qquad \forall o,d,p,p':p<p' \qquad (27)$$

$$tb_{pp'od} \leq M * q_{pod} \qquad \forall o,d,p,p':p \neq p' \qquad (28)$$

$$tb_{pp'od} \leq M * q_{p'od} \qquad \forall p,p',o,d,p \neq p' \forall o,d,p,p':p \neq p' \qquad (29)$$

$$tb_{pp'od} = 0 \qquad \forall o,d,p=p' \qquad (30)$$

$$qs_{pp'od} + qs_{p'pod} \leq 1 \qquad \forall o,d,p<p' \qquad (31)$$

$$tb_{pp'od} \leq M * qs_{p'pod} \qquad \forall p,o,d,p \neq p' \qquad (32)$$

$$tb_{pp'od} \geq Cl_o * qs_{p'pod} \qquad \forall p,o,d,p \neq p' \qquad (33)$$

Constraints (34) and (35) give the daily OR idle time and overtime.

$$idl_{od} = LT_o - \sum_{p} \sum_{t \le LT_o} x_{potd} \qquad \forall o, d \qquad (34)$$

$$ovt_{od} = \sum_{p} \sum_{t > LT_o} x_{potd} \qquad \forall o, d \qquad (35)$$

Constraint (36) ensures that overtime for each operating room on each day must be less than the allowed overtime.

$$ovt_{od} \le KT_o \qquad \forall o, d \qquad (36)$$

Constraints (37) and (38) express the type of variables.

$$x_{potd}, y_{pjtd}, z_{pjd}, q_{pod}, qs_{pp'od}, \delta_{pd_xi}, S_{od} \in \{0,1\} \qquad (37)$$

$$ft_{pj}, st_{pj}, ovt_{od}, IDT_{od}, tb_{pp'od} \in \{0, I^+\} \qquad (38)$$

4 SOLUTION METHODOLOGY

The Non-dominated Sorting Genetic Algorithm (NSGA-II) proposed by Deb et al.[18] is employed to solve multi-objective optimization problems for large-scale issues, given its broad acceptance. For more information, readers can refer to Deb et al.[18]. To enhance the NSGA-II solution, Simulated Annealing (SA) is utilized, generating high-quality solutions by examining each solution's neighborhood. SA's strong local search ability prevents NSGA-II from getting stuck in locally optimal solutions. Consequently, this study employs a hybrid NSGA-II algorithm with SA to resolve the multi-objective surgery scheduling problem. The pseudo-code of the NSGA-SA algorithm is:

Algorithm 1: The pseudo-code of the NSGA-SA algorithm

```
Define population size, crossover rate, mutation rate and the number of generation.
while t <= T_max do
    Generate the initial population randomly;
    Evaluate all three objective functions for each individual by using equations 1 to 3;
    Rank all individuals according to their non-dominance;
    Calculate the crowding distances for all individuals in the population;
    Apply crossover and mutation operators to population P and generate a new
      population Q;
    Apply SA for neighbourhood search;
    t = t + 1;
    while t <= T_max do
        Calculate the objective function values for each new population Q.;
        Combine P individuals with Q individuals to produce intermediate population.;
        Rank all individuals in intermediate population according to their non-dominance;
        Determine Pareto set at current generation;
        t = t + 1;
        Calculate the crowding distances for all individuals in the intermediate population;
        Apply crossover and mutation operators and neighbourhood search to population
          P and generate a new population Q;
    end
end
```

5 RESULTS

The model and its solution methods are evaluated using a dataset comprising 23 instances reflecting different hospital sizes, derived from a notable case study by Min and Yin[19].The Exact model is solved using the mathematical formulation encoded in GAMS 33 with the CPLEX solver, with a computational time of four hours as the stopping criterion. If a method fails to find a solution within this period, its column is marked with "-". The meta-heuristic algorithms are coded in MATLAB 2021a. Under certainty conditions, the meta-heuristic methods' values represent the average of 10 executions per instance. Table 1 details the results, comparing solutions based on their objective function and solution time. The assessment of the NSGA-SA algorithms and the Exact model indicates that the meta-heuristic algorithm yields high-quality solutions.

Table 1 results based on comparing the CPU time and Objective functions.

Instances	MLIP					NSGA-SA			
	f_1	f_2	f_3	F	CPU time	f_1	f_2	f_3	F
1	155528	27.11	4	0.216	0.08	146253.7	55.7	5	0.266
2	146063.3	197.16	8	0.323	1.01	156820	145.1	8	0.27
3	138296	350	10	-0.301	7.78	156100	160.12	10	-0.134
4	125380	309.25	13	-0.312	6.96	157040	165.36	10	-0.174
5	96337.5	628	19	-0.453	47.62	138397.2	188.4	12	-0.230
6	442760	142.4	10	-0.498	8.25	460920	60.3	10	-0.336
7	446100	72.33	15	-0.271	16.83	458480	160.6	15	-0.234
8	431120	94	20	0	16.67	440560	288.6	20	-0.149
9	418000	441	30	-0.508	16.79	423100	458	29	-2.289
10	397382	705.1	40	-0.5	99.29	415080	655.6	38	-0.141
11	-	-	-	-	-	394720	791.6	46	-0.112
12	959750	53	15	-0.31	6.96	937226	64.5	14	-0.170
13	945204	159.6	20	-0.317	18.05	925437.2	112.2	18	-0.128
14	912798.3	337.75	30	-0.53	17.26	931420	188.67	24	0.046
15	888511	903.2	40	-0.63	108.47	927700	187.4	27	-0.300
16	-	-	-	-	-	907160	347.3	32	0.044
17	-	-	-	-	-	889720	476	41	0.094
18	-	-	-	-	-	1971820	127	25	-0.114
19	-	-	-	-	-	1901100	342	50	-0.168
20	-	-	-	-	-	1827040	658.8	74	-0.112
21	-	-	-	-	-	1769540	596	96	-0.181
22	-	-	-	-	-	1749920	892	99	-0.250
23	-	-	-	-	-	1308640	5086	298	-0.510
Average	464516.4	315.7	19.5	-0.29	26.57	843225.8	530.7	43.5	-0.13

6 CONCLUSION

This paper presents a multi-objective mathematical model for operating room scheduling, incorporating surgical stages and resources to balance stakeholders' priorities. Given the problem's complexity, new meta-heuristic algorithms are proposed. Results demonstrate the exceptional performance of HNSGA-SA regarding objectives and CPU times. The model indicates that hospitals can enhance surgical services by scheduling more patients while simultaneously reducing overtime and idle time in operating rooms. Limitations include the absence of real-world data due to primary data unavailability. Though promising, the methodology necessitates real-world data validation for reliability.

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