Improving patient flow and delivery of care: a bed assignment optimization model

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Abstract

The world is ageing, healthcare professionals are a limited resource and, as a result, hospitals are facing constant bottlenecks. This increase in patient flow makes hospital bed management key to keep the system in sync. Choosing a bed for a patient is not a trivial task, given the different criteria and constraints that should be considered when assigning a patient. Although we are living in the era of innovation and technology, this matter has not been deeply explored yet. This thesis lies in a case study of a Portuguese public hospital, where this process is performed daily on a paper base by a nurse. Given the amount of information to be considered and the different stakeholders involved in the process, the information can end up being mistreated, leading to a deficient bed assignment. This thesis proposes a multi-objective mathematical model as a decision support tool. Different scenarios were designed to assess the model behavior with the variation of the hospital occupancy rate. The optimization of the formulation was performed using two different techniques, goal programming (GP) and lexicographic goal programming (LexGP). GP performed better across all scenarios in a smaller period, however, LexGP ended up mimicking more accurately the BA task. A sensitivity analysis was also performed to study how the model behaved when varying the batch dimension and the maximum number of transfers. It is important for the hospital to have a model developed in line with its decision criteria and goals that may positively impact its performance.

Keywords: Bed management, Bed Assignment, Multi-Objective model, Optimization, Decision support model

1.Introduction

The ageing of the population combined with the lack of general practitioners in outpatient clinics results in a constant hospital overcrowding. Patients are facing long waiting lists, long times in queue, long length of stay (LOS) and at times leave without being seen (LWBS). This increase in patient flow combined with limited resources makes hospital bed management (BM) key to keep the system in sync. An optimal bed assignment (BA) is central to avoid waste, reduce costs, increase revenues, improve efficiency and more important to guarantee a positive experience for the patient. (Maia (2016)) The uncertainty of many parameters, such as, the number of emergency admissions, discharges, movements and transfers between departments, LOS and variability in patients, makes hospital BM a complex and challenging task. (Adamski (2014))

This article addresses Hospital Beatriz Ângelo's (HBA) BA process, proposing a mathematical model as a future decision support tool for the bed manager. It is expected that this model will add value to the hospital through the improvement of its efficiency and assignment precision. This study contributes to the literature proposing a model that mimics the bed manager's practice, considering parameters, constraints and objectives that weren't previously explored in the literature. Additionally, it implements two different optimization techniques, allowing the comparison of its performance in this context. Particularly for HBA, it is important to have a model supported by its decision criteria and in line with its goals that may positively impact its performance.

2. Context

HBA is a Portuguese public hospital integrated in the National Health Service and operated under a public-private partnership program. HBA aims to improve its BA process and thus provide a fast and efficient response to patients' demand for beds, ensuring safety and quality of care. HBA intends to automate this process and therefore overcome the limitations of the current manual approach.

HBA's BA process is very complex, not only due to the criteria that should be considered when assigning a bed to a patient but also due to the several stakeholders involved.

Currently the BA is performed manually which presents several limitations such as:

- The assignment relies on the bed manager judgment
- There is a significant amount of possible combinations to be evaluated when assigning patients, making the decision process very complex to be manually performed
- The information is transmitted to the bed manager over the phone
- Human errors due to lack of complete and prompt information

3. Literature review

Hospital BA is a branch of the hospital BM field which focus the process of assigning patients into beds. Several analytical methods of OR have been used to approach this task. Demeester et al. (2010) was one of the first to use computational integer programming to approach BA through a single OF that maximizes the number of allocated patients and minimizes the number of transfers, considering the admission and discharge date, gender, quarantine conditions and needed treatment. This solution revealed to be impractical due to the required computational time, being a Tabu search procedure applied instead. Although this approach was successful, the fact that the arrival and discharge times were required to be known in advance did not leverage its adoption. Ã and Schaerf (2011) reformulated Demeester et al. (2010)'s model to improve search times, proposing two different local search procedures, however not solving the limitation of having to know the arrival and discharge times in advance. In a different study, Ceschia and Schaerf (2012) revisited the model, integrating the information on unplanned admissions and uncertain LOS. A penalty was applied ever since a delay in the admission date occurred. Both an ILP and a local neighborhood search algorithm were applied.. However, both methods achieved similar results for small dynamic scenarios, it was extremely difficult to find a balance between the components of the OF, and thus it would be interesting to explore a multi-objective approach. Ben, Guinet, and Hajri-gabouj (2012) proposed a ILP model for hospital bed planning occupancy by elective and acute patients, considering incompatibilities between pathologies, gender, contagious diseases and LOS. It focused the minimization of costs. Different solvers were used to optimize the model, being CPLEX and LINGO the most powerful solvers tested. Schmidt, Geisler, and Spreckelsen (2013) studied the elective patient admission and assignment planning through the definition of a cost function for patient admission considering adaptable LOS estimations and aggregated resources. The affinity between clinics and wards, the ward occupancy, the change of ward occupancy and the assignment delay were considered in the model's OF. Four algorithmic methodologies were evaluated, mixed integer programming, the longest expected processing time, the shortest expected processing time and random choice (heuristic approaches). The use of this assignment model resulted in a reduction of the dismissal ration by more than 30%. The exact approach presented a marginal advantage over the heuristic approaches of 3%, however, its computational times are fifty times larger than the computational times of the heuristic. Turhan and Bilgen (2016) solved the Patient Admission Scheduling (PAS) problem using two different heuristic approaches based on Mixed Integer Programming (MIP), namely, Fix and Relax (F&R) and Fix and Optimized (F&O). Solutions generated by F&R heuristic were used as input to the F&O heuristic and were iteratively improved until there was no sub problem left to solve. The OF considered minimizes the total penalties associated with assigning patients to rooms for the duration of their stay, considering patient LOS, room preference, admission date, specialism choice, and age. Starting from the first night, the optimization window was decided, from which the room costs for all patients staying within the period were calculated. This process was repeated until all nights within the planning horizon were investigated. F&R provided feasible solutions in short calculation times and F&O improved the initial solution received by the F&R in an iterative nature. Hoff (2017) developed a multi-objective model that maximizes the overall criticality of patients admitted and minimizes movements of previously admitted patients. The integer program model was used in Monte Carlo simulations. The model was created to determine the ideal number of private and semi-private rooms and the ideal timeframe over which to batch patient admissions.

4. Problem Characterization

When assigning a patient into a room, the bed manager should try to achieve the following objectives:

- Maximization of the assignments
- Maximization of patients' priority according to:
  - Boarding time (a patient who is waiting for a long time for a bed should have priority over a patient who isn't waiting for such a long time);
  - Occupancy of the patients' origin ward (if the occupation level of the origin ward is higher, that patient should be prioritized to avoid ward overloading);
  - Time of the day the bed is required (the MDH and surgical day hospital (SDH) close in the afternoon, therefore MDH and SDH patients should have priority over patients who come from the ED after a certain time of day,

otherwise they would have to go to the ED and wait there until a bed is free).
  - Patient's medical condition (patients in a more serious and critical clinical status should be prioritized);
- Minimization of the internal movements, considering patient's history (number of transfers a patient has already been subjected to and how long a patient has been accommodated in a room) and the type of transfer performed, if it is within or between a ward (a transfer within ward is preferred over a transfer between wards).
- Maximization of the affinity between clinical typologies and wards (there is a preference regarding which clinical typologies to allocate in a certain ward).
- Minimization of the differences in occupancy across wards (there is an interest in ensuring equity of occupancy across wards and avoid significant differences in terms of workload of the resources).

Moreover, the bed manager can only assign a bed to a patient when a set of constraints are respected:

- Two patients allocated in the same room should have the same gender;
- Two patients allocated in the same room should be categorized in the same clinical typology;
- Two infected patients allocated in the same room must have the same contagious disease;
- If a patient requires a certain equipment he/she must be allocated to a room with that equipment.

5. Methodology

The methodology was structured in four stages. It is represented in Figure 1. The first stage consisted of collecting information, interviews and job shadowing. This stage was crucial to understand the root of the problem and design a solution for it. The next stage consisted of information processing in which the information gathered in the previous stage was deeply analyzed and used to formulate a multi-objective mathematical model. In the third stage, four different scenarios were designed and the two multi-objective problem solving techniques, goal programming (GP) and lexicographic goal programming (LexGP), used to solve the model explored. In the fourth stage, a sensitivity analysis was performed to study the impact of the batch dimension and the maximum number of transfers on each OF. Finally, the results obtained with the different optimization techniques for the different scenarios (stage 3) and the sensitivity analysis (stage 4) are compared and interpreted in stage five.

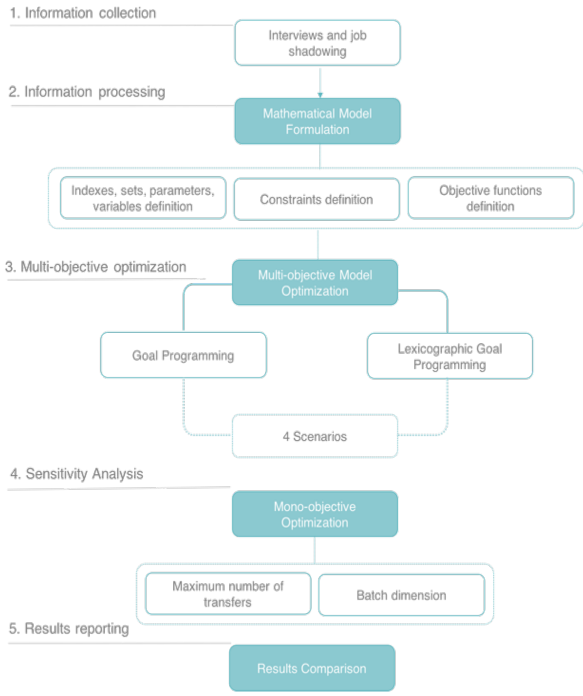

Figure 1 Methodology Framework

6. Mathematical Formulation

6.1. Model Formulation

To mimic the process described in chapter 4, the model was developed as a multi-objective ILP model composed by five OFs. The formulation assumes that patient's clinical typology and medical condition do not change during the decision period. It is also assumed that a patient cannot be discharged from the hospital without the bed manager's permission. The indexes, sets, parameters, constants, decision variable and objective functions considered in the formulation are presented below.

INDEXES

i	Patient
j	Room
e	Equipment
t	Clinical typology
s	Medical condition
w	Ward
g	Gender
c	Contagious disease
o	Patient's origin ward

SETS

P	Set of all patients
J	Set of rooms

E	Set of equipment
T	Set of clinical typologies
S	Set of medical conditions
W	Set of wards
G	Set of genders
C	Set of contagious diseases
O	Set of origin wards

PARAMETERS

$gen_{i,g}$	Gender g of patient i, $i \in P$, $g \in G$
$ct_{i,t}$	Clinical typolgy t of patient i, $i \in P$, $t \in T$
$cd_{i,c}$	Contagious disease c of patient i, $i \in P, c \in C$
$ori_{i,o}$	Origin o of patient i, $i \in P$, $o \in O$
$eqr_{i,e}$	Equipment e required by patient i, $i \in P$, $e \in E$
$wa_{j,w}$	Ward w of room j, $j \in J$, $w \in W$
cap_j	Capacity of room j, $j \in J$
$eqp_{e,w}$	Equipment e provided in ward w, $w \in W,\ e \in E$
ueq_e	Total units of equipment e available, $e \in E$
$ctwa_{t,w}$	Affinity between clinical typology t and ward w, $w \in W, t \in T$
$mc_{i,s}$	Medical condition s of patient i, $i \in P, s \in S$
td_o	Origin ward o affected by the time of the day $h, o \in O$
ocl_o	Occupation level of the origin ward o, $o \in O$
bt_i	Boarding time of patient i, $i \in P$
sc_s	Severity of medical condition s, $s \in S$
nt_i	Number of times patient i has been transferred, $i \in P$
ti_i	Time interval a patient , i has been in the room j, $i \in P$, $j \in J$
$y_{i,j}$	Patient i is currently assigned to room j, $i \in P$, $j \in J$
$nreques$	Total number of requests
h	Time of the day the model is run (h=1 if run after 7pm or h=0 of before 7pm)
$maxbt$	Maximum BT of the patients who are waiting for admission
$maxti$	Maximum time interval a patient has been in a room
$maxtr$	Maximum number of transfers patients have been subjected to

CONSTANTS

w_{td}	Weight of the time of the day over the priority of origin ward
w_{ol}	Weight of the occupation level of the patients' origin ward
w_{mc}	Weight of the patients' medical condition on patients' priority
w_{bt}	Weight of the BT
w_{bw}	Weight of transfers between wards
w_{iw}	Weight of transfers within ward
w_{nt}	Weight of the number of transfers patients have been submitted to
w_{ti}	Weight of the time interval a patient has been accommodated in a room

DECISION VARIABLE

$$x_{i,j} = \begin{cases} 1 \text{ if patient } i \text{ is assigned to a bed in} \\ 0 \text{ otherwise} \end{cases}$$

OBJECTIVE FUNCTIONS

f_1	Assignment capacity
f_2	Patient priority
f_3	Internal movements
f_4	Specialty-ward affinity
f_5	Occupancy difference across wards

The OFs are represented by equations 1 - 6:

$$Max\ f_1 = \sum_{i,j} x_{i,j} \tag{1}$$

$$Max\ f_2 = \sum_{i,j} x_{i,j} \times (1 - y_{i,j}) \left[\left[\frac{w_{mc}}{w_{ol} + w_{td}h + w_{bt} + w_{mc}} \sum_s sc_s\, mc_{i,s} \right] + \left[\frac{w_{td}h}{w_{ol} + w_{td}h + w_{bt} + w_{mc}} \sum_o td_o ori_{i,o} \right] + \left[\frac{w_{ol}}{w_{ol} + w_{td}h + w_{bt} + w_{mc}} \sum_o ocl_o ori_{i,o} \right] + \frac{w_{bt}}{w_{ol} + w_{td}h + w_{bt} + w_{mc}} \frac{bt_i}{max(bt_i) + 1^*} \right], i \in P, j \in J, o \in O, s \in S \tag{2}$$

$$Min\ f_3 = \sum_{i,j,jj,w,ww: j \neq jj, w \neq ww} x_{i,j} y_{i,jj} wa_{j,w} \left(w_{iw} wa_{jj,w} + w_{bw} wa_{jj,ww} \right) \left(w_{nt} \frac{nt_i}{maxtr + 1^*} + w_{ti} \frac{ti_i}{maxti + 1^*} \right) \tag{3}$$

$$Max\ f_4 = \sum_{i,j,t,w} ctwa_{t,w} x_{i,j} ct_{i,t} wa_{j,w}, i \in P, j \in J, w \in W, t \in T \quad (4)$$

$$Min\ f_5 = \sum_{w,ww} \frac{|oc_w - oc_{ww}|}{2} \quad (5)$$

*Guarantees that the denominator is never zero

Since the formulation is linear and equation 5.5 is nonlinear, it was submitted to linearization using Bertsimas and John N. Tsitsiklis (1997). Being rewritten as:

$$\sum_{w,ww} \frac{ocdif_{w,ww}}{2}, w \in W, ww \in W \quad (6)$$

s.t

$$oc_w - oc_{ww} \leq ocdif_{w,ww} \quad (7)$$

$$-(oc_w - oc_{ww}) \leq ocdif_{w,ww} \quad (8)$$

The constraints are represented by equations 5.9-5.18:

$$\sum_{j} x_{i,j} \leq 1 \quad (9)$$

$$\sum_{i} x_{i,j} \leq cap_j \quad (10)$$

$$eqr_{i,e} wa_{j,w} x_{i,j} - eqp_{e,w} \leq 0 \quad (11)$$

$$\sum_{i,j,w} x_{i,j} wa_{j,w} eqp_{e,w}\, eqr_{i,e} \leq ueq_e \quad (12)$$

$$\sum_{j} x_{i,j} = 1, \forall \sum_{j} y_{i,j} = 1, i \in P, j \in J \quad (13)$$

$$x_{i,j} + x_{ii,j} \leq 1, \forall\ i \neq ii, i \in P, ii \in P, j \in J, cap_j = 2, ct_{i,t} \neq ct_{ii,t}, t \in \mathrm{T} \quad (14)$$

$$x_{i,j} + x_{ii,j} \leq 1, \forall\ i \neq ii, cap_j = 2, cd_{i,c} \neq cd_{ii,c} \quad (15)$$

$$x_{i,j} + x_{ii,j} \leq 1, \forall\ i \neq ii, cap_j = 2, gen_{i,g} \neq gen_{ii,g} \quad (16)$$

$$oc_w = \sum_{i,j} x_{i,j} wa_{j,w} \quad (17)$$

$$x_{i,j} wa_{j,w} ct_{i,t} = 0, \forall\ ctwa_{t,w} = 0, i \in P, j \in J, w \in W, t \in \mathrm{T} \quad (18)$$

$$nr_{transf} = \sum_{i,j} -(x_{i,j} - y_{i,j}) y_{i,j} \quad (19)$$

$$nr_{transf} \leq 0.2\ nrequests \quad (20)$$

$$, \quad i, ii \in P, j, jj \in J, s \in S, e \in E, w, ww \in W, o \in O$$

6.2. Scenario Optimization

To assess how the formulation would respond to an increase in occupancy and a constant demand for beds, four different scenarios were tested. In the first scenario, the hospital was modeled as empty, having an occupancy of 0% and a request of 45 beds. This significant number of bed requests is consequence of the need to first populate the hospital. In the second scenario, 20 more beds were requested. The resultant inpatients distribution was then used as input for the third scenario, followed by a demand for 20 more beds. Finally, and due to the motivating model's capacity of 99 beds, 14 beds were still requested. These scenarios were sequentially solved, such that the hospital's inpatients distribution resulting from the previous scenario optimization would be used as input for the next scenario optimization. A diagram representing the optimization of the different scenarios is presented in Figure 2.

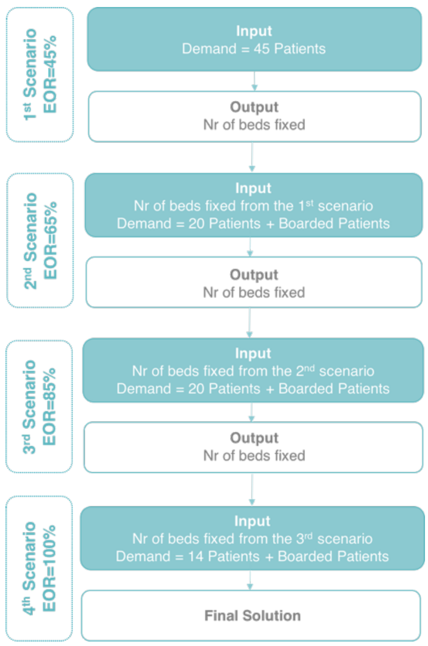

Figure 2 Solution approach

Both GP and LexGP methodologies were explored over the scenarios. The GP method minimizes the sum of the relative deviations of each objective to its respective goal, while the LexGP method solves prioritized objectives. The CPLEX solver from GAMS 24.8.5 was used as an optimization tool. The stopping criteria considered was the optimization time length of

500 seconds, which was the interval considered adequate to the demanding response time of bed requests HBA is under. A sensitivity analysis over the parameters batch dimension and the maximum number of transfers allowed was performed and will be further explored.

6.3. Assumptions

The formulation was validated over a motivating model, whose main characteristics are presented in Table 1.

Table 1 Motivating model characterization

	Motivating model
Wards	11
Rooms per ward	5
Double rooms per ward	4
Single rooms per ward	1
Beds	99
Clinical Typologies	12
Types of equipment	3
Origin wards	8

The formulation assumes that:

- The hospital configuration (number of single and double rooms), patient's clinical typology and medical condition do not change during the current decision period.
- The patient cannot be discharged from the hospital without the permission of the bed manager.
- The number of transfers suggested by the formulation shouldn't be higher that 20% of the total number of beds request.

7. Results

7.1. Multi-Objective Optimization

The proportion of the deviation between the solution obtained for each OF and its respective goal is presented for the different scenarios after applying GP and LexGP (Figure 3–7). Figure 8 presents the average of the proportion of the deviation between the solution and its respective goals across all OFs for each scenario. The proportion of the deviation was calculated such that for all objective functions, a 0% proportion the achievement of the goal, a positive proportion represents the overachievement of the target goal and a negative proportion represents its underachievement. Figure 9 presents the resource (time) usage associated with the optimization of each scenario using both techniques.

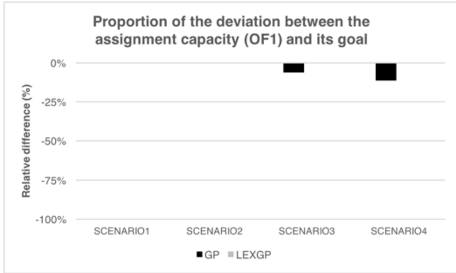

Figure 3 Proportion of the deviation between OF1 and its goal for each scenario using GP and LexGP

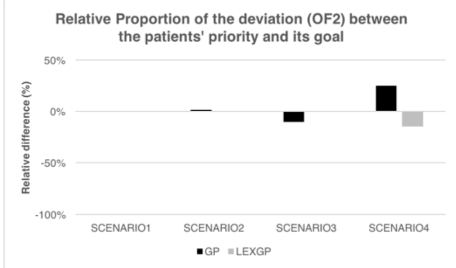

Figure 4 Proportion of the deviation between OF2 and its goal for each scenario using GP and LexGP

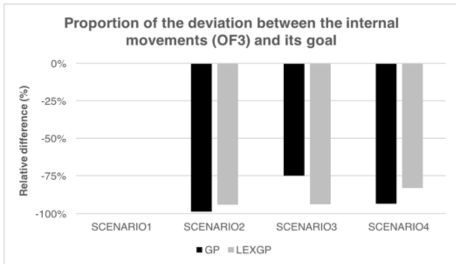

Figure 5 Proportion of the deviation between OF3 and its goal for each scenario using GP and LexGP

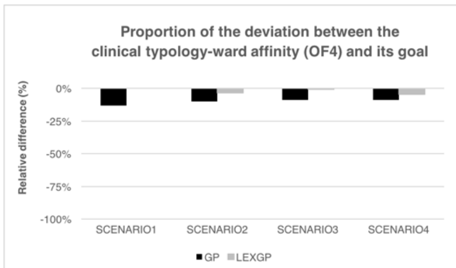

Figure 6 Proportion of the deviation between OF4 and its goal for each scenario using GP and LexGP

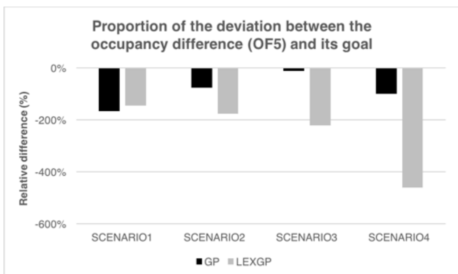

Figure 7 Proportion of the deviation between OF5 and its goal for each scenario using GP and LexGP

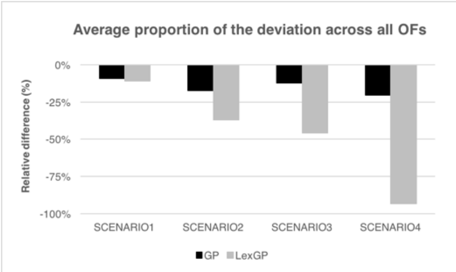

Figure 8 Average proportion of the OFs to its goals for each scenario using GP and LexGP

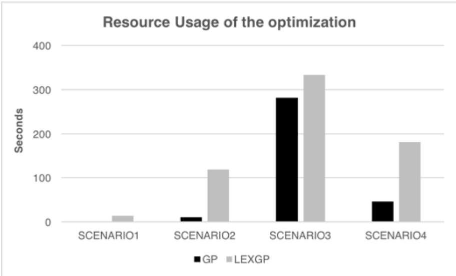

Figure 9 Resource usage of the optimization for each scenario using GP and LexGP

7.2. Sensitivity Analysis

After comparing both GP and LexGP methods, a sensitivity analysis was performed with the aim of studying how some variables, namely the batch dimension and the number of transfers allowed, impacted the dependent variables under study $(f_1, f_2, f_3, f_4, f_5)$.

Batch Dimension

The batch dimension corresponds to the number of requests to be considered when the model is run. Although it is expected the model to be run each time a new patient is registered in the bed request list or an inpatient is discharged, it was of interest to analyze how batching would impact the optimal solution.

Batches of two different dimensions were created, 10 and 20 patients, and the formulation was run starting with an initial bed occupancy rate of 45%. Given the hospital dimension of 99 beds, 4 runs of 10 patients and 2 runs of 20 patients were executed. The intersection points between these two types of runs occur at the EOR of 66% (65 beds) and 86% (85 beds), which are the ones used as reference to compare the results obtained.

The proportion of the deviation between the optimal solution obtained with a batch of size 10 and batch of size 20 for each OF is presented in Table 2.

Table 2 Proportion of the deviation between the optimal solution obtained with a batch of 10 and a batch of 20 patients

OF	Scenario	$\Delta_{batch10-20}$
F1	**2nd**	0%
	3rd	0%
F2	**2nd**	84%
	3rd	132%
F3	**2nd**	0%
	3rd	0%
F4	**2nd**	2%
	3rd	2%
F5	**2nd**	-46%
	3rd	-14%

Maximum number of transfers

Besides batching, it is also interesting to study how sensitive the model is to the parameter associated with the maximum number of transfers (equation 20). The following results reflect how sensitive the OFs are to this parameter. An initial bed occupancy rate of 45% was assumed. After optimizing each OF, the proportion of the deviation between the optimal solution obtained and its goal when varying the ratio between the number of transfers and the number of requests for the 2nd, 3rd and 4th scenarios is presented in Table 3.

Table 3 Proportion of the deviation between the optimal solution obtained when varying the maximum number of transfers

OF	Scenario	Δ_{0-20}	Δ_{20-40}	Δ_{40-60}	Δ_{60-80}
OF1	**2nd**	3%	0%	0%	0%
	3rd	7%	1%	1%	0%
	4th	1%	2%	0%	0%
OF2	**2nd**	49%	25%	19%	15%
	3rd	121%	37%	26%	19%
	4th	209%	78%	30%	30%
OF3	**2nd**	0%	0%	0%	0%
	3rd	0%	0%	0%	0%
	4th	0%	0%	0%	0%
OF4	**2nd**	3%	0%	0%	0%
	3rd	5%	3%	0%	0%
	4th	2%	2%	2%	1%
OF5	**2nd**	-61%	-64%	0%	0%
	3rd	-57%	-58%	0%	0%
	4th	-21%	-37%	-25%	0%

OF	Scenario	Δ_{80-100}	$\Delta_{100-120}$	$\Delta_{120-nocondition}$
OF1	**2nd**	3%	0%	0%
	3rd	7%	1%	1%
	4th	1%	2%	0%
OF2	**2nd**	49%	25%	19%
	3rd	121%	37%	26%
	4th	209%	78%	30%
OF3	**2nd**	0%	0%	0%
	3rd	0%	0%	0%
	4th	0%	0%	0%
OF4	**2nd**	3%	0%	0%
	3rd	5%	3%	0%
	4th	2%	2%	2%
OF5	**2nd**	-61%	-64%	0%
	3rd	-57%	-58%	0%
	4th	-21%	-37%	-25%

7. Discussion

LexGP outperformed GP's assignment capacity, OF1, in the 3rd and 4th scenarios, which was a phenomenon to be expected since LexGP prioritizes this equation above all, while GP assumes that no function has priority over another.

Respecting the priority function, OF2, LexGP reached the target goal for all scenarios except for the 4th scenario, which may be due to the constrained nature associated with the model dimension and the fact that OF1 limits the performance on OF2. On the other hand, GP overcame the target goal in the 2nd and 4th scenarios, which may be due to the freedom of GP to obtain the best final results at any "cost", meaning it may favor the results of this functions and compromise the others.

OF5 was ranked last by LexGP, and thus it was expected the results to be highly constrained by the deviations obtained in the previous optimizations, which cannot be negatively affected by this function optimization. On the other hand, GP consistently outperforms LexGP.

In the overall GP performed better than LexGP, across all scenarios. The better performance of GP when compared with LexGP was more evident with the increase of the expected bed occupancy. The difference on the average performance of LexGP across all objective functions and its poor resource usage (in average 76 seconds longer than GP) was expected given the highly-constrained nature of LexGP as the optimization was occurring. Concerning the resource usage, it is important to remember the LexGP's sequential optimization process is more time consuming than GP that minimizes all deviations at once. Furthermore, for both methods the computational burden is as heavier as the model's dimension, i.e, the hospital's occupancy rate.

To sum up, GP ended up providing better results in the overall compared with LexGP, however it is important to highlight that the difference between GP's and LexGP's performance on OF5 highly impacts the average of the proportion of the deviation across all OFs, since the difference between GP and LexGP performance is substantial particularly as the expected bed occupancy increases. On the other hand, GP did not attain the mimicking effect of LexGP since there was no preference factor added to the OFs and all equations ended up being equally weighted, which is reflected on the great results obtained in OF5 (least relevant function) and poor results in OF1 (most important function).

Concerning the sensitivity analysis related with the batch dimension, the results showed that the patient's priority function (OF2) and the difference in occupancy function (OF5) were the most affected/sensible to the variation of the batch size, performing better in a 20-patient batch. After increasing the batch of 10 to a batch of 20 patients, OF2 went through an increase in both scenarios, more significantly in the 3rd scenario. On the other hand, OF5 went through a decrease, which was positive since that equation was aimed to be minimized, for both scenarios as well. This increase in performance may be due to different motives. The maximum number of transfers, which is as high as the number of bed requests, and the EOR before the optimization, which is lower in a batch of size 20 than in a batch of size 10 (leaving more beds available in the moment of assigning patients), end up providing more flexibility to the model, and therefore, the BA. It is important to highlight that OF2 naturally tends to increase with the batch dimension since the OF tends to increase with the number of requests. Therefore, a batch of more patients may lead to a better assignment performance.

Regarding the effect of the ratio between the number of transfers and the number of requests, the results showed an impact of this parameter on the different OFs, particularly on OF2, meaning that a higher ratio between the number of transfers and the number of requests gives more flexibility to the model allowing the assignment of beds to patients with a higher priority associated. OF5 is also evidently impacted by this parameter particularly when the ratio varies between 0 and 40%, allowing a more equal distribution of patients across wards. A variation of the ratio from 0 to 20% represents a meaningful impact on the improvement of the OFs optimal solutions, providing more flexibility to the model. A tradeoff between the number of transfers and the assignment capacity should be explored by the hospital when defining this parameter.

8. Conclusion and Future Work

The aim of this article was to provide HBA with a tool to support the bed manager's decision making when assigning patients into beds. The multi-objective mathematical model meets this goal, considering all criteria inherent to the BA decision making process. Moreover, some of the elements that were highlighted by the bed manager as important in the process and absorbed by the model are not easily accessible by the bed manager in the moment of deciding since it not only requires access to different information systems but also it is not easy to balance manually so many parameters.

Additionally, it was also of interest to compare the performance of two different multi-objective techniques that haven't previously been compared in this context. Hence, to solve the formulation two different multi-objective problem solving techniques were applied, GP and LexGP. GP presented in average better results in terms of meeting the target goals for most scenarios in a smaller amount of time when compared to LexGP. However, LexGP ended up mimicking more accurately the BA process, due to the OFs prioritization according to its relevance. Contrasting with the LexGP method, the GP approach applied assigned no weights or ranked the five equations, mitigating the prioritization that is verified in the previous case. This reasoning was verified when the multi-objective formulation was optimized.

Concerning the sensitivity analysis performed, with the aim of studying how different parameters impacted each OF, two parameters were chosen, the batch dimension and the maximum number of transfers. It led to the conclusion that in fact a larger batch may generate better results offering more flexibility to the model, however it may be unrealistic to wait until there is a waiting list of a certain number of patients to perform the optimization in a real context, where there is no planning ahead and the hospital is looking for an immediate response to avoid boarding. Regarding the increase of the maximum number of transfers, similarly to the increase of the batch dimension, it led to an increase in the model's flexibility, allowing better results in some OFs. The decision whether to fix a batch dimension or decide on the maximum number of transfer comes with a trade-off, and the hospital should balance the pros and cons when choosing these parameters.

It is expected that this model will add value to the hospital not only through the improvement of its efficiency, assignment precision and service quality, but also reducing patient's BT, LOS and consequently, the overcrowding of its wards. This study contributes to the literature proposing a multi-objective model that mimics the bed manager's practice, considering parameters, constraints and objectives that haven't been previously explored. Particularly for HBA, it is important to have a model supported by its decision criteria and in line with its goals that may positively impact its performance. Although this model was specifically designed according to the HBA's requirements it is generic enough to be applied to different hospitals and enriched with additional constraints, for example, patient's mobility or additional isolation needs.

In a future perspective, there is still room to explore other multi-objective problem solving techniques and study how they may impact the model's performance in terms of the quality of results and resource usage. In this article only LexGP and GP were applied, and thus it is interesting to explore the weighted goal programming method which may overcome the absence of preference between the OFs when the GP was applied. To achieve this, as well as to add more precision to the model formulation weights, a multiple criteria decision analysis should be performed. Heuristic methodologies should be explored as well, since they may find good enough solutions in a smaller period. The clinical typologies considered in this model were related with the specialty unit's affinity to each ward and used as a constraint of compatibility between patients sharing a room. Regarding the latter, it is important to develop a more granular approach to classify patients based on their diagnosis. An eventual implementation approach was not deeply explored in this article; however, it would require the integration of HBA's information systems, such that it automatically updates the bed occupation status as well as receives as input the characteristics of the patients waiting for a bed.

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