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INVESTIGATING BIOGEOGRAPHY-BASED OPTIMISATION FOR PATIENT ADMISSION SCHEDULING PROBLEMS

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ABSTRACT

This paper derives its work from an interest 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 a way it can maximise medical treatment effectiveness and patients' comfort. In this paper too, we have investigate a newly created meta-heuristic optimisation algorithm, called Biogeography Based Optimization (BBO) based on the idea of migration of species between different habitats. To evaluate the performance of the proposed method, six instances of PASP data sets were used. The performance of the BBO algorithm was compared with other approaches that in the literature. Experimental results show that, the BBO needs more investigation for improving the obtained results.

Keywords: *Meta-Heuristic. Evolutionary Algorithms. Biogeography-Based Optimization. Patient Admission scheduling. Healthcare.*

1. INTRODUCTION

The central admission unit in health-care organizations is responsible for the process of allocating hospital beds to the patients waiting in the system. This unit is responsible for maximising the resource usage and at the same time minimise the duration of each patient stay [1, 2]. 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 empty bed 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 [3]. Thus making the task of assigning patients to bed very difficult and in need of a good knowledge and experience [4], otherwise it will lead to inefficiencies of the social benefits and/or monetary gains.

Numerous meta-heuristics approaches have been applied to solve PAS problems. The complexity of the PAS problem and the need for an optimisation algorithm to assistance the admission scheduler in making fast decisions motivate researches for tackling this problem. Moreover, Vancroonenburg categorised the problem as NP complete [5], which means that it cannot be solved in polynomial time. Consequently, an alternative algorithm (i.e., the BBO algorithm in this paper) is investigated for tackling the PAS problem. BBO is a newly created population based meta-heuristic algorithm, based on the idea of the migration of species between different islands. To our knowledge, this is the first time where the application of BBO to the patient admission problem is attempted. The BBO is an attractive algorithm because of its low dependence on parameter tuning as well as BBO has features in common with other biology-based optimization methods, such as GA[6, 7] and PSO[8, 9]. This makes BBO applicable to many of the same types of problems that GA and PSO are used for, namely, high-dimension problems with multiple local optima [10]. On the other hand, BBO have some unique features. First, as it have been noted previously mentioned, BBO is a population-based heuristic algorithm, BBO does not involve in reproducing or regenerating of the population not like the reproduction strategies in GA. BBO differs from ACO [11], ACO generates a new set of solutions with each iteration. While BBO maintains its own population from the first iteration to the last one, relying on migration operation to gradually adapt population.

This paper is organised as follows. Section II presents the definition and problem formulation for

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the patient admission-scheduling problem. Section III presents the description of the basic BBO, while Section IV presents the proposed method. Section V describes the experimental results obtained, and followed next by concluding remarks in Section VI.

2. PATIENT ADMISSION SCHEDULING

Patient admission scheduling problems deal with an assignment of patients to bed in an appropriate room/department in such a way it can maximise medical treatment effectiveness and patients' comfort [3]. The problem consists of set of hard and soft constraints. The feasible solution achieved once all the hard constraints are satisfied, and the soft constraints are minimised as much as possible by the objective function. The set of hard and soft constraints imposed to this problem are listed as below [3]:

- ***Hard constraints***

i. A maximum number of one patient per bed for each time slot (night).
ii. The number of patient must not exceed the room capacity for each night.
iii. The admission and discharge dates are fixed.
iv. The length-of-stay for each patient must be contiguous.
v. For each time slot (night) during the length-of-stay of a patient, s/he must be assigned to a bed.

- ***Soft constraints***

i. The number of room transfers should be minimised, where the room transfer is moving a patient from one room to another during his/her length of stay (we will tackle/deal with this constraint as a hard constraint).
ii. Patients in the same room-time slot should have the same gender unless the room characteristics allow for mixing genders. The room genders are Male (M), Female (F), Mix (M) or Depend (D) on the first patient that enters the room at each night.
iii. The department should be suitable for the patient's age.
iv. The specialism of the department should satisfy the specialism of the patient hosted in any room of this department.
v. The specialism of the room should satisfy the specialism of the patient assigned to it.
vi. The room should have the mandatory requirements of the patient pathology assigned to it.
vii. The room preferred should have the preferred requirements of the patient pathology assigned to it.
viii. 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 [12, 13]. It makes the search space smaller. However, [14-17] maintained the hard and soft constraints as in the original problem.

In this research, we used the original published dataset [17] which consists of 6 instances. The mathematical formulations for PASP and the features of the datasets can be found in [17]. 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.

3. BIOGEOGRAPHY-BASED OPTIMISATION

Biogeography is natural method in distribution species, where different geographical areas are consider as good habitat if they have high "Habitat Suitability Indexes" (HSI). These areas are characterised 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 a dependent variable.

BBO was first introduced by Simon [10] in which species move from one island 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 a good solution, and the low HSI habitat, represent a poor 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 [10] has illustrated how to use the principle of biogeography to design and implement the algorithms. The author has applied the algorithm on real life problem (sensor selection problem for aircraft engine health estimation) and

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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 benchmark functions). Other applications of BBO can be found in as sensor selection [10], scheduling problem [18, 19], data clustering [20], image segmentation [21, 22], satellite image classification [23], feature extraction [24], optimal meter placement [25], ground water detection [26], parameter estimation [27] and power system optimisation [28-30]. To our knowledge, this will be the first time that BBO algorithm used on the patient admission-scheduling problem.

4. 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.

4.1. 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 Figure 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., (i) maximum one patient per bedtime slot (HD1), and (ii) the number of patients per night in the room cannot exceed its capacity (HD2).

	N1	N2	N3	....			Nn
B1							
B2	Pi	Pi	Pi	Pi			
B3							
⋮							
				Pj	Pj	Pj	
Bm							

Figure 1: The Solution Representation Matrix.

4.2. Neighbourhood Structure

In this work, we use three neighbourhood structures as follows:

- Nbs1 (move): move one patient is selected at random and move to a new bed randomly,
- Nbs2 (swap): choose two patients and swap the beds, and
- 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 neighbourhood structures are applied during the mutation operation and repair mechanism. The details of each neighbourhood structures are as follows:

Nbs1: Move operation

Assume that we want to move patient P1 from bed B2 to a new bed select at random. 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 P1 to B3. Later, find a new bed for the patient that earlier bedded in B3. Figure 2 illustrates the previous example.

Nbs2: Swap operation

Two patients are selected at random (assume P2 and P3), and the stay period of the 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 illustrates the previous example.

Nbs3: Swap and move operations

Two patients are selected at random (assume P1 and P3) and swap the beds. In this case, P1 is now in B4, but P3 cannot be in B2 because it will violate the hard constraint (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 in order to obtain a feasible schedule. Figure 4 illustrates the previous example.

4.3. The algorithm

Figure 5 represents the pseudo code of the BBO algorithm. Also shown in Figure 5 is how the algorithm randomly initialises the population. The solutions then sorted in ascending 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 [10]:

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

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

Where n is the population size, and Ki is the rank of solution i (the first solution is the best and has the highest rank, and the last solution is the worst

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and has the lowest rank), *I* and *E* are the maximum immigration rate and the maximum emigration rate respectively, where the default value for them is 1 (one). The migration operation then performed in order 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 an unfeasible solution, a repair function will be performed (see Section 4.4) 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 neighbourhood structures (Nbs1 or Nbs2) will be randomly selected for each solution, and if the second neighbourhood structure (Nbs2) failed, then the third neighbourhood structure (Nbs3) is chosen. The population is finally, updated by replacing the worst solution with the best found.

4.4. Repair mechanism

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

5. EXPERIMENTAL RESULTS

The proposed algorithm was implemented using Java and simulations were performed on Intel® Core™ i3-4130 (CPU 3.4 GHz) PC with 4 GB 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 to 946 seconds. Note that, in the problem definition, the maximum running time is set to 3000 seconds. Based on our preliminary experiments, our algorithm reached the stagnant state after 200 iterations, which need about 150-250 seconds in most of the cases. Thus, it is of no significance to prolong the search to 3000 seconds. Table I shows the parameter setting for the proposed algorithm, which were determined after some preliminary experiments.

Table I: Parameter Settings of the Proposed Algorithm.

Parameter	Value
Population size	50
Mutation rate	0.001

We compare the results that obtained from BBO with other available approaches in the literature as shown in

Table *II*. The algorithms in comparison are Bilgin et al. (2008) and Ceschia and Schaerf (2011). Again, the best results are in bold.

The best results highlighted in bold. We can clearly see that Ceschia and Schaerf (2011) outperformed the other approaches in comparisons. We believed that Ceschia and Schaerf (2011) can achieved better solutions, since their approach allows the flexibility of jumping from unfeasible to feasible regions during the search processes. Our approaches however, only deal with feasible solution that limits the search in search space. Figure 6 shows the performance of the BBO for each datasets, as show in this figure, BBO reach to stagnant state at earlier time of the search, since it cannot achieve significant improvements after the first 200 iterations for the six instances of PASP.

6. CONCLUSION AND FUTURE WORK

In this paper, we have presented a search methodology that combines the principle of the geography theories i.e., Biogeography-based Optimisation. The performance of the approach tested on the original dataset of PASP. Experimental results show that BBO is not able to produce favourable results in comparison with state-of-the-art. The proposed approach shows that it reached to the stagnant state at the early of the search. We believed that BBO needs further investigations and improvements, such as, hybridising the BBO with other meta-heuristic algorithms in order to create a balance between the exploration and exploitation capability that offered by BBO. This will be the subject of our future work.

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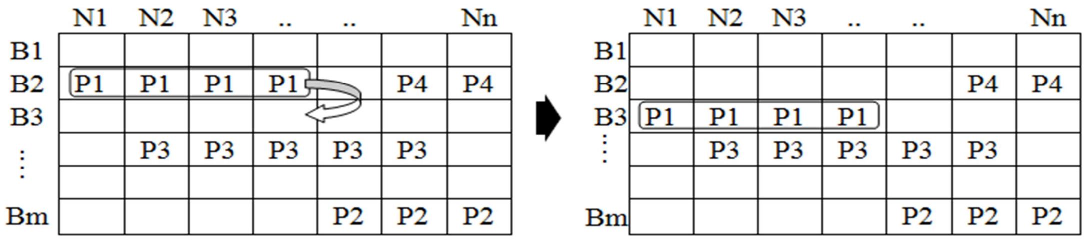
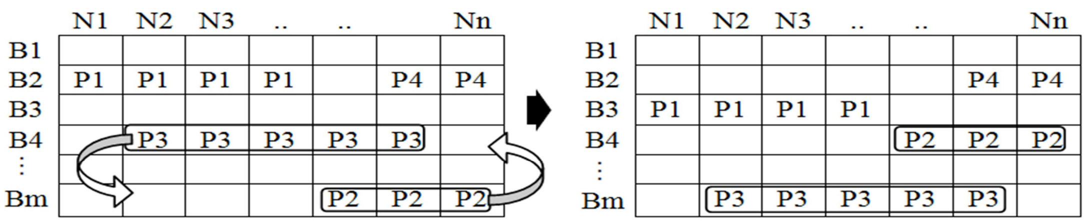


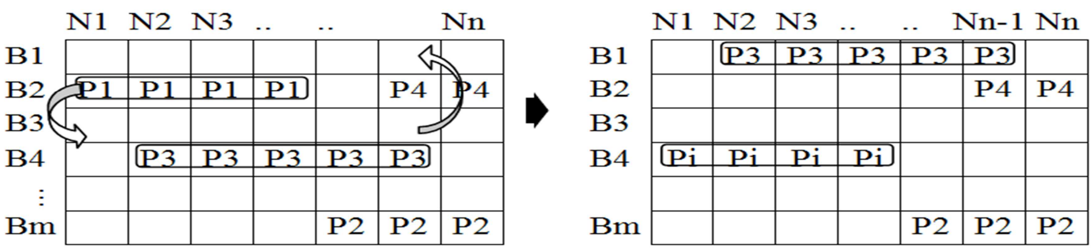
(a) Before move **(b) After move**

Figure 2: The Neighbourhood Structure - Nbs1.



(a) Before swap **(b) After swap**

Figure 3: The Neighbourhood Structure - Nbs2.



(a) Before swap and move **(b) After swap and move**

Figure 4: The Neighbourhood Structure - Nbs3.

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```
1 maxGen          ← the max number of generation (Iteration)
2 popSize         ← the population Size
3 Population      ← {} // create empty population
4 Best            ← ∅
5 numOfSIV        ← the number of patients
6 For i=1:popSize
7     Population  ← Population ∪ new random solution
8 End for
9 For gIndx=1:maxGen
10  Sort ( Population )// based on the quality
11  Best ← Population(1)     //the first solution in the population
12  For i=1:popSize
13       Calculate the value of immigration rate (λ) and emigration rate (μ) base on the equation 1 and 2,
         respectively.
         //execute the migration operation on Population(i)
          Si ← Population(i)              //current solution
          Select a Random number R between 0 and 1
          If R < λi then
            For k=1: numOfSIV   // SIVk represent the kth 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
14  End for
16  For i=1:popSize
17       //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
                                 //neighbourhood 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: SwapAndMove( P1 , P2 )
            End if
          End if
18  End for
19  Sort (Population) // based on the quality
20  If Population (popSize) > Best              //if last solution worse than Best solution
21       Population(popSize)← Best              // then replace it with the Best one
22  End if
23 End for
24 Sort ( Population )        // based on the quality
25 return Population(1)       // return the first solution in the population (Best Solution)
```

Figure 5: The Pseudo Code of the BBO Algorithm.

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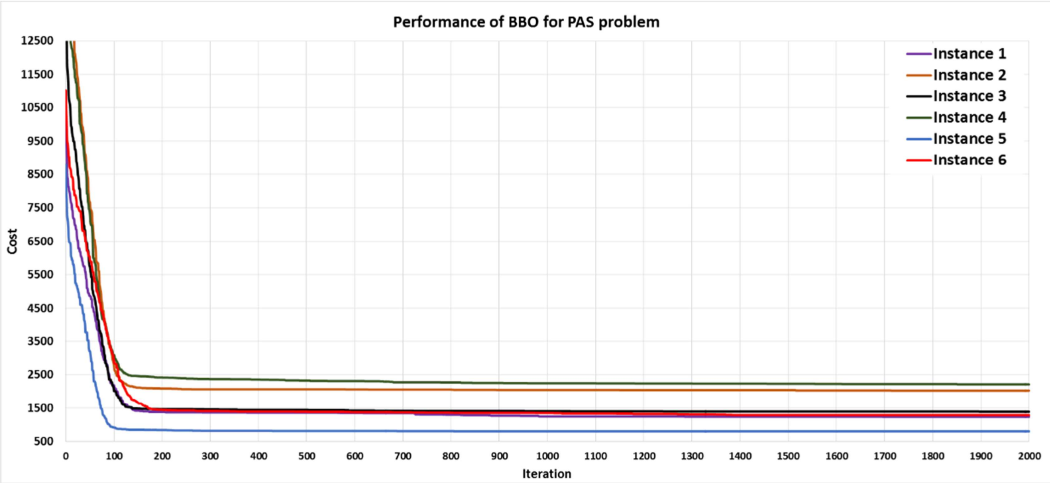

Figure 6: The Best Solution Found in Each Iteration of BBO (for Instances from 1 to 6).

Table II. Comparisons with State-Of-The-Art.

Instance No.	BBO				Bilgin et al. (2008)		Ceschia and Schaerf (2011)		
	Min	*Avg.*	*Std.*	*Avg. Time*	*Avg.*	*Std.*	*Min*	*Avg.*	*Std.*
1	1233.4	1312.8	59.5	686.3	830.36	18.8	659.2	**665.61**	33.2
2	2027.0	2088.9	60.4	945.7	1382.28	14.2	1143.6	**1150.96**	53.8
3	1385.2	1433.7	41.7	790.0	923.16	20.7	776.6	**786.67**	57.1
4	2211.0	2301.5	69.9	902.5	1608.68	29.2	1176.0	**1190.58**	86.4
5	800.8	828.9	28.3	592.6	661.52	4.0	625.6	**631.87**	24.6
6	1283.2	1317.1	37.9	684.7	955.04	20.1	801.2	**811.18**	62.2