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ON SOLVING THE PATIENT BED ASSIGNMENT PROBLEM IN PANDEMIC SITUATIONS

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Abstract. Patient admission is a routine task in healthcare facilities, but during pandemics like COVID-19 and Mpox, hospital management becomes significantly more complex. Consequently, hospitals may struggle to meet all patient demands, especially when the number of available beds is limited compared to the number of incoming patients. During the COVID-19 pandemic, the Tunisian Ministry of Health implemented strict assignment protocols, prioritizing patients based on severity to ensure timely care and efficient resource use. However, despite numerous efforts and resource allocation, Tunisian hospitals remained unprepared for large-scale emergencies, highlighting ongoing challenges in resource management. This paper investigates the patient bed assignment problem in pandemic situations and proposes a linear programming model to optimize resource allocation while minimizing patient rejections, bed transfers, and associated costs. A sensitivity analysis is conducted to assess the impact of various input parameters on the overall assignment costs. The model is validated using real data from Tunisian hospitals, demonstrating its effectiveness in improving hospital admission capacity.

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1. Introduction

In recent years, the world has been facing the rapid spread of a new pandemic. COVID-19 is an infectious disease that presents unexpected challenges to nations around the world. It is a virus with a highly contagious nature, affects all age categories without exception, and impacts several countries [32]. According to recent updates from the World Health Organization, COVID-19 caused 5 million deaths and over 600 million confirmed cases. Following the current situation in Tunisia, North of Africa, the pandemic continues to be a concern for the country, and to this date (August 2023), new variants of COVID-19 could potentially lead to another wave of infections and deaths.

Even with the infrastructure of countries and the availability of medical resources, many healthcare units find themselves dealing with a large number of patients that exceeds the capacity of hospitals. To respond to the increased demand and the needs of hospitals, many countries choose to increase material resources like oxygen concentrators, ICU beds, and other medical types of equipment. Taking the example of France, in 2021, around 10 000 new beds have been added to French hospitals, presenting an increase of 15% in the total number of

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hospital beds. Also, a specific increase in intensive care beds in the United States is over 20%, to treat severe COVID-19 cases. In Germany, 12 000 beds have been mobilized, according to the Robert Koch Institute, an increase of 20% [12].

In some countries with limited resources, many technical solutions are used to decrease the spread of diseases and ensure health care for all patients. In Tunisia, some hospitals created new pandemic units (PU) to deal with this issue, while many other hospitals divided the emergency department (ED) into two units. The first unit is dedicated to patients with acute injuries or illnesses, and the second is for patients with infectious diseases. Both healthcare units deal with urgent and critical medical situations that require prompt attention and care, as delays can have severe consequences for patients' health outcomes.

By examining the situations in different nations, we notice that admitting patients to hospitals during pandemics presents a major challenge for many healthcare organizations. They are looking to optimize patients' assignment to beds while considering the limited number of resources. The situation can change from one country to another depending on the availability of beds (ICU beds, oxygenated beds, etc.) and patient requirements.

The patient bed assignment problem (PBAP) tries to model these situations. It aims to manage a set of available beds and assign them to patients who require critical medical assistance [27]. The PBAP is presented as an optimization problem for the first time by Demeester *et al.* [11]. The main objective is to minimize the assignment costs, considering the hospital resource availability, and the patient's needs independent of the contagious state of patients and the category of beds. Since, many researchers have proposed different models of the PBAP problems with different solution approaches [2, 5, 20, 22, 29].

In this paper, we propose a new model for a problem called the Hospital Bed Assignment Problem in Emergencies (HBAPE). This problem is a variant of the classical PBAP. HBAPE differs by adding new restrictions and considering a new objective function combining three types of costs (or penalties), while also offering hospitals improved forecasting and planning tools to better prepare for future health crises. The constraints ensure that each patient must be assigned, based on his state, to a specific category of bed and each patient must occupy the same bed during their period of stay. The objective function is to minimize the three costs: the cost of assigning patients to bed (Cost of violating a set of constraints), the cost of declining patients due to the unavailability of beds, and the cost of transferring patients from one bed to another, during their period of stay (LOS).

The remainder of this paper is organized as follows: we present the previous works on hospital bed assignments in normal and pandemic situations in Section 2. In Section 3, we describe the patient bed assignment process and continue with the new mathematical model of the patient bed assignment. Then, in Section 4, we test our model with a set of instances and compare the obtained results. Finally, the conclusion of this study is presented in Section 5.

2. Literature review

The patient bed assignment problem (PBAP) has been extensively studied and adapted since its introduction by Demeester *et al.* [11]. Variants of PBAP are generally classified into static and dynamic problems based on time-dependency. The static PBAP assumes that each elective patient is assigned to a single available bed for a predefined admission period [1]. This version of PBAP focuses on fulfilling specific constraints, which can be classified as hard or soft. Hard constraints, such as room capacity, gender, age, and necessary equipment policies, must be strictly adhered to. In contrast, soft constraints, including room properties, transfer requirements, and the degree of specialization, may be violated but often incur penalties in the objective function [25].

The dynamic version of PBAP addresses real-time challenges such as urgent patient admissions, rescheduling needs, and uncertainties in stay durations and arrival times [7]. As with the static PBAP, some soft constraints may be treated as hard constraints in dynamic scenarios [4, 8, 9, 31]. Both versions of PBAP are classified as NP-hard problems, prompting researchers to propose various solution techniques, including exact and heuristic methods.

Initial solutions for the static PBAP were developed using hybrid tabu-search (TS) methods [11], focusing on minimizing total assignment costs. Subsequent approaches employed simulated annealing with local search [7], hyper-heuristic strategies [4], and column generation-based heuristics [26], among others. More recent work has used advanced heuristics such as fix-and-optimize (FO) and fix-and-relax (FR) techniques [30], and Min-conflict heuristic approach [21], as well as hybrid methods that combine simulated annealing and genetic algorithms [13, 14]. Similarly, exact methods such as those proposed by Bastos *et al.* [3] and Liu *et al.* [25] have been developed to improve solution quality for specific reference instances.

PBAP can also be viewed as a framework for resource assignment problems (RAP). During pandemic scenarios, this framework has been applied to optimize hospital resource utilization, particularly in bed management in the intensive care unit (ICU) and emergency department (ED). Brandeau *et al.* [6] reviewed RAP literature, highlighting a focus on human resources over bed management. However, few studies have addressed the assignment of patients to ICU beds during the COVID-19 pandemic. For example, Li *et al.* [24] analyzed ICU bed assignments in China, while Meares *et al.* [17] applied queueing theory to estimate ICU bed needs in the USA. Similarly, Garcia *et al.* [16] used discrete event simulation models, and Jena *et al.* [23] employed fuzzy rule-based approaches to prioritize bed assignments under resource constraints.

Other studies have extended RAP applications to emergency department scheduling, operating room planning, and recovery room management. These include linear programming models, metaheuristic solutions, and hybrid optimization techniques. For example, Chaieb *et al.* [10] proposed a hybrid three-level approach to solving the recovery room scheduling and planning problem for the Kingdom of Saudi Arabia hospital (IRRPSP). This study aims to maximize the number of assigned patients in beds and the number of patients treated by nurses, subject to a set of constraints regarding the capacity of rooms, the treatment deadlines, and the caregivers' maximum daily load [10]. The first phase of the proposed model is modeled as linear programming. The objective function is to determine the number of patients admitted to hospitals regarding the availability of rooms supposing that there are two different rooms with recovery beds and respiratory machines. The IRRPSP is considered a highly constrained problem with a large number of both soft and hard constraints.

Recent work has introduced multi-objective mixed integer linear programming (MILP) to minimize installation costs, reduce patient rejections, and optimize travel distances [15]. In addition, several studies have proposed customized approaches to improve bed planning on daily, weekly or monthly horizons. Bachouch *et al.* [2] deals with PBAP over a time horizon. They supposed that the assignment problem is a variant of the planning problem. A bed planning is generated using an integer linear model for French hospitals. Due to the high demand, a decision support tool is developed for elective and acute patients. A comparative study uses three software: LINGO of LINDO SYSTEMS, GLPK, and CPLEX of ILOG. More recently, Taramasco *et al.* in [28] presented a new binary model for the PBAP based on hard and soft constraints, aiming to reduce the number of unsatisfied ones. This paper supposed that assigning patients to beds should consider the emergency level of each one independently of their age. Depending on their states, a specific bed, critical or normal, will be allocated. An autonomous bat algorithm is implemented, to find the best solution. The authors proposed another study [29], where a new meta-heuristic based on vapor-liquid equilibrium is developed to maximize, this time, soft constraints using the same restrictions. Taramasco *et al.* supposed that patients can be assigned to normal beds if the critical one is unavailable. They guaranteed the assignment regardless of the LOS. However, if we suppose that all patients occupy the bed until recovery, and if the number of patients requiring normal beds increases rapidly facing the existing ones, the problem may be unbalanced. In an assignment process, the LOS has to be considered for each patient in a predefined horizon period.

The evolution of PBAP research demonstrates its adaptability to various healthcare challenges. From managing elective admissions in static settings to addressing urgent needs in dynamic scenarios, PBAP solutions have provided critical insights into resource allocation in healthcare systems. To present the main research directions in both emergency and normal situations, we report in Table 1 a taxonomy of recent works, classified according to their objectives, solution approaches, and key constraints such as:

– **State of Patients (SP)** presents the emergency level of each one.
– **Length of Stay (LOS)** of patients or the recovery period.

- **Age of Patients (AP)**.
- **Gender Policies (GP)**, male or female.
- **Transfer of Patients (TP)** from one bed to another.
- **Bed or Room Types (TB/R)**, critical, normal, recovery, or respiratory, etc.

Numerous papers in the literature have addressed scheduling and bed assignment problems in hospital departments. These studies consistently demonstrate their importance for both patients and hospitals, as they aim to achieve health and cost-efficiency objectives.

As a result, many decision-support tools have been developed to help hospital managers make better and more optimal assignment decisions, thereby improving capacity utilization and limiting budget overruns. To better situate our contribution, we extend this taxonomy by positioning our Hospital Bed Assignment Problem in Emergencies (HBAPE) against prior LP-based models. Earlier works such as Bachouch *et al.* [2] considered hospital bed planning with refusal penalties but were restricted to two patient states (acute and elective), under static deterministic assumptions. Likewise, Taramasco *et al.* [28, 29] focused on minimizing unsatisfied constraints or maximizing soft constraint satisfaction, but again limited patient states to two levels and did not explicitly make model rejections. Our prior work [19] introduced a bi-objective formulation considering patient assignment and inter-hospital distances, but still with simplified categories of beds and patients. By contrast, the HBAPE advances the literature along several dimensions. First, we explicitly model three types of beds (ICU/critical, respiratory, and normal), whereas most previous studies only considered two. Second, we incorporate three levels of patient severity (minimum, medium, and maximum risk), which provides a more realistic classification compared to the two-state models previously used. Third, our single-objective deterministic formulation integrates three penalty components simultaneously: rejection penalties, inappropriate assignments, and patient transfers. This richer objective captures the complexity of pandemic triage more faithfully than earlier single- or bi-objective approaches. Finally, unlike prior studies that were often validated on small or synthetic datasets, our model is tested on a real dataset from Tunisian hospitals (over 1500 patients, 32 instances) and includes a sensitivity analysis, which provides stronger empirical grounding and practical relevance.

3. Problem description

Our problem aims to solve the assignment of COVID-19 patients to a specific bed in Tunisia Country. According to the Tunisian Ministry of Health, three main categories of COVID-19 patients are considered. The first type is composed of cases with a minimum risk when the patient's age ranges below 50 years, and oxygen rates exceeding 90%, they must follow the recommendations and instructions of doctors and should stay under control for at least one day. The second category contains patients with medium-risk (critical cases) that must be assigned to a respiratory bed for a minimum of two days, the patients' ages are >50 years (or <50 years), and their oxygen rates are <90% (or >90%). The last category of states is the severe cases, patients with maximum risk, their ages are more or equal to 50 years and their oxygen rates are less or equal to 90% and they are called to be assigned to the ICU for three days (see Tab. 2).

Daily, the medical staff meet to discuss the state of new patients. If the state is Maximum risk and an ICU bed is available, the patient is admitted. If the patient's state is Maximum risk or Medium risk and the ICU bed is not available, the staff will check if there exists an oxygen bed and then a normal bed before assignment. We note that for patients with Maximum risk the normal and oxygen beds should be equipped with additional equipment to be ICU beds. If a patient with minimum risk is present a normal bed is required, see Figure 1.

The daily problem of the HBAPE in the Hospital of Sousse-Tunisia can be summarized as follows: A set of patients p with an oxygen rate o_p and age a_p should be assigned to a specific bed b that should not exceed the capacity of beds q_b during a period los_p. We consider three types of bed resources and other assumptions, as follows:

- Each patient must be assigned to one of the following type of bed:
  (1) Critical (ICU bed),

TABLE 1. A taxonomy of related works.

Problem variants	Objective function		Objective function components							Problem features						Situations		Methods		Reference
	Maximization	Minimization	Assignment Costs	Transfer Costs	Rejection Costs	Waiting Time	Covered Constraints	Unsatisfied Constraints	Number of Assigned Patients	SP	LOS	AP	GP	TP	TB/R	Normal	Emergency	Exact method	Approximate method	
Admission scheduling problem (ASP)		✓	✓	✓						✓	✓		✓			✓			✓	[11]
Hospital bed planning problem (HBPP)		✓			✓	✓				✓	✓	✓	✓			✓		✓		[2]
Patients scheduling problem in emergency department (PSP)		✓				✓									✓	✓		✓		[18]
						✓				✓		✓	✓		✓	✓			✓	[19]
Patient bed assignment problem (PBAP)		✓	✓	✓								✓	✓	✓		✓			✓	[13]
		✓						✓				✓	✓	✓	✓	✓			✓	[21]
		✓						✓		✓		✓	✓		✓	✓			✓	[28]
	✓						✓			✓		✓	✓		✓	✓			✓	[29]
Integrated recovery room planning and scheduling problem (IRRPSP)	✓								✓	✓	✓				✓		✓		✓	[10]
Hospital Bed assignment problem (HBAPE)		✓	✓	✓	✓					✓	✓	✓		✓	✓		✓	✓	✓	This paper

TABLE 2. Classification of patient's health status adopted in HBAPE.

Patient's state	Oxygen rate	Patient's age	Recommendations
Minimum risk	>90%	<50	Should stay under control at least one day
Medium risk	<90% (or >90%)	<50 (or >50)	Should stay under control at least two days
Maximum risk	≤90%	≥ 50	Should stay under control at least three days

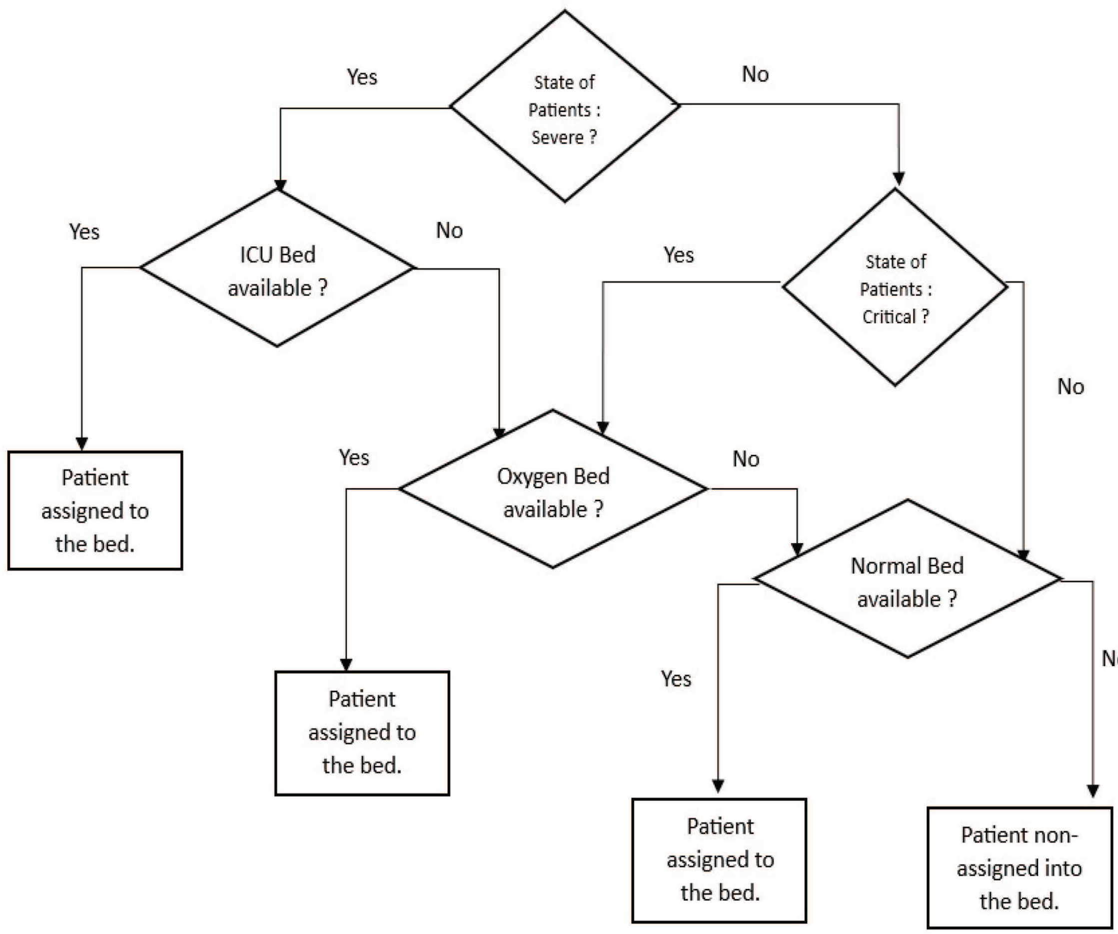

FIGURE 1. Admission process for acute patients in the hospital of Sousse.

(2) Respiratory,
(3) Normal.

– Patients that arrive at the hospital are assigned immediately to only one available bed, and each bed can be occupied by only one patient at a time.
– The severity and/or risk of patients is determined based on two parameters:
  - **The patient's age**: 1: More or equal to 50 years, 2: Otherwise.
  - **The oxygen rates**: 0: Less or equal to 90%, 1: Otherwise.
– **The length of stay** for each patient is known and varies according to his state:

- Patient with minimum risk: 1 Day.
- Patient with medium risk: 2 Days.
- Patient with maximum risk: 3 Days.

4. Mathematical model

We propose a new optimization model to minimize the cost of assigning patients to inappropriate beds and the penalty of declining and transferring patients from one bed to another during their period of stay. In what follows we enumerate the different symbols:

Index	
P	Number of patients
B	Number of different types of Beds
D	Number of days
Parameters	
q_b	Capacity per type of bed b
a_p	Age of patient p
o_p	Oxygen rate of patient p
j_p	Hospitalization beginning period of patient p
los_p	Length of stay of patient p
c_{pb}	Cost of assigning patient p to bed b
w_{pb}	Cost of transferring patient p from bed b
w_p	Penalty incurred by declining patient p

Decision variables

$$S_{pb} = \begin{cases} 1 & \text{if patient } p \text{ is assigned to } a \text{ bed } b; \\ 0 & \text{Otherwise.} \end{cases}$$

$$X_{pbd} = \begin{cases} 1 & \text{if patient } p \text{ is assigned to } a \text{ bed } b \text{ at day } d; \\ 0 & \text{Otherwise.} \end{cases}$$

$$T_{pbd} = \begin{cases} 1 & \text{if patient } p \text{ is transferred from bed } b \text{ at day } d; \\ 0 & \text{Otherwise.} \end{cases}$$

$$NA_p = \begin{cases} los_p & \text{if patient } p \text{ is refused to be assigned to } a \text{ bed } b; \\ 0 & \text{Otherwise.} \end{cases}$$

The PBAP consists to assign patients to hospital beds in a way that minimizes three main costs. It is given by (1), based on two existing models of [2, 29].

$$\text{Min } Z(x) = \underbrace{\sum_{p\in P} w_p \times \frac{NA_p}{los_p}}_{A} + \underbrace{\sum_{p\in P}\sum_{b\in B} c_{pb} \times S_{pb}}_{B} + \underbrace{\sum_{p\in P}\sum_{d\in D}\sum_{b\in B} w_{pb} \times T_{pbd}}_{C} \tag{1}$$

where the different costs A, B, and C represent:

- A is the cost of declining patients [2]: When a patient cannot be assigned a bed due to unavailability.
- B reports the cost of assigning patient p to bed of type b.
- C is the cost of transferring patient p between beds during their stay [13].

It is important to note that we did not apply any weighting between the three terms of the objective function. Indeed, the three costs represent penalties rather than monetary or heterogeneous costs. They are all expressed on the same scale and have the same order of magnitude. Consequently, introducing weighting factors would not provide additional modeling accuracy and could artificially privilege one decision type (rejection, assignment, transfer) over the others, as discussed in Section 5.2. To achieve this, our model follows a set of constraints.

Constraints (2), assigning Patients to Beds: Each patient must be assigned to exactly one bed of type b, on day d.

$$\sum_{b\in B} X_{pbd} \leq 1 \quad \forall p \in P, d \in D. \tag{2}$$

Constraints (3), bed capacity constraints: The total number of patients p assigned to a specific bed type b cannot exceed the total available beds of that type.

$$\sum_{p\in P} X_{pbd} \leq q_b \quad \forall b \in B, d \in D. \tag{3}$$

Constraints (4), prioritizing critical patients [29]: Patients are categorized into three different risk levels based on their age a_p and oxygen o_p levels.

(1) Patients with maximum risk, should be assigned to a critical bed. But if there isn't a respiratory and/or normal bed will be equipped as a critical bed.
(2) Patients with medium risk require a respiratory bed. In case there is no respiratory bed available, a normal bed will be equipped as a respiratory.
(3) Patients with minimum risk. A normal bed must be assigned to a patient.

$$X_{pbd} \times (o_p + a_p) \leq b \quad \forall p \in P,\ b \in B, d \in [j_p, j_p + los_p]. \tag{4}$$

The constraints (5) and (6), unassigned patients: Each patient is assigned to an available bed for a period equal to his/her length of stay [2]. If no suitable bed is available, patients p are considered, so the variable NA_p takes a value equal to their length of stay

$$\sum_{d\in D} X_{pbd} = los_p \times S_{pb} \qquad \forall p \in P, b \in B \tag{5}$$

$$\sum_{b\in B} \sum_{d\in[j_p, j_p+los_p]} X_{pbd} + NA_p = los_p \qquad \forall p \in P. \tag{6}$$

Constraints (7), transfer constraints: Patients should not be transferred from one-bed b to another during their days of stay.

$$X_{pbd} - X_{pbd+1} \leq T_{pbd} \quad \forall p \in P, b \in B\ d \in [j_p, j_p + los_p]. \tag{7}$$

5. Experimental results and evaluation

In this section, we carried out 32 data instances to evaluate the proposed model, containing more than 1500 patients with different optimization criteria. The main aim of the computational experiments is to study the advantages of the proposed modeling by extracting the optimality of the solution and the computational time needed to reach it.

Firstly, we describe in Section 5.1 the benchmark instances. Secondly, in Section 5.2 we demonstrate and discuss the quality of the obtained solutions. Then, Section 5.3 presents a comparative study. Finally, Section 5.4 proposes a sensitivity analysis.

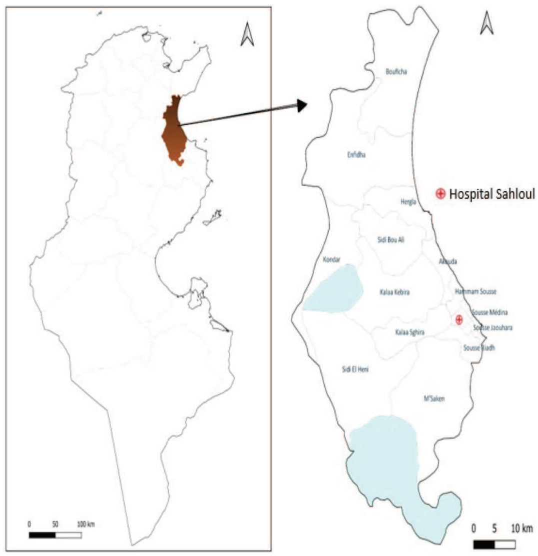

FIGURE 2. Sahloul extracted hospital localisation in Sousse-Tunisia from QGIS.

5.1. Computational environment and benchmark instances

The case study presented in this research was initiated by the Hospital of Sousse Tunisia (see Fig. 2). Real data are provided to test our modeling and solving approach. During our internship at the Hospital of Sousse, from January to March 2022, we observed the arrival of patients at different times of the day, ranging from early morning to late evening. This allowed us to gain a comprehensive understanding of the hospital's operations. Through our internship experience and data collection efforts, we were able to construct a set of benchmark instances from the collected data. The provided realistic instances contain all the relevant information regarding 1,500 patients, scheduled for $D = 7$ days, 116 beds with a variable number of ICU beds, respiratory machines, and basic beds. From the provided data, we generate two different groups of instances, categorized by: small and large sizes. The properties of these instances are detailed in Tables 3 and 4.

In the first group of instances from 1 to 16, the number of patients increases without exceeding 50% of the number of beds. However, in large instances, from 17 to 32, the number of patients goes beyond 2 times the number of beds and more. The small set of instances has some differences in their structure. This group is characterized by the heterogeneity of the number of beds, with several critical cases ranging from 5% to 20%. Unlike the second group, which has the same number of beds and a few critical states with 10% and 20%, these instances are homogeneous compared to the other ones.

To solve program (1), we used the IBM ILOG CPLEX Optimization Studio V12.4 with default optimization parameters, on a laptop with an Intel(R) Core(TM) i5-1135G7-2.40GHz and 8Gb RAM.

5.2. Results and discussion

In this part, we discuss the results of computational experiments obtained with Cplex carried out on the HBAPE benchmark reported in the previous section. We present the total cost based on the assignment cost, the patient's declining cost, and the transfer cost. Also, the percentage of acute patient admission, the admission rate (AR), and the required time for the solution process. We use abstract units of cost based on [2] to generate a solution. In practice, the penalty parameters were set to values within the same order of magnitude (*e.g.*, around 10–15 units), ensuring that the different components of the objective function remain on a comparable scale. This choice reflects the relative weight of each criterion without imposing a disproportionate dominance

Table 3. Small sized instances.

Instances	Beds				Patients	
	Critical	Respiratory	Normal	Tot.beds	Tot.Patients	Critical cases
I1					76	5%
I2			38	63	82	10%
I3					88	15%
I4		13			88	20%
I5					124	5%
I6	12		78	103	134	10%
I7					134	15%
I8					144	20%
I9					146	5%
I10		22	78	112	146	10%
I11					157	15%
I12					157	20%
I13					162	5%
I14	16	22	78	116	162	10%
I15					174	15%
I16					174	20%

Table 4. Large sized instances.

Instances	Beds				Patients	
	Critical	Respiratory	Normal	Tot.beds	Tot.Patients	Critical cases
I17					232	10%
I18					232	20%
I19					348	10%
I20					348	20%
I21					464	10%
I22					464	20%
I23					580	10%
I24	16	22	78	116	580	20%
I25					696	10%
I26					696	20%
I27					812	10%
I28					812	20%
I29					928	10%
I30					928	20%
I31					1044	10%
I32					1044	20%

of one component over the others. As the transfer cost is a new parameter in the assignment process compared to the works of [2,29], we choose to study the effect of this cost on the objective function. We tried to generate two solutions with transfer (TR) parameters and without, presented in Tables 5 and 6.

We notice that the obtained cost with TR is lower than the cost without TR, for the first set of instances. However, both experiments yield similar results after the 25th instance when the number of patients surpasses 6 times the number of available beds. This finding suggests that transferring a patient to a different bed before their stay ends could be a cost-effective solution to discharge beds for new patients. Even if, in the second set, the costs are very close, and the number of critical cases admitted is significant compared to the results without

Table 5. Comparaison between optimal solutions for the HBAPE: small set of instances with/without transfer carried out on Cplex.

(A) Small sized instances with transfer				(B) Small sized instances without transfer			
Instances	Cost	AR	CPU Time	Instances	Cost	AR	CPU Time
I1	**3250**	**70%**	1.63	I1	3760	5%	0.88
I2	**3510**	**72%**	1.02	I2	4020	10%	0.8
I3	**3770**	**75%**	0.98	I3	4270	15%	0.9
I4	**3770**	**75%**	0.87	I4	4220	20%	0.83
I5	**5230**	**78%**	**1.05**	I5	140	5%	1.29
I6	**5670**	**77%**	**1.01**	I6	6560	10%	1.04
I7	**5670**	**77%**	0.96	I7	6500	15%	0.91
I8	**6170**	**72%**	**1.10**	I8	7200	20%	1.12
I9	**6230**	**73%**	**1.14**	I9	7230	5%	1.18
I10	**6180**	**77%**	1.18	I10	7160	10%	0.88
I11	**6730**	**71%**	1.18	I11	7620	15%	0.93
I12	**6730**	**71%**	1.38	I12	7530	20%	1.08
I13	**7020**	**67%**	1.47	I13	8020	5%	0.92
I14	**6940**	**72%**	1.37	I14	7930	10%	1.0
I15	**7540**	**67%**	1.32	I15	8440	15%	0.89
I16	**7540**	**67%**	1.63	I16	8350	20%	1.39

Notes. Bold values indicate the best (optimal) results obtained for each scenario.

Table 6. Comparaison between optimal solutions for the HBAPE: Large set of instances with/without transfer carried out on Cplex.

(A) Large sized instances with transfer				(B) Large sized instances without transfer			
Instances	Cost	AR	CPU Time	Instances	Cost	AR	CPU Time
I17	**10 440**	**48%**	2.89	I17	11 140	9%	**1.92**
I18	**10 460**	**50%**	1.81	I18	11 140	20%	**1.36**
I19	**16 240**	**30%**	1.94	I19	16 700	10%	**1.66**
I20	**16 710**	**33%**	1.68	I20	17 040	20%	1.68
I21	**22 040**	**23%**	1.69	I21	22 750	10%	1.69
I22	**22 040**	**25%**	1.59	I22	22 260	20%	1.59
I23	**27 810**	**19%**	2.15	I23	27 850	10%	2.15
I24	**27 840**	20%	2.09	I24	28 400	20%	2.09
I25	**33 640**	**16%**	2.97	I25	33 640	10%	2.97
I26	**33 870**	17%	2.78	I26	34 100	17%	2.78
I27	**39 340**	**14%**	3.90	I27	39 440	10%	**3.84**
I28	**39 630**	14%	4.02	I28	39 800	14%	**3.08**
I29	**45 360**	**13%**	3.98	I29	45 420	10%	3.98
I30	**45 410**	13%	3.15	I30	45 500	13%	**3.08**
I31	**51 000**	**11%**	4.52	I31	51 060	10%	4.52
I32	**51 040**	11%	**4.32**	I32	51 200	11%	4.38

Notes. Bold values indicate the best (optimal) results obtained for each scenario.

TR. It is evident that the transfer variable has an important effect on the proposed model, and the optimal solution is given when the total cost contains the transfer parameters.

Also, the results obtained indicate that the total cost of the patient assignment is impacted by the number of patients. To investigate this relationship, we fixed the number of available beds and varied the number of patients and the percentage of critical cases in the first set of instances. The results demonstrate that the total

TABLE 7. Total cost of the best solutions obtained by the GA for 16 small-sized instances, each executed 30 times.

Measure	I1	I2	I3	I4	I5	I6	I7	I8
Best	3315.04	3580.52	3845.44	3845.48	5334.71	5783.41	5783.44	6293.44
Median	3315.9	3581.68	3846.28	3846.19	5335.72	5784.85	5784.7	6294.3
Mean	3315.95	3581.47	3846.29	3846.33	5335.67	5784.58	5784.57	6294.38
Worst	3316.89	3582.19	3847.23	3847.32	5336.57	5785.39	5785.39	6295.32
std	0.55	0.52	0.58	0.56	0.63	0.65	0.58	0.58
Measure	I9	I10	I11	I12	I13	I14	I15	I16
Best	6354.69	6303.67	6864.61	6864.74	7160.43	7078.86	7690.82	7690.82
Median	6355.37	6304.59	6865.60	6865.65	7161.53	7079.62	7691.86	7691.92
Mean	6355.49	6304.56	6865.62	6865.70	7161.36	7079.70	7691.78	7691.82
Worst	6356.58	6305.46	6866.58	6866.58	7162.40	7080.48	7692.68	7692.71
std	0.56	0.44	0.56	0.57	0.65	0.48	0.54	0.60

cost increases as the number of patients assigned to a set of beds increases. For instance, with 103 available beds, the total cost varies between 5000 and 6300 units. Moreover, increasing the percentage of critical cases also leads to an increase in the total cost. In the second set of instances, shown in Table 5, the total cost exceeds 10 000 units when the number of patients exceeds 200, and the percentages of critical cases make an unreadable change in the objective solution because the data is very close in terms of the number of beds and patients so with the same number of beds and a slight change in the percentage of critical cases of patients we can have almost the same solution. There is a significant difference between the first and second sets, not only in the total cost but also in the percentage of critical cases admitted to the hospitals.

In terms of computation time (CPU Time per min), our model is typically solved within an acceptable CPU time. However, this parameter is impacted by the number of patients, and in the second set of instances, real data sets may require more time to produce a solution than others. This could potentially pose a challenge when the number of patients exceeds 2000.

The results obtained highlight key trade-offs in the patient bed assignment process. One notable observation is that while our model effectively minimizes patient rejections, it does so by allowing limited transfers between beds, ensuring optimal bed utilization. This trade-off is particularly apparent in large-scale instances where bed availability is restricted. In such cases, the rejection cost becomes a dominant factor, emphasizing the need for flexible hospital policies to manage high-demand situations.

To further investigate the efficiency of our proposed approach, we implemented a Genetic Algorithm (GA) as a metaheuristic solver to complement the exact solutions provided by CPLEX. The GA was configured with the following parameters: population size $M = 30$, crossover probability XOVR $= 0.75$, mutation rate MUTR $= 0.08$, generation gap GGAP $= 0.75$, and number of generations NG $= 1000$. The GA produced solutions that are consistently near-optimal, with a gap of approximately 2% to 3% from the optimal cost obtained by CPLEX, as presented in Tables 7 and 8. Importantly, the GA preserves the impact of the transfer cost (TR) in the assignment process, generating similar trends as observed with CPLEX: solutions with TR consistently yield lower total costs than those without TR, confirming the significance of patient transfers in reducing overall assignment cost. Moreover, the GA required a relatively short runtime, typically less than one minute for all instances, making it suitable for real-time or larger-scale applications.

In comparison, CPLEX guarantees the optimal solution in all cases, but its computation time increases significantly as the number of patients grows beyond 1500, reaching impractical levels for instances with around 2000 patients. These observations suggest that while CPLEX is preferable for small to medium-sized instances where optimality is critical, the GA provides a computationally efficient alternative for larger instances, offering a reasonable trade-off between solution quality and runtime. Therefore, our proposed model demonstrates

TABLE 8. Total cost of the best solutions obtained by the GA for 16 large-sized instances, each executed 30 times.

Measure	I17	I18	I19	I20	I21	I22	I23	I24
Best	10 648.85	10 669.23	16 564.83	17 044.20	22 480.86	22 480.90	28 366.22	28 396.81
Median	10 649.96	10 670.08	16 565.85	17 045.23	22 481.95	22 482.01	28 367.39	28 397.79
Mean	10 649.80	10 670.23	16 565.77	17 045.18	22 481.84	22 481.93	28 367.28	28 397.78
Worst	10 650.73	10 671.17	16 566.79	17 046.17	22 482.79	22 482.77	28 368.19	28 398.72
std	0.62	0.52	0.56	0.65	0.57	0.58	0.55	0.63
Measure	I25	I26	I27	I28	I29	I30	I31	I32
Best	34 312.86	34 547.43	40 126.82	40 422.64	46 267.22	46 318.25	51 020.10	51 060.80
Median	34 313.80	34 548.17	40 127.73	40 423.67	46 268.20	46 319.00	51 021.10	51 061.96
Mean	34 313.81	34 548.27	40 127.78	40 423.61	46 268.19	46 319.04	51 021.08	51 061.88
Worst	34 314.77	34 549.36	40 128.77	40 424.59	46 269.19	46 320.00	51 021.98	51 062.74
std	0.65	0.62	0.59	0.66	0.50	0.53	0.63	0.59

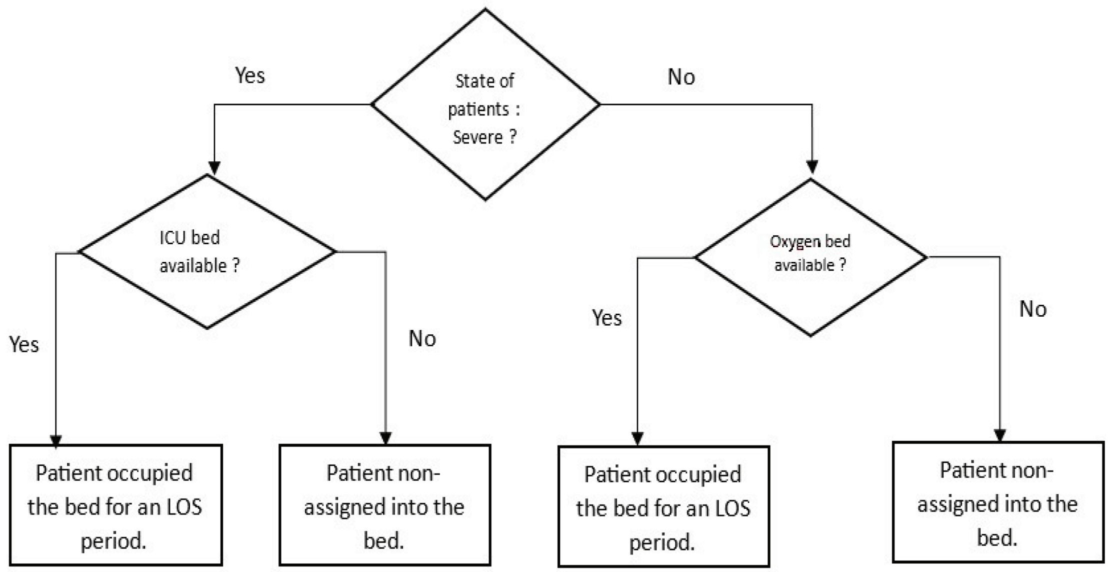

FIGURE 3. Admission process for the IRRPSP problem.

flexibility, as it can leverage exact solvers for moderate problem sizes and metaheuristics for large-scale scenarios where computational efficiency becomes essential.

5.3. Comparative study

In order to judge that our obtained results are significant, a comparative study is required to be accomplished. In this context, we choose to compare the results obtained from our proposal and those obtained in other studies using Cplex. For this purpose, we selected two related works from the literature to compare firstly the percentage of patients admitted, and then the values of the objective function.

According to the real case study IRRPSP of Marouane *et al.*, [10] in 2022 in the hospital of Jaddah, the main idea was to check the contagious state of each Covid patient and assign them to a specific bed. If a suitable

TABLE 9. Comparaison of the optimal solution between the IRRPSP and the HBAP Cplex Solution.

Instance ID	IRRPSP Solution			HBAPE solution			Gap%
	NAPA	Total admission rate	CPU time	NAPA	Total admission rate	CPU time	
I1	4	72%	**0.19**	**4**	**72%**	1.63	0
I2	8	72%	**0.31**	**8**	**72%**	0.92	0
I3	12	72%	**0.9**	**13**	**75%**	0.98	8
I4	12	72%	**0.83**	**18**	**75%**	0.87	33
I5	6	78%	1.29	**6**	**78%**	**1.05**	0
I6	12	77%	1.04	**14**	**77%**	**1.01**	14
I7	12	77%	**0.91**	**20**	**77%**	0.96	40
I8	12	72%	1.12	**29**	**72%**	**1.10**	59
I9	7	73%	1.18	**7**	**73%**	**1.14**	0
I10	12	77%	**0.88**	**14**	**77%**	1.18	14
I11	12	71%	**0.93**	**23**	**71%**	1.18	48
I12	12	71%	**1.08**	**32**	**71%**	1.38	62.5
I13	8	67%	**0.92**	**8**	**67%**	1.47	0
I14	16	72%	**1.0**	**17**	**72%**	1.37	6
I15	16	67%	**0.89**	**26**	**67%**	1.32	38.5
I16	16	67%	**1.39**	**35**	**67%**	1.63	54
I17	16	48%	**1.92**	**24**	**48%**	2.89	33
I18	16	50%	**1.36**	**46**	**50%**	1.81	65
I19	16	30%	**1.66**	**36**	**30%**	1.94	56
I20	16	33%	1.68	**70**	**33%**	1.68	77
I21	16	23%	1.69	**45**	**23%**	1.69	64.5
I22	16	25%	1.59	**94**	**25%**	1.59	83
I23	16	19%	2.15	**60**	**19%**	2.15	73
I24	16	20%	2.09	**115**	20%	2.09	86
I25	16	16%	2.97	70	**16%**	2.97	77
I26	16	17%	2.78	**116**	17%	2.78	73
I27	16	14%	**3.84**	**80**	**14%**	3.90	80
I28	16	14%	**3.08**	**116**	14%	4.02	62.5
I29	16	13%	3.98	**90**	**13%**	3.98	82
I30	16	13%	**3.08**	**116**	13%	3.15	53
I31	16	11%	4.52	**100**	**11%**	4.52	84
I32	16	11%	4.38	**116**	11%	**4.32**	47.5

Notes. Bold values indicate the best (optimal) results obtained for each scenario.

bed is not available, the patient cannot be assigned to a bed. The admission process is inspired by [10], and is sketched in Figure 3. To study the number of acute patients admitted (NAPA) and to compare the results obtained by our proposal, drawing from the framework outlined in this article, we decided to adapt our data and model it according to the provided mathematical formulation, by taking into account only two types of bed resources and two contagious levels. The result obtained by our modeling formulation, as depicted in Table 9 demonstrates substantial improvements compared to the existing model. Specifically, our approach exhibits a significantly higher admission rate for acute patients.

We further explored the inverse scenario, we chose to apply the existing benchmarks to our model, as illustrated in Table 10, with a number of beds exceeding 300 for the respiratory beds (NRM), and 800 for the recovery beds (NRB) and the number of patients varies between 500 and 900 for the critical patients (NCP)

TABLE 10. Comparaison of the solution quality between the IRRPSP Cplex Solution and the PBAP Cplex Solution.

Instances	Instances characteristics				Cplex Solution	
	NCP	NSP	NRM	NRB	IRRPSP Solution	HBAPE Solution
I1	177	354	182	350	527	527
I2	204	408	182	350	532	532
I3	229	458	210	406	600	616
I4	240	479	210	406	600	616
I5	267	533	266	532	600	798
I6	340	679	312	622	600	934
I7	415	829	358	716	600	1074
I8	479	958	420	839	600	1200

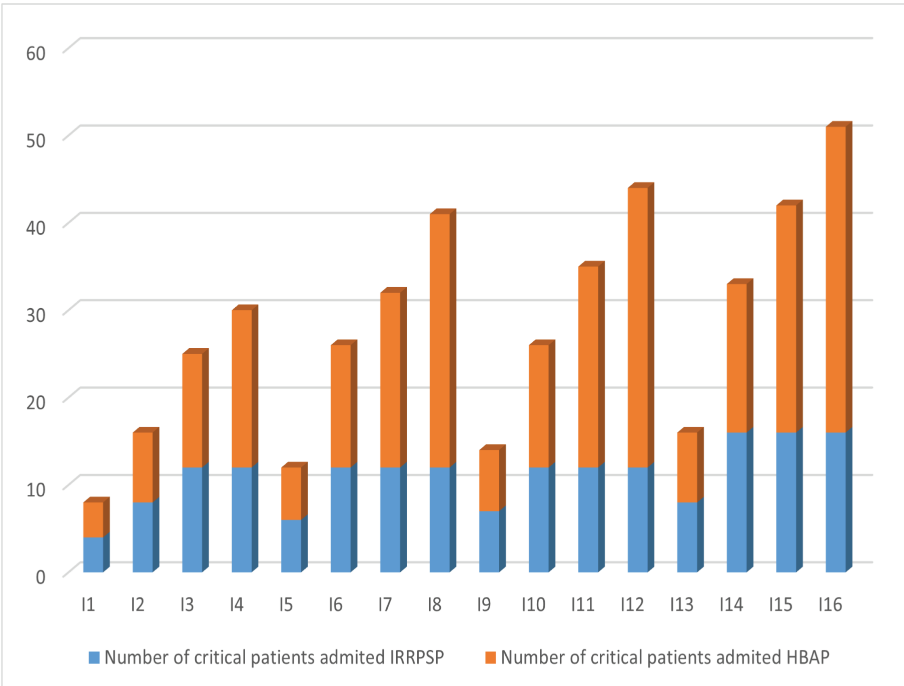

FIGURE 4. Number of acute patients admitted: Small sized instances.

and the severe one (NSP). Upon running the model using CPLEX, we discovered that our solution surpasses the performance of the pre-existing approach with a Gap of more than 50%. The comparison extends beyond these tables; upon examining Figures 4 and 5, it becomes evident that our solution significantly outperforms the IRRPSP model in terms of optimality.

In addition, based on the work of Khouloud *et al.* [13], another comparative study is reported in Table 11. We adapted our model to the existing one, supposing that there exists only the assignment cost and the transferring cost. Carried on our data set, the result showed that the existing model, upon running with the Cplex solver, generates a near-optimal solution in an acceptable CPU time.

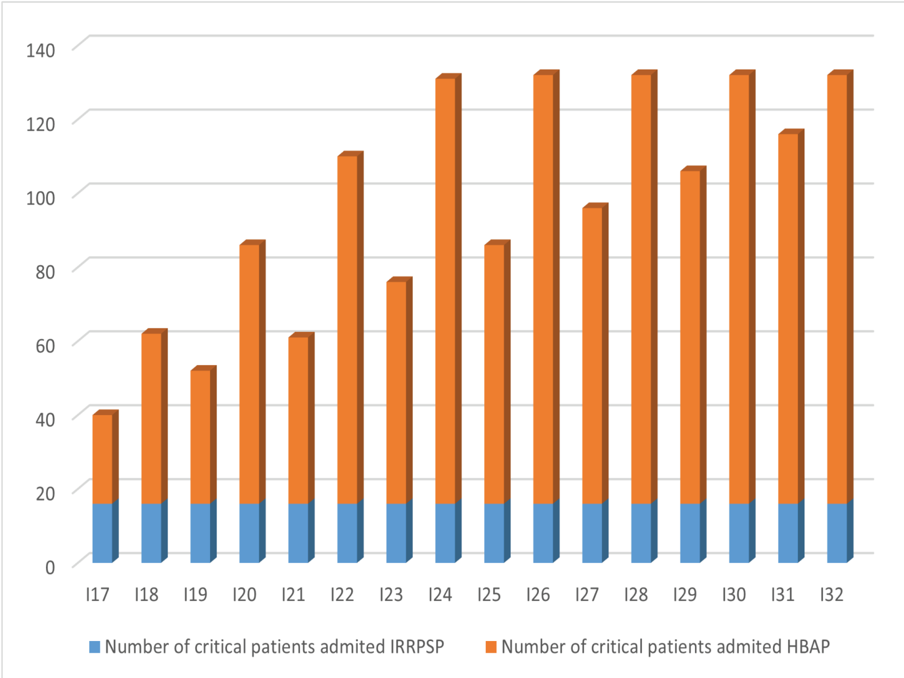

FIGURE 5. Number of acute patients admitted: Large sized instances.

However, our model provides an optimal cost. Figures 6 and 7, details the difference between the obtained costs of assigning patients to beds in the two studies.

According to the results in both previous comparative studies, we ensure that our model proposes a significant solution, better than the existing model, with an optimal number of satisfied patients in an acceptable CPU time.

Beyond the COVID-19 context, the proposed model is generic and can be adapted to other healthcare scenarios by redefining parameters. For example, risk categories based on age and oxygen saturation could, in the case of Ebola, be replaced by indicators such as fever intensity or hemorrhagic symptoms, while in routine hospital management, they could reflect surgical priorities or comorbidity levels. Likewise, bed categories and transfer rules can be adjusted to local infrastructures and policies. These adaptations require only parameter changes, not structural modifications, which illustrates the robustness of the approach.

5.4. Sensitivity analysis

This section presents a sensitivity analysis to evaluate how variations in input parameters affect the optimal solution. Specifically, we examine the impact of changes in the rejection cost on the assignment decision. Given the importance of this cost in the patient assignment process, we analyze the model's sensitivity by progressively increasing the rejection penalty. The study was conducted on two sets of instances:

- Small-sized instances (S9, S10, and S16).
- Large-sized instances (S20, S22, and S32).

As shown in Figure 8, in the small instances, the assignment cost starts increasing significantly when the rejection penalty exceeds 60%. For large instances, this effect is observed when the rejection penalty reaches 61%.

Moreover, instances S16 and S21 provide additional insights; while the number of beds remained unchanged, the number of patients increased from 174 to 464. As a result, the total rejection cost had a significant impact on the optimal solution, leading to a 60% and 61% increase in total costs, respectively.

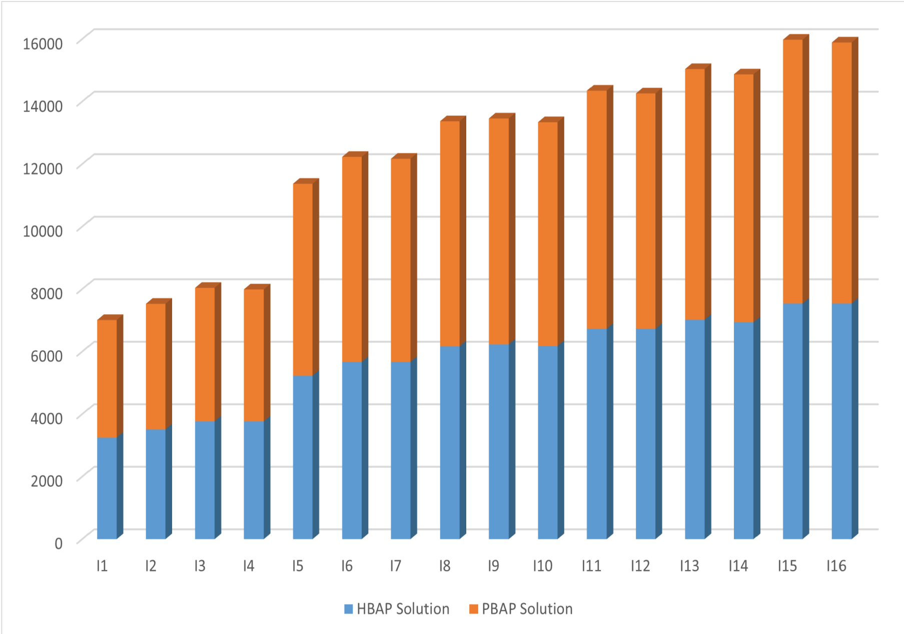

FIGURE 6. Cost of assigning patients in beds: Small-sized instances.

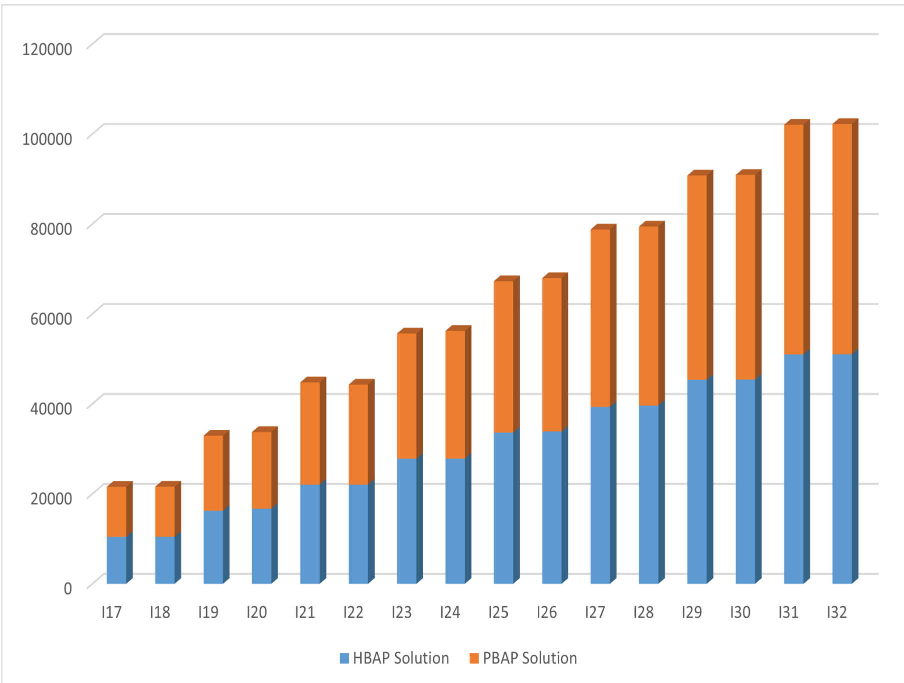

FIGURE 7. Cost of assigning patients in beds: Large-sized instances.

FIGURE 8. Sensitivity analysis when rejection cost is increasing.

TABLE 11. Comparison of the optimal solution between the PBAP and the HBAPE Cplex approach.

Instances	PBAP Solution		HBAPE Solution	
	Cost	CPU time (min)	Cost	CPU time (min)
I1	3520	**0.88**	**3250**	1.63
I2	3800	**0.8**	**3510**	1.02
I3	3050	**0.9**	**3770**	0.98
I4	4030	**0.83**	**3770**	0.87
I5	6050	1.29	**5230**	**1.05**
I6	6170	1.04	**5670**	**1.01**
I7	6320	**0.91**	**5670**	0.96
I8	6620	1.12	**6170**	**1.10**
I9	7120	1.18	**6230**	**1.14**
I10	7260	**0.88**	**6180**	1.18
I11	7730	**0.93**	**6730**	1.18
I12	7950	**1.08**	**6730**	1.38
I13	8120	**0.92**	**7020**	1.47
I14	7830	**1.0**	**6940**	1.37
I15	8240	**0.89**	**7540**	1.32
I16	8550	**1.39**	**7540**	1.63
I17	11 040	**1.92**	**10 440**	2.89
I18	11 140	**1.36**	**10 460**	1.81
I19	16 930	**1.66**	**16 240**	1.94
I20	17 340	1.68	**16 710**	1.68
I21	22 950	1.69	**22 040**	1.69
I22	22 860	1.59	**22 040**	1.59
I23	28 050	2.15	**27 810**	2.15
I24	28 400	2.09	**27 840**	2.09
I25	33 700	2.97	33 640	2.97
I26	34 220	2.78	**33 870**	2.78
I27	39 520	**3.84**	**39 340**	3.90
I28	39 930	**3.08**	**39 630**	4.02
I29	45 540	3.98	**45 360**	3.98
I30	45 620	**3.08**	**45 410**	3.15
I31	51 120	4.52	**51 000**	4.52
I32	51 140	4.38	**51 040**	**4.32**

Notes. Bold values indicate the best (optimal) results obtained for each scenario.

These findings demonstrate that the rejection cost plays a crucial role in the overall patient allocation strategy. By adjusting the rejection penalty and analyzing the resulting variations in the assignment and total costs, we gain valuable insights into the model's sensitivity to changes in key parameters.

From previous analyses, we observed that both the number of critical patients and the total number of patients influence the optimal solution. This sensitivity analysis further highlights that the rejection penalty is a key factor in determining total costs. As shown in Figure 8, increasing the rejection penalty leads to:

- A rise in the assignment cost, as hospitals prioritize admitting more patients to avoid high rejection penalties.
- A slight variation in the transfer cost, indicating that reassignments remain limited even under cost pressure.
- A decrease in the rejection cost, as hospitals seek to minimize patient rejections by optimizing available resources.

These insights suggest that hospitals may choose to accept more patients, regardless of their health conditions, once the rejection cost surpasses a certain threshold. This trade-off between rejection penalties and assignment decisions can be crucial for optimizing bed management strategies during emergency situations.

6. Conclusions

This paper introduced a novel optimization model for the patient bed assignment problem in pandemic situations. The model aims to minimize penalties associated with patient allocation, including the cost of assigning patients to specific beds, the cost of rejecting acute patients, and the cost of transferring patients between beds. Our formulation also addresses equity by incorporating age and oxygen saturation into constraints that define risk categories, thereby prioritizing critical patients. As a linear program, the model is computationally efficient and can be integrated into hospital information systems. Nevertheless, practical deployment may face challenges, particularly the need for sufficiently detailed patient data and adequate staff training to interpret the optimization outputs. To evaluate our approach, we generated new HBA benchmark instances from real hospital data in Tunisia during the pandemic. An exact method was then used to validate the model, demonstrating its efficiency with an acceptance rate exceeding 70%. Furthermore, the model was tested with a Genetic Algorithm (GA) across all instances, yielding near-optimal results quickly and confirming its flexibility and efficiency for practical use, complementing the exact solutions provided by CPLEX.

A sensitivity analysis was conducted to assess the impact of variations in key input parameters, particularly rejection penalties, on the optimal solution. The results indicate that beyond a certain threshold, increasing rejection costs leads to a significant rise in total assignment costs, pushing hospitals to prioritize patient acceptance over cost minimization. This highlights the trade-off between resource constraints and patient care optimization.

Future work could extend this model by incorporating a multi-objective approach to dynamically balance these costs. Additionally, relying solely on the exact method to validate our model may not be sufficient. Thus, developing a new approach integrating artificial intelligence techniques could be a valuable method for predicting patient states before their assignment. By classifying each patient with precise parameters in the first stage, the model can then proceed to optimize different costs resulting from patient bed assignments in the second stage.

Data availability statement

Data/code are available on request from the authors

References

[1] Z.A. Abdalkareem, A. Amir, M.A. Al-Betar, P. Ekhan and A.I. Hammouri, Healthcare scheduling in optimization context: a review. *Health Technol.* **11** (2021) 445–469.

[2] R.B. Bachouch, A. Guinet and S. Hajri-Gabouj, An integer linear model for hospital bed planning. *Int. J. Prod. Econ.* **140** (2012) 833–843.

[3] L.S.L. Bastos, J.F. Marchesi, S. Hamacher and J.L. Fleck, A mixed integer programming approach to the patient admission scheduling problem. *Eur. J. Oper. Res.* **273** (2019) 831–840.

[4] B. Bilgin, P. Demeester, M. Misir, W. Vancroonenburg and G. Vanden Berghe, One hyper-heuristic approach to two timetabling problems in health care. *J. Heuristics* **18** (2012) 401–434.

[5] S. Brailsford and J. Vissers, OR in healthcare: a European perspective. *Eur. J. Oper. Res.* **212** (2011) 223–234.

[6] M.L. Brandeau, Allocating resources to control infectious diseases. *Oper. Res. Health Care* (2005) 443–464.

[7] S. Ceschia and A. Schaerf, Local search and lower bounds for the patient admission scheduling problem. *Comput. Oper. Res.* **38** (2011) 1452–1463.

[8] S. Ceschia and A. Schaerf, Modeling and solving the dynamic patient admission scheduling problem under uncertainty. *Artif. Intell. Med.* **56** (2012) 199–205.

[9] S. Ceschia and A. Schaerf, Dynamic patient admission scheduling with operating room constraints, flexible horizons, and patient delays. *J. Scheduling* **19** (2016) 377–389.

[10] M. Chaieb, D.B. Sassi, J. Jemai and K. Mellouli, Challenges and solutions for the integrated recovery room planning and scheduling problem during COVID-19 pandemic. *Med. Biol. Eng. Comput.* **60** (2022) 1295–1311.

[11] P. Demeester, W. Souffriau, P. De Causmaecker and G. Vanden Berghe, A hybrid tabu search algorithm for automatically assigning patients to beds. *Artif. Intell. Med.* **48** (2010) 61–70.

[12] C.A. Demetriou, S. Achilleos, A. Quattrocchi, J. Gabel, E. Critselis, C. Constantinou, N. Nicolaou, G. Ambrosio, C.M. Bennett, N. Le Meur and J.A. Critchley, Impact of the COVID-19 pandemic on total, sex-and age-specific all-cause mortality in 20 countries worldwide during 2020: results from the C-MOR project. *Int. J. Epidemiol.* **52** (2023) 664–676.

[13] K. Dorgham, I. Nouaouri, H. Ben-Romdhane and S. Krichen, A hybrid simulated annealing approach for the patient bed assignment problem. *Proc. Comput. Sci.* **159** (2019) 408–417.

[14] K. Dorgham, H. Ben-Romdhane, I. Nouaouri and S. Krichen, A decision support system for smart health care, in IoT and ICT for Healthcare Applications. Springer International Publishing, Cham (2020) 85–98.

[15] L. Eriskin, M. Karatas and Y.-J. Zheng, A robust multi-objective model for healthcare resource management and location planning during pandemics. *Ann. Oper. Res.* **335** (2024) 1471–1518.

[16] D. Garcia-Vicuña, L. Esparza and F. Mallor, Hospital preparedness during epidemics using simulation: the case of COVID-19. *Cent. Eur. J. Oper. Res.* **30** (2022) 213–249.

[17] I.E. Haines and M.P. Jones, When a system breaks: a queuing theory model for the number of intensive care beds needed during the COVID-19 pandemic. *Med. J. Aust.* (2020) 1.

[18] M. Harzi, J.-F. Condotta, I. Nouaouri and S. Krichen, Scheduling patients in emergency department by considering material resources. *Proc. Comput. Sci.* **112** (2017) 713–722.

[19] M. Harzi, J.-F. Condotta, I. Nouaouri and S. Krichen, Using the hybrid ILS/VND method for solving the patients scheduling problem in emergency department: a case study. *Proc. Comput. Sci.* **126** (2018) 733–742.

[20] H. Jedidi, H. Ben-Romdhane, I. Nouaouri and S. Krichen, A two-stage approach combining machine learning and optimization for the hospital patient bed assignment problem in emergencies. *Proced. Comput. Sci.* **246** (2024) 4316–4324.

[21] H. Jedidi, I. Nouaouri, H. Ben-Romdhane and S. Krichen, Min-conflict heuristic approach for elective patient bed assignment problem, in 2024 10th International Conference on Control, Decision and Information Technologies (CoDIT), Vallette, Malta. IEEE-Xplore (2024) 1424–1429. DOI: 10.1109/CoDIT62066.2024.10708386.

[22] H. Jedidi, H. Ben-Romdhane, I. Nouaouri and S. Krichen, Bi-objective hospital bed assignment problem in emergencies, in International Conference on Decision Aid and Artificial Intelligence (ICODAI 2024). Atlantis Press (2025) 136–146.

[23] K.K. Jena, S.K. Bhoi, M. Prasad and D. Puthal, A fuzzy rule-based efficient hospital bed management approach for coronavirus disease-19 infected patients. *Neural Comput. App.* **34** (2022) 11361–11382.

[24] R. Li, C. Rivers, Q. Tan, M.B. Murray, E. Toner and M. Lipsitch, The demand for inpatient and ICU beds for COVID-19 in the US: lessons from Chinese cities. MedRxiv (2020).

[25] H. Liu, Y. Wang and J.-K. Hao, Solving the patient admission scheduling problem using constraint aggregation. *Eur. J. Oper. Res.* **316** (2024) 85–99.

[26] T.M. Range, R.M. Lusby, and J. Larsen, A column generation approach for solving the patient admission scheduling problem. *Eur. J. Oper. Res.* **235** (2014) 252–264.

[27] V.L. Smith-Daniels, S.B. Schweikhart and D.E. Smith-Daniels, Capacity management in health care services: Review and future research directions. *Decis. Sci.* **19** (1988) 889–919.

[28] C. Taramasco, R. Olivares, R. Munoz, R. Soto, M. Villar and V.H.C. de Albuquerque, The patient bed assignment problem solved by autonomous bat algorithm. *Appl. Soft Comput.* **81** (2019) 105484.

[29] C. Taramasco, B. Crawford, R. Soto, E.M. Cortés-Toro and R. Olivares, A new metaheuristic based on vapor-liquid equilibrium for solving a new patient bed assignment problem. *Expert Syst. App.* **158** (2020) 113506.

[30] A.M. Turhan and B. Bilgen, Mixed integer programming based heuristics for the patient admission scheduling problem. *Comput. Oper. Res.* **80** (2017) 38–49.

[31] C. Wang, F. Yang and Q.-L. Li, Optimal decision of dynamic bed allocation and patient admission with buffer wards during an epidemic. *Mathematics* **11** (2023) 687.

[32] H. Yang, H. Liu and G. Li, A novel prediction model based on decomposition-integration and error correction for COVID-19 daily confirmed and death cases. *Comput. Biol. Med.* **156** (2023) 106674.