



A Hybrid Simulated Annealing Approach for the Patient Bed Assignment Problem

Khouloud Dorgham, Issam Nouaouri, Hajer Ben-Romdhane, Saoussen Krichen

► To cite this version:

Khouloud Dorgham, Issam Nouaouri, Hajer Ben-Romdhane, Saoussen Krichen. A Hybrid Simulated Annealing Approach for the Patient Bed Assignment Problem. *Procedia Computer Science*, 2019, 159, pp.408 - 417. <10.1016/j.procs.2019.09.195>. <hal-03489155>

HAL Id: hal-03489155

<https://hal.science/hal-03489155v1>

Submitted on 20 Jul 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC BY-NC 4.0 - Attribution - Non-commercial use - International License



23rd International Conference on Knowledge-Based and Intelligent Information & Engineering Systems

A Hybrid Simulated Annealing Approach for the Patient Bed Assignment Problem

Khouloud Dorgham^{a,b*}, Issam Nouaouri^b, Hajer Ben-Romdhane^a, Saoussen Krichen^a

^aUniversité de Tunis, Institut Supérieur de Gestion de Tunis, LARODEC laboratory, Tunisia.

^bUniversité d'Artois, LGI2A, F-62400 Béthune, France.

Abstract

We address, in this paper, a very recurring problem within hospitals that consists in assigning elective patients to a limited number of beds. Especially when dealing with patients requiring urgent intervention, this problem becomes more complex and the time factor becomes the most critical. In such situations, a set of patients are to be examined and their clinical states are to be well specified in order to decide whether they need admission and hospitalization or not. In case of hospitalization, the hospital staff should assign patients to beds while taking into account beds availability in terms of specialization and patient needs. All these actions should be well planned in order to maximize the quality of service in the hospitals. This challenging problem can be modeled as an assignment problem that handles a set of patients to be assigned to a set of beds over a given time horizon, while taking into account availability constraints expressed in terms of beds, medical necessity and patient demands. Due to its \mathcal{NP} -hardness, the problem is mainly solved using approximate approaches, especially for large-scaled instances. We propose a hybrid simulated annealing approach, combining both advantages of simulated annealing (SA), that provides a local search, and genetic algorithm, that provides a global search, to enhance the performance of SA. The experimental results show that the proposed metaheuristic generates high-quality solutions for several benchmark instances from the literature with regards to the basic simulated annealing approach.

© 2019 The Author(s). Published by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (<https://creativecommons.org/licenses/by-nc-nd/4.0/>)

Peer-review under responsibility of KES International.

Keywords: Assignment problem, Hybrid Simulated annealing, Inpatient bed assignment

* Khouloud Dorgham

E-mail address: khouloud_dorgham@yahoo.fr

1. Introduction

In recent years, the interest in problems related to healthcare optimization has considerably increased. Within this context, the patient admission scheduling problem (PASP) and the patient bed assignment problem (PBAP) are decisional problems of notable interest at the operational level.

The PBAP, which is a sub-task of the PASP, aims to assign patients to suitable beds in the appropriate departments specialized in treating their clinical state and in compliance with: medical constraints, patient's needs, and bed availability. In general, patients can be either inpatients or outpatients. Inpatients spend several days or nights in a hospital, they can be emergency (arrive randomly) or elective (planned before), whereas outpatients are not hospitalized overnight. Assigning patients to beds in a variety of hospital rooms can therefore be challenging. In fact, Vancroonenburg et al. [30] demonstrated that the PBAP is \mathcal{NP} -hard.

The static variant of PBAP, as defined in this paper, aims at assigning elective patients to appropriate rooms. Admission dates and average length-of-stay (LoS) of each patient are defined a priori. This situation can be modeled by minimizing the costs and respecting capacity constraint, gender policy, assignment requirements and patients specialities needs. The goal of the PBAP is increasing the patients comfort and maximizing medical treatment effectiveness.

To deal with this problem, we propose a hybrid simulated annealing approach (HSA) that integrates the advantages of genetic algorithm into simulated annealing to reinforce its performance. The main idea of the proposed method is applying the genetic operators; selection, crossover and mutation, to the population that has been generated at each temperature by simulated annealing to provoke maturation. The results indicate the effectiveness of the algorithm we proposed on this \mathcal{NP} -hard problem with promising results.

This paper is structured as follows: section 2 presents an overview of the PBAP addressed in the literature. the problem formulation is described in section 3. Section 4 addresses the hybrid based heuristic developed in this study. The computational results are reported in section 5 and the conclusion is given in section 6 with some future research directions.

2. Related work

This section is devoted to present an overview of existing works in the literature related to the studied problem. Besides, we review the use of the simulated annealing approach in the literature.

2.1. A review on the Patient Bed Assignment Problem

The PBAP knew several extensions over the years. We distinguish between two aspects; static and dynamic problems. In static problems, a stream of patients are present simultaneously for the assignment and the length of their stays is known a priori. However, dynamic PBAPs deals with a sequence of urgent patients arriving over time, without any prior information, so that patients are assigned to beds one by one. Besides, the LoS is unknown because patients admission and discharge dates are not fixed a priori.

In the literature, the study of hospital bed assignment is quite recent. The problem was first modeled by [10] that consider a set of patients which arrive at a hospital over a certain period of time, the hospital comprises a set of rooms, each with a given capacity and characteristics. The main decisions are about beds to be assigned while satisfying several constraints (e.g., room capacity, gender, age, mandatory equipment, etc.). These constraints can either be hard constraints (required to be satisfied), or soft constraints, which have some variable values that are penalized in the objective function if the conditions on the variables are violated. Moreover, a perceived cost is associated with each patient to room assignment relating to the appropriateness of that assignment. The objective is to minimize the total cost of these assignments. The authors developed a hybrid tabu-search (TS) method to solve the problem and generated a series of experiments on six produced data instances related to Belgian hospitals.

The same problem was investigated by Bilgin et al. [6]. The authors designed a hyper-heuristic (HH) approach to improve the results on the six benchmark instances of [10], and provided seven new and more complex benchmark instances. More recently, Ceschia and Schaerf [7] proposed a new mathematical formulation for the PBAP, by reducing the overall number of decision variables. They solved the problem using a simulated annealing approach and computed some new lower bounds and upper bounds values and obtained the best-known solutions on all of the available PBAP

benchmarks. In [1], the authors proposed a decision support tool based on an integer linear program (ILP) for hospital bed planning in order to find available beds for elective and emergency patients by treating two different cases: (1) if there is no available bed for an elective patient, the physician can change his/her admission day, or (2) the patient can be transferred to another hospital. As pointed out by Range et al. [22], an improvement of the previous results is achieved by designing a column generation approach that gives good performance for the small instances of the PBAP problem, but for larger instances the approach needs further refinements. In [12], the authors designed a biogeography based optimization metaheuristic to solve the PBAP. However, they stated that their approach needs more improvements in order to enhance the computational results. Turhan and Bilgen [29], proposed a two Mixed Integer Programming (MIP) based heuristics that decompose the problem instances into sub-problems considering patient LoS, room preference, admission date, specialism choice, and age. The proposed approach produced good feasible solutions even for the larger instances. Recently, Guido et al. [11] proposed a matheuristic solution framework, named FiNeMath, that combined fix and relax heuristic and fix and optimize heuristic with the large neighborhood searches heuristic (LNS) to solve the PBAP model. Bastos et al. in [2], proposed an exact method to solve a MIP formulation of the PBAP. The designed approach generates new best solutions for 9 out of 13 tested benchmark instances with an important number of patients and different planning horizons.

In other studies, the authors were particularly interested in maximizing the number of admitted patients. To do so, they used the critical state of patient as a factor to select them from a waiting list. In [9], the authors proposed three values of clinical priority in their model for supporting week hospital management. Also, Legrain et al. [16] managed the access to a radiotherapy center by considering a high-priority and a low-priority patients classification.

To get closer to the real-life problems, many studies managed the dynamic PAS problem or PAS under uncertainty. The dynamic version of PBAP was introduced in [8], where the problem is dynamically solved by a metaheuristic method using daily rescheduling, considering urgent patients and uncertain LoS. Besides, Vancroonenburg et al. [31] studied PBAP in a dynamic context, by introducing an estimated LoS for each patient and proposing two ILP models; one considering only new patient arrivals and the other taking into account future planned arrivals. Schmidt et al. [25] developed a decision support system for bed management in hospital which considers patient priority, stochastic LoS, and dynamic adjustment of the plan in response to uncertainty. The problem is properly described through an ILP model, and an exact approach is compared with various heuristic strategies. Thomas et al. [28] proposed a decision support system to manage the PASP and the PBAP in real-time and flexible way; a user can specify whether bed attributes, gender and room-type requirements should be hard or soft constraints; hard constraints are on isolation requirements and capacity constraints.

Table 1 reports the main approaches used in the literature to deal with the PBAP.

Table 1. Overview of the PBAP addressed in the reviewed papers

Approaches	PBAP	
	Static	Dynamic
Tabu search	[10]	-
Simulated annealing	[7]	-
Hyper-heuristic	[6]	-
Exact method	[1]	[1]
Column generation	[22]	-
Biogeography Based Optimization	[12]	-
Fix-and-Relax+Fix-and-Optimize	[29]	-
LNS + Fix-and-Relax	[11]	-
Exact method	[2]	-
Simulated annealing	-	[8]
Exact methods	-	[25][28][31]

2.2. A review on the use of Simulated Annealing Approaches

Several heuristic algorithms have been proposed over years to solve the PBAP. Simulated Annealing is one of the most promising technique to date that obtain high quality solutions in small CPU time. We summarize in this part the main works based on SA approach and provide an overview of the various application areas of this heuristic.

The SA approach is based on a Monte Carlo model that was firstly used by Metropolis et al. [20] to simulate energy levels in cooling solids. In 1983, Kirkpatrick et al. [15] were the first to develop SA to solve combinatorial optimization problems. SA algorithms differs from each other with respect to the following factors: neighborhood search, cooling schedule and stopping criterion. As is shown in Table 2, many approaches based on SA metaheuristic with different parameters configuration, combined with many other well known heuristics, were proposed to solve problems for several domains.

In [23], [26] and [27] the authors combined the advantageous features of SA and TS to solve respectively the dynamic facility layout problem, vehicle routing problem and machine loading problem. For the dynamic shared-taxi problem, Jung et al. [14] developed a hybrid SA approach to dynamically assign passenger request. Hiermann et al. [13] proposed a SA hyper-heuristic approach to tackle a multimodal home-healthcare scheduling problem. In [19] and [21], the container stacking problem and the DFLP are solved by an efficient hybrid ant colony-SA algorithm. Lin et al. [17] present a new approach called the annealing-genetic algorithm for solving some well known optimization problems; (1) multiconstraint zero-one knapsack problem, (2) set partitioning problem and (3) traveling salesman problem.

Table 2. Overview of the SA approaches addressed in the literature

Approaches	Cooling schedule		Stop criteria		Initial solution
	Geometric	other	Max iteration	Min temperature	
SA + Tabu search [27]	-	✓	✓	-	Push-Forward Insertion
SA + Tabu search [26]	-	✓	✓	✓	Shortest processing time
SA + look-ahead / look-back [18]	✓	-	-	✓	Pairwise exchange
SA + Ant colony [19]	✓	-	✓	-	Ant colony
SA + Tabu search [23]	✓	-	✓	-	Random search
SA [24]	✓	-	✓	-	SA
SA + Ant colony [21]	✓	-	✓	-	Ant colony
SA + Genetic algorithm [14]	✓	-	✓	✓	Genetic algorithm
SA + Hyper heuristic [13]	-	✓	✓	-	Constraint programming
SA + Insertion heuristic [14]	✓	-	✓	-	Random search
SA + Genetic algorithm (This paper)	✓	-	✓	✓	Genetic algorithm

3. Problem statement

In this paper, we consider the static PBAP, in which only elective patients are treated. We present the fundamental aspects of the original problem provided by Demeester et al. in [10], and then reformulated by Ceschia and Schaerf [7] to model a simplified version that is commonly used.

For hospitalization, an admission date is fixed to the patient, based on the length of a waiting list. Nowadays, bad management needs very long waiting times when patient bed demand exceeds availability. PBAP consists of assigning set of patients to set of beds. The aim is to find a suitable bed for each patient.

For each patient, the admission and discharge dates, gender (male or female), age and speciality needed are known. Furthermore, in a hospital there is a set of beds, each bed is located in a particular room, and each room belongs to a particular department. The main characteristic of the room is its equipment, specialism it offers and capacity, which belongs to the number of available beds (single, double, etc.). Rooms have a gender policy; the gender of patients in the same room should obey the gender policy of the room. In addition, some departments (e.g. pediatrics, gerontology) have an age policy, which signifies that the department can only admit patients of a certain age. Each patient has to spend his/her period of hospitalization in not more than one room; the transfer of patient between rooms for all their LoS is not allowed.

Several constraints are applied in the process of assigning patients to room. They are classified as either hard or soft constraints. If the conditions on the variables are violated, a penalty is incurred in the objective function in order to limit violations of these constraints. We use the same constraint weights reported by Demeester et al in [10]. The objective is to optimize the overall patient assignment by respecting all the hard constraints to the problem and enhance the quality of the solution by minimizing the total sum of penalized violations. As defined in [7], the problem

includes one hard constraint; the room-capacity, and three soft constraints; (1) Room-gender, (2) patient-room cost that merges (departments, specialisms, room features, age, and preferences), and finally (3) patient-transfer constraint.

3.1. Mathematical formulation

The mathematical model of the problem adopted in this work refers to the reformulation of the PBAP proposed by Ceschia and Schaerf in [8]. We start by enumerating the notations that we use throughout the paper in Table 3.

Table 3. Notations used in the PBAP model

Symbols	Explanations
Sets/Parameters	
$p \in P$	Set of patients
$p \in P_M$	Set of male patients
$p \in P_F$	Set of female patients
$r \in R$	Set of rooms
$d \in D$	Set of planning days
D_p	Set of days in which the patient p is present in the hospital
$C_{p,r}$	Penalty of assigning patient p to room r
Cap_r	Number of beds available in a room r
W_{RG}	Weight of room gender policy constraint
W_{Tr}	Weight of transfer constraint
Decision variables	
$x_{p,r,d}$	1 if patient p is assigned to a bed in room r in day d , 0 otherwise
$t_{p,r,d}$	1 if patient p is transferred from room r in day d , 0 otherwise
$m_{r,d}$	1 if there is at least one male patient in room r in day d , 0 otherwise
$f_{r,d}$	1 if there is at least one female patient in room r in day d , 0 otherwise
$b_{r,d}$	1 if there are both male and female patients in room r in day d , 0 otherwise

• Objective function

Minimize the total penalties associated with assigning patients to rooms during their period of stay. Composed by three different cost components: (1) the cost of assigning patients to rooms with a combined penalty of constraints, then (2) the cost of violating the room gender policy, and (3) the cost associated with a transfer.

Minimize

$$\sum_{p \in P, r \in R, d \in D} C_{p,r} \cdot x_{p,r,d} + \sum_{r \in R, d \in D} W_{RG} \cdot b_{r,d} + \sum_{p \in P, r \in R, d \in D} W_{Tr} \cdot t_{p,r,d} \quad (1)$$

• Constraints

- Every patient should be assigned to one room.

$$\sum_{r \in R} x_{p,r,d} = 1, \forall p \in P, d \in D_p \quad (2)$$

- The number of patients assigned to room must not be greater than the number of available beds.

$$\sum_{p \in P} x_{p,r,d} \leq Cap_r, \forall r \in R, d \in D \quad (3)$$

- For each day, the gender of the patients in the same room should obey the gender policy of the room.

$$x_{p,r,d} \leq f_{r,d} \forall p \in P_F, r \in R, d \in D \quad (4)$$

$$x_{p,r,d} \leq m_{r,d}, \forall p \in P_M, r \in R, d \in D \quad (5)$$

$$m_{r,d} + f_{r,d} - 1 \leq b_{r,d}, \forall r \in R, d \in D \quad (6)$$

- Patients should not be transferred from one room to another.

$$x_{p,r,d} - x_{p,r,d+1} \leq t_{p,r,d}, \forall p \in P, r \in R, d \in D_p \quad (7)$$

4. A New Hybrid Simulated Annealing Approach

In this study, we propose a new hybrid simulated annealing approach to solve the PBAP. The purpose behind the hybridization of methods is to improve the performance of the solution approach to deal with complex problems, by combining their advantages and narrowing down their limits [4]. In the literature, the choice of approaches to combine depends of the desired effect. In our case, we choose to augment the simulated annealing with the genetic algorithm. In the remaining of this section, we briefly present the simulated annealing approach and the genetic algorithm. Then, we introduce the hybrid meta-heuristic algorithm proposed in this work.

4.1. Simulated annealing

SA is a generic probabilistic combinatorial search technique inspired by the physical process of annealing (melt a solid and cool it slowly) originated in statistical mechanics. Starting from an initial solution, a random neighborhood is generated. Neighborhoods that improve the cost function are always accepted. The main procedure consists of a loop that randomly generates, at each iteration, a neighboring solution of the current state and compute the difference in the objective function values. If the objective function value is improved, then replace the current solution by the new one, else, accept a move with probability. Once an equilibrium state is reached, the temperature is gradually decreased according to a geometric cooling schedule until reaching the minimum temperature level which represent the stopping criteria used in our approach. As any other optimization technique, SA has strengths and weaknesses. Among its strength points are the relative ease of implementation and the ability to provide reasonably good solutions for many combinatorial problems. But, if the temperature decreases too much, we can turn out in the case of local minimum. Besides, the quality of the final solution depends on the starting point.

4.2. Genetic algorithm

Genetic algorithm (GA) is a search heuristic that simulates the process of natural selection where the fittest individuals are selected for reproduction in order to produce offsprings of the next generation. GA is based on a set of genetic operators namely crossover, mutation, and selection used in creating the offspring of the next generation. Among its advantage comparing to SA, is the search from a rich database of populations instead of a single state that significantly reduce the probability of being blocked into a local minimum. And this is the reason for using it besides to several other solution approaches to enhance their performances [3][5]. However, its major limit is the premature convergence.

4.3. Hybrid simulated annealing

Hybrid algorithm combining SA and GA has been proposed to solve combinatorial optimization problems in the literature, such as the multiconstraint zero-one knapsack problem and the traveling salesman problem in [17]. In this study we also propose such a hybrid metaheuristic algorithm for the PBAP.

Our proposal HSA is motivated by the idea of improving the performance of SA by the advantages of the genetic algorithms. Thus, HSA starts working from a population, which takes the advantage from GA because searching from many states simultaneously is more efficient than searching from a single point. The process of this approach consists of combining GA with SA in an iterative manner. In the first phase, the genetic operators are used to evolve the population: GA generates a set of initial random solutions and then uses selection, crossover and mutation operators. The obtained solutions are then sent to the SA for further improvement. Because SA is a single-state method, it will be applied to each solution in the population. Once the SA is performed for all solutions of the GA, the best solutions obtained from SA are nominated for the next generation of GA. The algorithm continue until the minimum temperature stopping criteria is reached. The proposed method is given by algorithm 1.

Algorithm 1 Hybrid simulated annealing

Initialization: populationSize, $T_0 > 0$, T_{min} , α ; ($0 \leq \alpha \leq 1$)
 Randomly generate an initial population X_0
 Apply genetic operators to create X_1
 Calculate the fitness value and the cost for each solution in X_1
 $T \leftarrow T_0$
 $k \leftarrow 1$
while $T > T_{min}$ **do**
 $n \leftarrow 0$
 $CurrentSolution \leftarrow LowstCost$ in X_k
 while $n \leq populationSize$ **do**
 Pick a neighborhood solution $NewSolution$ from the $CurrentSolution$
 $\Delta C \leftarrow cost(NewSolution) - cost(CurrentSolution)$
 if $\Delta C \geq 0$ **then**
 $CurrentSolution \leftarrow NewSolution$
 else
 Generate a random number $r \in (0, 1)$
 if $min(1, \exp(-\Delta C/T)) > r$ **then**
 $X_k' \leftarrow NewSolution$
 $CurrentSolution \leftarrow NewSolution$
 end if
 end if
 $n \leftarrow n + 1$
end while
 Apply genetic operators to X_k' to create X_{k+1}
 Calculate the fitness value and the cost for each solution in X_{k+1}
if $LowstCost$ in $X_{k+1} < CurrentSolution$ **then**
 $CurrentSolution \leftarrow LowCost$ in X_{k+1}
end if
 $T_{k+1} = \alpha * T_k$
 $k \leftarrow k + 1$
end while

5. Computational experiments

In this section, firstly we introduce the benchmark instances and the experimental settings, then we present our experimental results. To prove the efficiency of our approach, our algorithm will be validated by the results obtained on several benchmark instances from the literature with small and large sizes.

5.1. Experimental Settings

The experiments are carried out on 13 existing benchmark instances provided in [6] and [7]. Instances from 1 to 7 have a planning horizon of 14 days, these instances are smaller compared to the instances from 8 to 13 with planning horizon between 21 to 91 days. The properties of the benchmark instances are given in Table 5. As is shown, there is a difference between the instances related to their structure. Instances from 1 to 6 are characterized by the homogeneity of the rooms, with a few different room features and patient number. Unlike instances from 7 to 13, that are characterized by heterogeneous situations, with several number of patients. For the instance 13, patients have multiple specialisms; he/she can be assigned to different specialism during a patient's stay. The parameters configuration of SA and GA are shown in what follows.

Table 4. Parameters configuration

	Parameters	Values
GA	Population size	100
	Crossover rate	0.8
	Mutation rate	0.05
SA	Start temperature T_0	1000
	Stop temperature T_{min}	0.01
	Cooling rate α	0.94

Table 5. Characteristics of the benchmark instances

Instance	#Beds	#Patients	#Rooms	#Departments
1	286	652	98	14
2	465	755	151	14
3	395	708	131	14
4	471	746	155	14
5	325	587	102	14
6	313	685	104	14
7	472	519	168	14
8	441	895	148	21
9	310	1400	105	28
10	308	1575	104	56
11	318	2514	107	91
12	310	2750	105	84
13	368	907	125	28

5.2. Experimental results

In this section, we report and discuss the results of the computational experiments carried out on the benchmark instances reported in Table 5. We conduct an experimental comparison between SA and the HSA in order to improve the quality of the found solutions and test the efficiency of the proposed method to solve the PBAP.

It is evident from Table 6 that HSA outperforms the classic SA. With most datasets, the proposed HSA algorithm is showing a good performance and giving the highest satisfaction and lowest cost values in many cases. The proposed approach presents two main steps; search by the annealing and evolution by the genetic operators. The initial cost of each instances is the cost of a random assignment. Our proposal gives better results compared to the results of SA for those sets of instances, with an average improvement of 2.7% even on solving instances from 8-13 which are characterized by a significantly higher number of patients and considerably longer planning periods.

For the PBAB, we can see that combining the features of GA with those of SA helped to improve the performance of SA and allowed HSA to obtain better results on all instances, with an average improvement of 2.55% with the small instances (1-7), and 2.88% improvement with the larger instances (8-13).

With regards to the computation time, our algorithm solved the problem in a very acceptable CPU times depending on the dataset size. Besides, the CPU time is not adopted as an important criterion to address the performance of algorithm because the whole decision-making and planning exercise are of an offline type. However, the computational time depends on the coding and structure of the program. A better configuration of the parameters of T_0 ; T_{min} ; population size; and generation size would reduce the CPU time of the algorithm.

Table 6. Comparison of the experimental results obtained by SA and HSA

Instance	Simulated annealing		Hybrid simulated annealing		Improvement (%)
	Time (s)	Cost	Time (s)	Cost	
1	7.0	602.0	16.0	602.0	0
2	50.0	1065.0	67.3	1002.5	5.5
3	13.4	709.2	24.0	680.6	4.0
4	17.8	1012.0	32.6	995.3	1.6
5	8.6	594.3	19.0	576.0	3.1
6	10.5	724.0	21.3	705.2	2.5
7	2.4	635.0	6.0	641.3	0
8	4.9	2489.0	12.7	2396.3	3.7
9	6.2	9926.0	15.0	9896.6	0.3
10	5.0	6595.0	13.6	6263.8	5.0
11	8.2	7565.0	18.6	7634.4	0
12	9.3	11769.3	21.0	11261.4	4.3
13	5.8	3267.8	14.5	3169.1	2.9

6. Conclusion and future work

The PBAP is a challenging problem that points out the assignment of patient to beds while satisfying their preferences and ensuring their comfort. In this paper, we proposed a hybrid simulated annealing algorithm for the patient bed assignment problem with the objective of minimizing the total penalty cost of different soft constraints. The idea is to improve the results provided by the SA through integrating a seeding step that prepares the initial solution using the genetic operators. The key property of this approach is the merge of the advantages of GA and SA. Using computer simulations on various benchmark instances, it was shown that the proposed algorithm outperforms significantly the classic SA. The results obtained by this new approach are promising and improve in a considerable way the best known results. Future works will investigate the online patient bed assignment problem while considering real-time requests, refining our model and testing the proposed metaheuristic on more large scale instances.

References

- [1] Rym Ben Bachouch, Alain Guinet, and Sonia Hajri-Gabouj. An integer linear model for hospital bed planning. *International Journal of Production Economics*, 140(2):833–843, 2012.
- [2] Leonardo SL Bastos, Janaina F Marchesi, Silvio Hamacher, and Julia L Fleck. A mixed integer programming approach to the patient admission scheduling problem. *European Journal of Operational Research*, 273(3):831–840, 2019.
- [3] Hajer Ben-Romdhane and Saoussen Krichen. An adaptive approach for monitoring evolutionary algorithms behavior for dynamic environments. *The 2018 Conference on Artificial Life: A Hybrid of the European Conference on Artificial Life (ECAL) and the International Conference on the Synthesis and Simulation of Living Systems (ALIFE)*, (29):460–466, 2017.
- [4] Hajer Ben-Romdhane, Enrique Alba, and Saoussen Krichen. Towards a dynamic modeling of the predator prey problem. *Applied Intelligence*, 44(4):755–770, 2016.
- [5] Hajer Ben-Romdhane, Saoussen Krichen, and Enrique Alba. A bi-population based scheme for an explicit exploration/exploitation trade-off in dynamic environments. *Journal of Experimental & Theoretical Artificial Intelligence*, 29(3):453–479, 2017.
- [6] Burak Bilgin, Peter Demeester, Mustafa Misir, Wim Vancroonenburg, and Greet Vanden Berghe. One hyper-heuristic approach to two timetabling problems in health care. *Journal of Heuristics*, 18(3):401–434, 2012.
- [7] Sara Ceschia and Andrea Schaerf. Local search and lower bounds for the patient admission scheduling problem. *Computers & Operations Research*, 38(10):1452–1463, 2011.
- [8] Sara Ceschia and Andrea Schaerf. Modeling and solving the dynamic patient admission scheduling problem under uncertainty. *Artificial intelligence in medicine*, 56(3):199–205, 2012.
- [9] Domenico Conforti, Francesca Guerriero, Rosita Guido, Marco Matucci Cerinic, and Maria Letizia Conforti. An optimal decision making model for supporting week hospital management. *Health care management science*, 14(1):74–88, 2011.
- [10] Peter Demeester, Wouter Souffriau, Patrick De Causmaecker, and Greet Vanden Berghe. A hybrid tabu search algorithm for automatically assigning patients to beds. *Artificial Intelligence in Medicine*, 48(1):61–70, 2010.
- [11] Rosita Guido, Maria Carmela Groccia, and Domenico Conforti. An efficient matheuristic for offline patient-to-bed assignment problems. *European Journal of Operational Research*, 268(2):486–503, 2018.
- [12] Abdelaziz Hammouri and Basem Alrifat. Investigating biogeography-based optimisation for patient admission scheduling problems. *Journal of Theoretical & Applied Information Technology*, 70(3), 2014.

- [13] Gerhard Hiermann, Matthias Prandstetter, Andrea Rendl, Jakob Puchinger, and Günther R Raidl. Metaheuristics for solving a multimodal home-healthcare scheduling problem. *Central European Journal of Operations Research*, 23(1):89–113, 2015.
- [14] Jaeyoung Jung, R Jayakrishnan, and Ji Young Park. Dynamic shared-taxi dispatch algorithm with hybrid-simulated annealing. *Computer-Aided Civil and Infrastructure Engineering*, 31(4):275–291, 2016.
- [15] Scott Kirkpatrick, C Daniel Gelatt, and Mario P Vecchi. Optimization by simulated annealing. *science*, 220(4598):671–680, 1983.
- [16] Antoine Legrain, Marie-Andrée Fortin, Nadia Lahrichi, and Louis-Martin Rousseau. Online stochastic optimization of radiotherapy patient scheduling. *Health care management science*, 18(2):110–123, 2015.
- [17] Feng-Tse Lin, Cheng-Yan Kao, and Ching-Chi Hsu. Applying the genetic approach to simulated annealing in solving some np-hard problems. *IEEE Transactions on systems, man, and cybernetics*, 23(6):1752–1767, 1993.
- [18] Alan R McKendall Jr, Jin Shang, and Saravanan Kuppusamy. Simulated annealing heuristics for the dynamic facility layout problem. *Computers & operations research*, 33(8):2431–2444, 2006.
- [19] Alan R McKendall Jr, Jin Shang, and Jin Shang. Hybrid ant systems for the dynamic facility layout problem. *Computers & Operations Research*, 33(3):790–803, 2006.
- [20] Nicholas Metropolis, Arianna W Rosenbluth, Marshall N Rosenbluth, Augusta H Teller, and Edward Teller. Equation of state calculations by fast computing machines. *The journal of chemical physics*, 21(6):1087–1092, 1953.
- [21] Riadh Moussi, Jalel Euch, Adnan Yassine, Ndèye Fatma Ndiaye, et al. A hybrid ant colony and simulated annealing algorithm to solve the container stacking problem at seaport terminal. *International Journal of Operational Research*, 24(4):399–422, 2015.
- [22] Troels Martin Range, Richard Martin Lusby, and Jesper Larsen. A column generation approach for solving the patient admission scheduling problem. *European Journal of Operational Research*, 235(1):252–264, 2014.
- [23] Ramazan Şahin and Orhan Türkbey. A new hybrid tabu-simulated annealing heuristic for the dynamic facility layout problem. *International Journal of Production Research*, 47(24):6855–6873, 2009.
- [24] Ramazan Şahin, Kadir Ertoğral, and Orhan Türkbey. A simulated annealing heuristic for the dynamic layout problem with budget constraint. *Computers & Industrial Engineering*, 59(2):308–313, 2010.
- [25] Robert Schmidt, Sandra Geisler, and Cord Spreckelsen. Decision support for hospital bed management using adaptable individual length of stay estimations and shared resources. *BMC medical informatics and decision making*, 13(1):3, 2013.
- [26] Rahul Swarnkar and MK Tiwari. Modeling machine loading problem of fmss and its solution methodology using a hybrid tabu search and simulated annealing-based heuristic approach. *Robotics and Computer-Integrated Manufacturing*, 20(3):199–209, 2004.
- [27] Sam R Thangiah, Ibrahim H Osman, and Tong Sun. Hybrid genetic algorithm, simulated annealing and tabu search methods for vehicle routing problems with time windows. *Computer Science Department, Slippery Rock University, Technical Report SRU CpSc-TR-94-27*, 69, 1994.
- [28] Bex George Thomas, Srinivas Bollapragada, Kunter Akbay, David Toledano, Peter Katlic, Onur Dulgeroglu, and Dan Yang. Automated bed assignments in a complex and dynamic hospital environment. *Interfaces*, 43(5):435–448, 2013.
- [29] Aykut Melih Turhan and Bilge Bilgen. Mixed integer programming based heuristics for the patient admission scheduling problem. *Computers & Operations Research*, 80:38–49, 2017.
- [30] W Vancroonenburg, D Goossens, and FCR Spijksma. On the complexity of the patient assignment problem. *Tech. rep., Tech. rep.*, 2011.
- [31] Wim Vancroonenburg, Patrick De Causmaecker, and Greet Vanden Berghe. Patient-to-room assignment planning in a dynamic context. In *Proceedings of the 9th International Conference on the Practice and Theory of Automated Timetabling (PATAT-2012)*, pages 193–208. Citeseer, 2012.