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Biogeography Based Optimization with Guided Bed Selection Mechanism for Patient Admission Scheduling Problems

[1]Abdel Aziz I. Hammouri, [2]Mohammed Alweshah,
[3]Essa Abdullah Hezzam and [1]Mohammed Asmaran
[1]Department of Computer Information Systems,
[2]Department of Computer Science, Al-Balqa Applied University, Al-Salt, Jordan
[3]College of Computer Science and Engineering, Taibah University,
Madina al Munawwara, Saudi Arabia

Abstract: This study derives its work from aninterest in the development of an automated approach to tackle highly constrained Patient Admission Scheduling Problems (PASP). It is concerned with an assignment of patients to bed in an appropriate department in such away it can maximize medical treatment effectiveness andpatient's comfort. In this study we have investigate anewly created meta-heuristic optimization algorithm, called Biogeography Based Optimization (BBO) based onthe idea of migration of species between different habitats. We have integrate the BBO algorithm with aguided bed selection mechanism. The performance of the proposed approach is verified using standard bench mark datasets. Experimental results show that the BBO with aguided bed selection mechanism is able to obtain better results than the BBO with a random bed selection mechanism and is able to obtain a competitive results when compared to other approaches in the literature.

Key words: Timetabling, patient admission scheduling, healthcare, meta-heuristic, evolutionary algorithms, biogeography based optimization

INTRODUCTION

The central admission unit in health care organizations is responsible for the process of allocating hospital beds to the patients waiting inthe system. This unit is responsible for maximizing the resource usage and at the same time minimize the duration of each patient stay (Vissers *et al*., 2007; Gemmel and Dierdonck, 1999). However, there are different types of patients that arrive at the hospital. Some of them are in a critical condition and may need immediate attention. While, adding others to a waiting list until, a suitable and emptybed found. The occupying of beds operation is subjected to some constraints concerning to the medical equipment in the room, the medical skills of the department staff and the patient's room preference (Demeester *et al*., 2010). Thus, making the task of assigning patients to bed very difficult and in need of a good knowledge and experience (Ayvaz and Huh, 2010) otherwise it will lead to inefficiencies of the social benefits and/or monetary gains. Patient admission problems are atype of scheduling problems. Wren (1996) defines scheduling as: "the arrangement of objects into a pattern in time or space in such a way that some goalsare achieved or nearly achieved and those constraints on the way objects may bearranged are satisfied or nearly satisfied" Pinedo (1995) defines scheduling as: "scheduling concerns the allocation of limited resources to tasks over time, it is adecision-making process that has as a goal the optimization of one or more objectives". Hence, researchers have given prominence to complex evolutionary methods, inspired by biological processes and evolution and devised from the analogy of natural evolution and biological activities. These complex methods include: Genetic Algorithms (Gas) Differential Evaluation (DE) (Slowik and Bialko, 2008) Ant Colony Optimization (ACO) (Socha and Blum, 2007) Particle Swarm Optimization (PSO) (Alrifai *et al*., 2014; Hammouri *et al*., 2013) Electro magnetism-like Mechanism (EM) algorithm (Wang *et al*., 2008) Harmony Search (HS) algorithm and many others (Kattan and Abdullah, 2011; Kawam and Mansour, 2012; Hammouri and Abdullah, 2014). Inspired by biogeographic concepts, Biogeography Based Optimization (BBO) is anevolutionary algorithm and meta-heuristic. The key motivation of this study is to optimize the performance of the classification system by finding optimal values for the weights obtained from the PNN.

The contribution of this study is to employ the BBO algorithm in addressing the patient admission problem. BBO is a newly created population basedmeta-heuristic algorithm, based on the idea of the migration of species

Corresponding Author: Abdel Aziz I. Hammouri, Department of Computer Information Systems, Al-Balqa Applied University, Al-Salt, Jordan

between different is lands. We embedded BBO with a guided bed selection mechanism. Experimental results show that the BBO with a guided bed selection mechanism isable to obtain better results than the BBO with arandom bed selection mechanism and competitive with state-of-the-art.

Biogeography based optimization: Biogeography is natural method in distribution species where different geographical areas areconsider as good habitat if they have high "Habitat Suitability Indexes" (HSI). These areas arecharacterized by number of independent variables (features) like temperature, rainfall, diversity of topographic features and diversity of vegetation, known as "Suitability Index Variables" (SIVs). The Habitat Suitability Index (HSI) meanwhile is adependent variable. BBO was first introduced by Simon (2008) in which species move from one is land to another looking for a good habitat. In BBO, the Habitat Suitability Index (HSI) shows the degree of its goodness of the solutions where the high HSI habitat represents agood solution and the low HSI habitat, represent apoor solution. Poor solutions accept many changes by inheriting the good features from good solutions. This operation known as migration operation can improves the quality of the poor solution as much as possible. In addition, BBO has other operation known as the mutation operation that can modify one or more solution feature(s) randomly based on the pre-calculated probability value, increasing the diversity between the solutions in the population.

Simon (2008) has illustrated how to use the principle of biogeography to design and implement the algorithms. The researcher has applied the algorithmon real life problem (sensor selection problem for aircraft engine health estimation) and on 14 benchmark functions. The comparisons with other algorithms have shown an outstanding performance of BBO over the other algorithms in both experiments (real life problem and bench mark functions). Other applications of BBO can befound in as sensor selection (Simon, 2008) scheduling problem (Rahmati and Zandieh, 2012; Yin and Li, 2011) image segmentation (Chatterjee *et al*., 2012) satellite image classification (Panchal *et al*., 2009) feature extraction (Panchal *et al*., 2009) optimal meter placement (Jamuna and Swarup, 2011) ground water detection (Panchal *et al*., 2009) parameter estimation (Wang and Xu, 2011) and power system optimization (Rarick *et al*., 2009; Roy *et al*., 2009; Bhattacharya and Chattopadhyay, 2011). To our knowledge this will be the first time that BBO algorithm used on the patient admission-scheduling problem.

Patient Admission Scheduling (PASP): The basic elements of the problem at hand are patients, rooms, departments and timeslots (night). Each patient has a specific treatment requirements (in terms of nursing and medical equipment) gender, age category, room preference and the firstday and the duration of his/her stay. The duration sare known in advance and are not changed duringthe stay. Each room has existing medical equipment, the number of beds and the department associate with it. Each department defines the treatment that the rooms are equipped. A time slot corresponds to a night. The plan horizon is corresponding to the set of all timeslots. The objective is to optimize the overall patient assignment, i.e., satisfy the patient preferences, while respecting all the hard constraints to the problem. Hard constraints need to be satisfied. The hard constraints involve are:

- Maximum one patient per bed-timeslot
- The admission and discharge dates are known in advanced and fixed
- The length-of-stay for each patient iscontiguous
- The patient must be assigned to a bed foreach timeslot during of his stay in thehospital
- For each night, the number of patients in aroom cannot exceed its capacity

The quality of a solution is determined by theviolation of the soft constraints. Soft constraints areapplied either to patients or to rooms or to patients and rooms at the same time. The objective function is the weighted sum of all the violations of the soft constraints. This problem tries to minimize the violation of the soft constraints. Soft constraints involve are:

- Patients in the same room-time slot should have the same gender
- The number of room transfers should be minimized
- The ward of the patient should satisfy the requirement of his/her pathology
- The room of the patient should besatisfied the mandatory/preferred requirements of his/her pathology
- The room of the patient should satisfy the specialism of his/her pathology
- The room preference of the patient should be satisfied

To increase the complexity of the problem we changed the first soft constraint to be an additional hard constraint. In this case, the problem is treated as in (Ceschia and Schaerf, 2011, 2009). It makes the search space smaller. However, (Bilgin *et al*., 2012; Demeester *et al*., 2010; Hammouri and Alrifai, 2014) maintained the hard and soft constraints as in the original problem.

In this research we used the original published dataset (Bilgin *et al*., 2012) which consists of 6 instances. The mathematical formulations for PASP and the features of the datasets can be found in (Bilgin *et al*., 2012). Note that the patients that have the same admission and discharge date and the patients admitted after the planning horizon are not included in this problem.

MATERIALS AND METHODS

Proposed method: Our proposed method starts with the feasible "initial solutions" and then having those solutions improved by BBO algorithm. The initial solutions generated are as follow: randomly assigning the patients to the available beds and then adding or removing operators until a feasible solution found. The details of the proposed method are as presented and outlined in the next subsections.

Solution representation: The solution is represented as a two dimensional matrix where the number of columns is equal to the planning horizon and the number of rows is equal to the number of beds in all departments (as shown in Fig. 1 the rows represent the beds and the columns represent the nights. The entries of the matrix represent the patient ID. This representation helps in not violating two of the five hard constraints, i.e., maximum one patient perbedtime slot (HD1) and the number of patients per night in the room cannot exceed its capacity (HD2).

Neighbourhood structure: In this study, we use three neighborhood structures as follows:

- Nbs1 (move): move one patient is selectedat random and move to a new bed randomly
- Nbs2 (swap): choose two patients and swap the beds
- Nbs3 (swap and move): as in Nbs2 but if the suitable length of stay cannot be found from the swap operation, patient will then moved to other new random bed

Note that the neighborhood structures are applied during the mutation operation and repair mechanism. The details of each neighborhood structures are as follows.

Nbs1; move operation: In move operation, assume that we want to move patient P1 from bed B2 to a new bed select atrandom. In this case, move the patient P1 with 4 nights stay to a new bed that can cover all stays (B3 in this example). If bed B3 already has occupied patient then release the patient in B3 and move P1to B3. Later, find a new bed for the patient that earlier bedded in B3. Figure 2 shown the previous example.

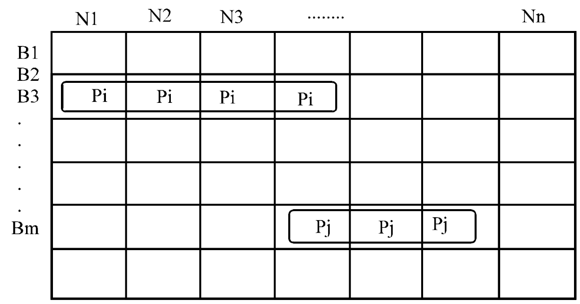

Fig. 1: The solution representation matrix

Nbs2; swap operation: In swap operation, two patients are selected atrandom (assume P2 and P3) and the stay period ofthe two patients must have at least one intersection. Swap the beds accordingly, i.e., P2 (from the last bed Bm) is moved to bed B4 and P3 from B4 is moved to the last bed. Figure 3 shown the previous example.

Nbs3; swap and move operations: In swap and move operations, two patients areselected at random (assume P1 and P3) and swapthe beds. In this case, P1 is now in B4 but P3 cannot be in B2 because it will violate the hardconstraint (i.e., two patients in one bed) where P3 and P4 will be together in B2 at night Nn-1. Thus, P3 needs to be moved to other available bed at random i.e., B1 in this example, instead of B2 inorder to obtain a feasible schedule. Figure 4 shown the previous example.

The algorithm: In the previous research Hammouri and Alrifai (2014), the BBO algorithm hasbeen applied with Random Bed Selection mechanism (BBO-RBS) for solving PASP. Experimental results showed that BBO-RBS is no table to produce favorable results in comparison with state-of-the-art. Thus, in this study we embedding a guided bed selection mechanism with the BBO algorithm in order to improve the quality of the solutions the BBO algorithm in order to improve the quality of the solutions as explained in study. The BBO-RBS algorithm has been presented in Fig. 2.

BBO with random bed selection (BBO-RBS): The pseudo code of the BBO algorithm. The solutions then sorted in as cending order (with respect to the quality of the solution). After that the immigration rate (λ) and emigration rate (μ) are calculated based on the following two equations (Simon, 2008):

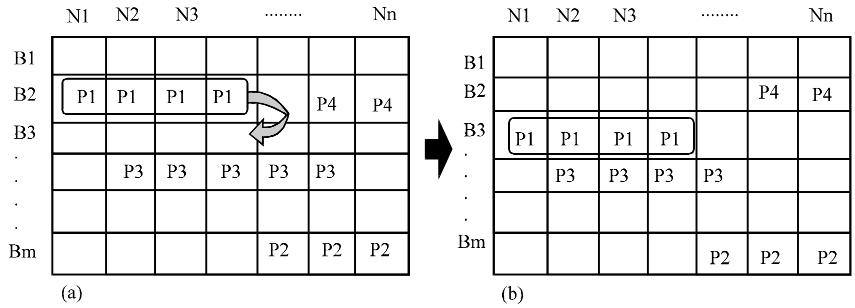

Fig. 2: The neighborhood structure-Nbs1: a) Before move and b) After move

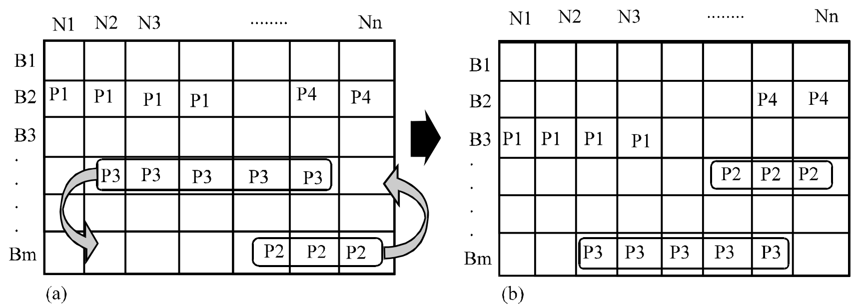

Fig. 3: The neighborhood structure-Nbs2: a) Before swap and b) After swap

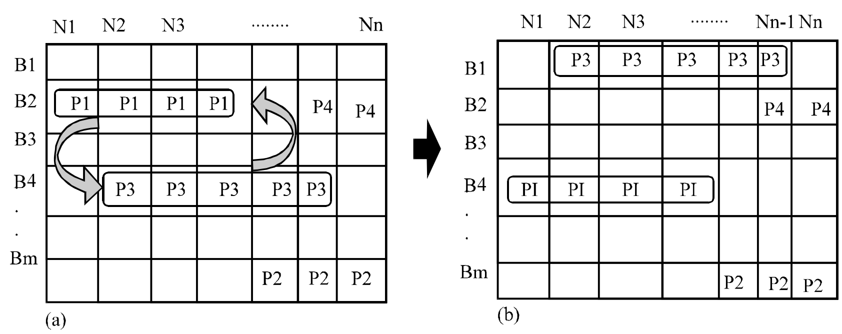

Fig. 4: The neighborhood structure-Nbs3: a) Before swap move and b) After swap move

$$\lambda_i = I(1 - \frac{K_i}{n}) \quad (1)$$

$$\mu_i = E(\frac{K_i}{n}) \quad (2)$$

Where:

n = The population size

K_i = The rank of solution i (the first solution is the best and has the highest rank and the last solution is the worstand has the lowest rank)

I and E = The maximum immigration rate

The maximum emigration rate respectively where the default value for them is 1. The migration operation then performed inorder to improve the quality of the solutions. The migration operation used to migrate solution's features (SIV) from the good solutions (high HSI) to the poor ones (low HSI). In the case of anunfeasible solution, a repair function will be performed to bring the unfeasible solution back to feasibility. All the solutions in the population will have the mutation operation performed on them where one of the first two neighborhood structures (Nbs1 or Nbs2) will berandomly selected for each solution and if the second neighborhood structure (Nbs2) failed, then the third neighborhood structure (Nbs3) is chosen. The population is finally, updated by replacing the worst solution with the best found.

BBO with guided bed selection (BBO-GBS): The guided bed selection mechanism is used within the neighborhood structure in the BBO algorithm. For each patient we created three groups of beds. To do this we sort the beds in an ascending order based on the penalty of transferring the patient from the current bed to a new bed. Later the listdivided into three possible equal parts. Algorithm shows the pseudo code of the guided bed selection.

The Guided Bed Selection (GBS) mechanism used by the neighborhood structure when selecting a new bed for patient is where the GBS mechanism tries to find bed in the first group of beds. If it fails it then tries to find bed from the next group and soon. The search performed in each group as follows: firstly, a random bed index selected (Starting Bed Index). If the bed is suitable/available for the patient then it will be reserved. Otherwise, the search is sequentially performed until the end of the group. If no bed is available (from Starting Bed Index to the last index in the group) then the search continues from the first index of the group (to the starting bed index) in order to coverall the indexes in the group. This search mechanism helps to avoid the duplicate selection of the same bed several times as well as the use of a random starting bed index to get the advantage of keeping some degree of randomness in the search operation.

Algorithm 1 (The pseudo code of the BBO algorithm 1):

```
maxGen←the max number of generation (Iteration)
popSize←the population Size
Population←{} // create empty population
Best←∅
num Of SIV→the number of patients
For I = 1:popSize
      Population←Population U new random solution
End for
For gIndx = 1: maxGen
Sort (Population )//based on the quality
Best←Population (1)//the first solution in the population
For i = 1:popSize
   Calculate the value of immigration rate (λ) and emigration rate (μ) base
on Eq. 1 and 2, respectively.//execute the migration operation on Population
(i)
    Si ← Population(i) //current solution
    Select a Random number R between 0 and 1If R < λi then
   For k=1: numOfSIV // SIVk represent the k th Patient in Solution.
   Select another solution (lets say Sj) using a roulette wheel selection
 with a probability proportional to μj migrate the current SIVk from Sj to Si
    End for
    If Si is not feasible then
            apply a repair mechanism // as in section 4.4
  end if
 End if
End for
For I=1:popSize
 //execute the mutation operation on Population(i)
   Si ← Population(i)  //current solution
   Select a Random number R between 0 and 1
   If R < 0.5 then // we use 0.5 to select one of the first two neighborhood
structure with an equal chance
   Select random patient P and random Bed B from Si
   Execute Nbs1: move( P, B )
Else
  Select two random patients P1 and P2 from Si
  // with overlapping in staying period
  Execute Nbs2: swap( P1 , P2 )
  If the above swap is failed then
    Execute Nbs3: Swap And Move( P1, P2 )
 End if
End if
End for
Sort (Population) // based on the quality
If Population (popSize) > Best //if last solution worst
   Population(popSize)← Best //than Best solution
 End if //then replace it with the Best one
End for
Sort ( Population ) // based on the quality
return Population(1)//return the first solution in the population (Best
Solution)
```

Algorithm 2 (Guided bed selection pseudo code):

```
Input: patient Id#
Output: Bed Id#
For Li = 1-3
   // Li : is the list index of three groups of bed
 StartingBedIndex = random [ 1, size(List(Li))]
For i = 1 to size(List(Li))
   // the following equation is used to deal with
   // list as circular list
 //Bi: is the bed index in the list
Bi = ( i + StartingBedIndex ) modulus (size(List(Li)))
if bed (Bi) is available and
      can be reserved for the patient then
            return bed (Bi)
End if
 End for
End for
```

Repair mechanism: A repair mechanism employed to ensure the feasibility of the solutions after the migration operation where the migration operation leads insome cases to unfeasibility. The repair mechanism works by reassigning the patients that violate the hard constraints to a new bed that satisfies all thehard constraints. This process is repeated until the feasible solution is found (satisfies all the hard constraints for all patients).

RESULTS AND DISCUSSION

Experimental results: The proposed algorithm was implemented using Java and simulations were performed on Core TMi3-4130 (CPU 3.4 GHz) PC with 4GB RAM. We executed the experiments for 10 independent runs. The termination criterion is set as the maximum number of iterations which is equal to 2000 that caused the running time from 593-946 sec for BBO-RBS and from 672-1201 sec for BBO-GBS. Note that in the competition, the maximum running time to set to 3000 seconds. Based on our preliminary experiments, our algorithm reached the stagnant state at earlier time in the search process (within the first 500 iterations) which need about 150-250 sec in most of the cases. Thus, it is of no significance toprolong the search to 3000 sec. Table 1 shows the parameter setting for the proposed algorithm which were determined after some preliminaryexperiments.

Comparisons between variants of BBO: Table 2 shows the results of the results of Minimum (Min) Maximum

Table 1: Parameter settings of the proposed algorithm

Parameters	Values
Population size	50.000
Mutation rate	0.001

Table 2: Experimental results of the comparisons between variants of BBO

	BBO-RBS			
Instance No.	Min	Avg.	Std.	Time
1	1233.4	1312.8	59.5	686.3
2	2027.0	2088.9	60.4	945.7
3	1385.2	1433.7	41.7	790.0
4	2211.0	2301.5	69.9	902.5
5	800.8	828.9	28.3	592.6
6	1283.2	1317.1	37.9	684.7
BBO-GBS				
1	850.6	878.3	35.2	672.4
2	1418.4	1460.6	43.3	1210.0
3	962.6	976.4	10.4	1047.8
4	1610.6	1636.2	16.2	1201.2
5	714.3	729.2	12.7	774.4
6	1004.4	1027.8	27.2	946.3

Table 3: p-values obtained between different version of the algorithms

Instance No.	BBO-RBS vs. BBO-GBS
1	0.0007
2	0.0002
3	0.0003
4	0.0000
5	0.0000
6	0.0000

Table 4. Comparisons with state-of-the-art

	BBO-GBS		
Instance No.	Min.	Avg.	Std.
1	850.6	878.30	35.2
2	1418.4	1460.6	43.3
3	962.6	976.40	10.4
4	1610.6	1636.2	16.2
5	714.3	729.20	12.7
6	1004.4	1027.8	27.2
GD (Panchal *et al.*, 2009)			
1	830.36	N/A	18.8
2	1382.28	N/A	14.2
3	923.16	N/A	20.7
4	1608.68	N/A	29.2
5	661.52	N/A	4.0
6	955.04	N/A	20.1
SA (Rahmati and Zandieh, 2012)			
1	659.2	665.610	33.2
2	1143.6	1150.96	53.8
3	776.6	786.670	57.1
4	1176.0	1190.58	86.4
5	625.6	631.870	24.6
6	801.2	811.180	62.2

(Max), Average (Avg), Standard Deviation (Std) and CPU time of the best result (Time) in seconds out of 10 runs. The best results presented in bold.

As shown in Table 2, we can deduce that the BBO-GBS algorithm out performs the BBO-RBS algorithm in comparisons on all the instances interms of the penalty cost. The comparisons in terms of the computational time shows that the BBO-RBS takes less computational time compared to BBO-GBS. This can be due to the reason that the guided bed selection mechanism enforces the selection of the bed with low penalty cost (that starts with the first group of bed, followed by the second group and the last group) which will ofcourse takes a longer time than the random bed selection. However, the guided bed selection mechanism leads to better solution.

Figure 5 shows almost the same trend of best solutions found during the search, indicating that the algorithm works similarly on the different datasets, despite the differences in the complexity of the parameter value Population size 50 Mutation rate 0.001 datasets and the landscape of the search space. In most cases, the BBO algorithm reaches the stagnant state after the first 300 iterations as shown clearly in the algorithm 1 about 95% of the improvements in BBO obtained within the first 500 iterations and about 98% of the improvements achieved withinthe first 1000 iterations. In addition, the guided bed selection mechanism improves the quality of thesolution in between 25-30% for all instances (except for instance 5 where it is about 12%). It observed clearly that the BBO-GBS is much better than BBO-GBS Fig. 5.

We executed a statistical test to examine if there isany significant difference between the proposed algorithms here with the significance interval of 95% (α = 0.05).We execut e a comparison between"BBO with random bed selection " and "BBO withguided bed selection " (coded as BBO-RBS vs.BBO-GBS). Table 3 shows the p-values for thetested instances where the presented p-values indicate enough evidence to conclude that there are significant differences between the algorithms in comparisons ($p<0.05$).

Comparisons with the state-of-the-art: In this study, we compare our best results (obtained from BBO-GBS) with other availableapproaches in the literature as shown in Table 4. The algorithms in comparison are Great Deluge (GD) (Panchal *et al.*, 2010) and Simulated Annealing (SA) (Rahmati and Zandieh, 2012). Thebest results are in bold.The best results highlighted in bold. We can clearlysee that SA outperformed the other approaches incomparisons. However, our approach still needsmore improvement in order to outperform the otherapproaches in the literature. We believed that SAcan achieved better solutions, since their approach allows the flexibility of jumping from unfeasible tofeasible regions during the search processes. Our approaches however, only deal with feasible solution that limits the search in search space.

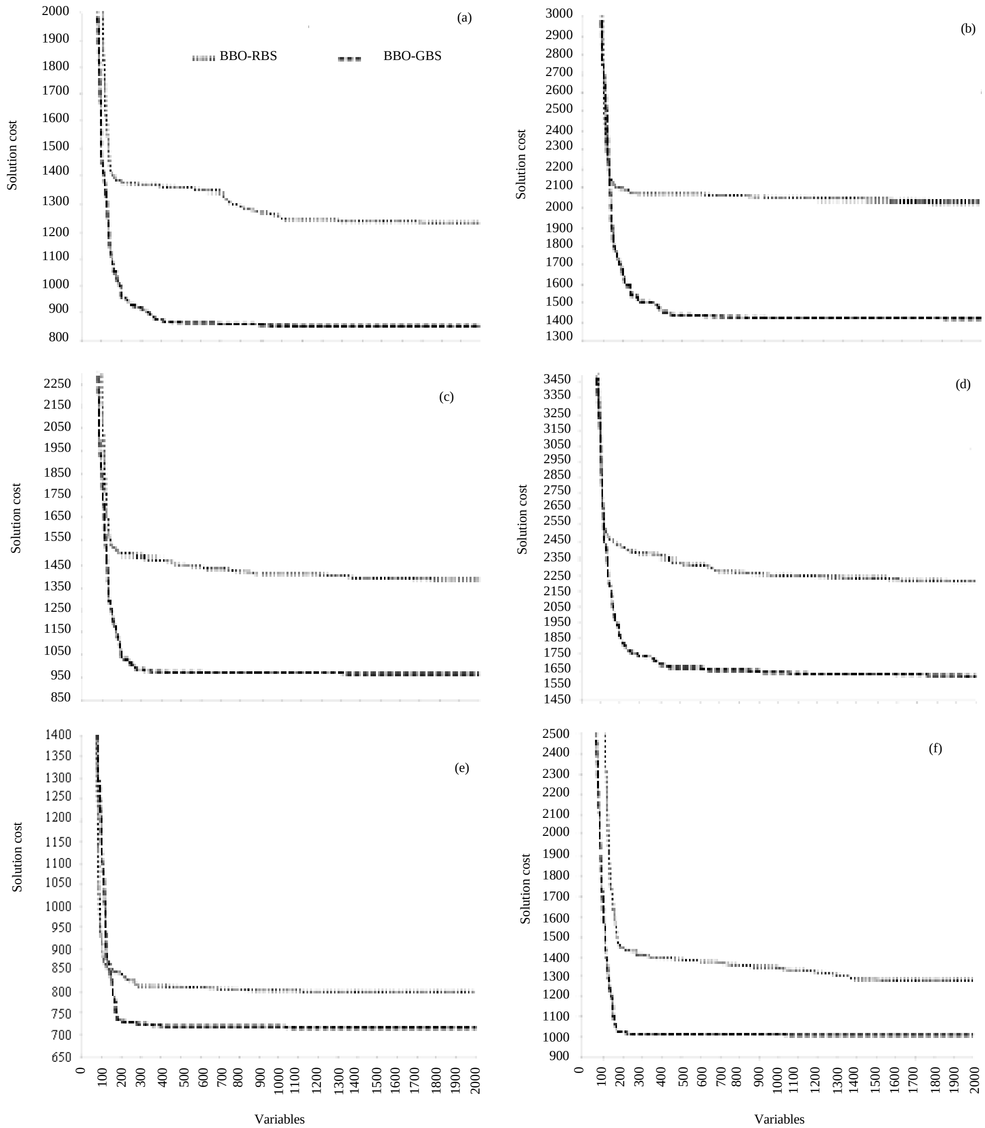

Fig. 5: The best solution found in each of the itratiob (for instances from 1-6): a) Instance 1; b) Instance 2; c) Instance 3; d) Instance 4; e) Instance 5; f) Instance 6

CONCLUSION

In this study, we have presented a search methodology that combines the principle of the geography theories, i.e., biogeography based optimization. We proposed a new version of the BBO coded as BBO-GBS. The performance of the approach rigorously tested on 6 bench mark datasets of patient admission scheduling problem. Experimental results show that BBO-GB sout performed the BBO-RBS. This indicates the importance of using the GBS mechanism with BBO in finding (near) optimal solutions for the PASP. Moreover, BBO-GBS is able to produce favorable results in comparison with state-of-the-art with lesser computational time. However, the proposed approach shows that it reached the stagnant state at the early of the search. We believed that this needs further investigations. This will be the subject of our future work.

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