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Fusion of two metaheuristic approaches to solve the flight gate assignment problem

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Abstract

One of the most important activity in airport operations is the gate scheduling. It is concerned with finding an assignment of flights to terminal and ramp positions (gates), and an assignment of the start and completion times of the processing of a flight at its position. The objectives related to the flight gate assignment problem (FGAP) include the minimization of the number of flights assigned to remote terminals and the minimization of the total walking distance. The main aim of this research is to find a methodology to solve the FGAP. In this paper, we propose a hybrid approach called Biogeography-based Bee Colony Optimization (B-BCO). This approach is obtained fusing two metaheuristics: biogeography-based (BBO) and bee colony optimization (BCO) algorithms. The proposed B-BCO model integrates the BBO migration operator into to bee's search behaviour. Results highlight better performances of the proposed approach in solving FGAP when compared to BCO.

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Keywords: Flight gate assignment; Bee Colony Optimization; Biogeography Based Optimization; Multicriteria analysis

1. Introduction

In recent decades, there has been a strong increase in air traffic, up to hundreds of daily flights in large international airports. Therefore, airport operations have become more complex. The flight gate assignment problem is encountered by gate managers at an airport on a periodic basis. This assignment should be made so as to balance carrier efficiency and passenger comfort, while providing buffers for unexpected events that cause assignment

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disruptions. The gate assignment problem can be seen as a scheduling problem. Gate scheduling defines the assignment of flights to terminals or ramps, called gates. It is a key activity for airport operations. Flight schedule defines the period required to carry out operations to process a flight and the gate assigned to that flight.

The most important objective of flight gate assignment problem (FGAP) is to minimize the distance walked by passengers and the distance between connecting flights.

In an airport three main distances can be considered:

- the distance between the gate and the check-in area;
- the distance from gate to gate for transfer passengers;
- the distance between the baggage claim area (check-out) and the arrival gate.

The most important information for gate scheduling are referred to the arrival and departure time, the type of aircraft, and connections between pairs of successive flights served by the same aircraft. In the following sections, we describe the methodology used for the model of the Biogeography-based Bee Colony Optimization (B-BCO), obtained by the fusion of the Biogeography-Based optimization (BBO) and Bee Colony Optimization (BCO). We have considered the case of the international airport of Milan-Malpensa to test the proposed method. Finally, in Section 6, some concluding remarks are given.

2. Literature review

In literature, there are numerous mathematical models for flights assignment to gates. A detailed survey is given by Dorndorf et al. (2007). Exact algorithms are rarely used for allocation of flights to a gate. Babic et al. (1984) formulated the gate assignment problem as a linear problem. A branch-and-bound algorithm is used to minimize the walking distance and to find the optimal solution, but transfer passengers are not considered.

Most papers present heuristic approaches. Xu and Bailey (2001) define a tabu search algorithm for an airport with the aim of minimizing the passenger walking distances, considering connecting flights. A two-stage algorithm is proposed to solve the problem. It uses both a greedy strategy to minimize the number of un-gated flights, and an improved tabu search heuristic to minimize the total connection time. Drexl and Nikulin (2008) consider multiple objectives such as minimizing the number of ungated flights and the total walking distances, as well as maximization of the total gate assignment preference score.

Modeling the flight-gate assignment problem as a clique-partitioning problem can be found in Dorndorf et al. (2008). They solve the problem by using an ejection chain heuristics. Other models try to improve the performance of static gate assignment by taking into account stochastic flight delays. Hassounah and Steuart (1993) show that planned buffer times could improve schedule punctuality. Yan and Chang (1998) and Yan and Huo (2001) use in their static gate assignment problems a fixed buffer time between two contiguous flights assigned to the same gate, in order to hold stochastic flight delays. Yan and Chang (1998) formulated the airport gate assignment as a multi-commodity network flow problem. Yan and Huo (2001) formulate a dual objective 0–1 integer programming model for the aircraft position allocation. The first objective is minimizing the passenger walking time, while the second objective aims at minimizing passenger waiting time. Yan et al. (2002) propose a simulation framework, that is not only able to analyze the effects of stochastic flight delays on static gate assignments, but can also evaluate flexible buffer times and real-time gate assignment rules.

Some authors take into account the dynamic character of the FGAP. A delayed departure may delay the arrival of another aircraft scheduled to the same gate, or require the flight to be reassigned. Bolat (2000) proposes mathematical models and heuristic procedures to provide solutions with a minimum dispersion of idle time periods for the FGAP.

Other authors focus on the design of so-called rule-based expert systems. An expert system uses production rules to produce assignments, but at a cost of large number of factors to be taken into account. The most crucial task is to identify all the rules, put in order by importance and list them appropriately. Hamzwawi (1986) introduces a rule-based system for simulating the assignment of gates to flights and for evaluating the effects of particular rules on gate utilization. Gosling (1990) describes an expert system for gate assignment that has been applied to a major hub of Denver Stapleton airport. Srihari and Muthukrishnan (1991) use a similar approach to solving the FGAP, applying additionally the sensitivity analysis. Cheng (1997) describes the integration of mathematical programming techniques into a knowledge-based gate assignment system to provide partial parallel assignments with multiple objectives. Both optimization and rule-based approaches have been combined with simulation analysis in Baron (1969). A comparison of different metaheuristics (Genetic Algorithm, Tabu Search, Simulated Annealing) applied to the FGAP has been carried out by Cheng et al. (2012). Moreover, Hu and Di Paolo (2009) have proposed an improved Genetic Algorithm applied to the FGAP considering a multi-objective function. These metaheuristics differ from the proposed B-BCO algorithm because they are based on a solution *improvement* approach possibly not efficient with NP-hard problems subject to very strict constraints, like in the FGAP. In fact, these approaches can easily generate infeasible solutions that should be properly penalized through a carefully designed fitness function. Instead, the B-BCO algorithm is based on a solution *construction* approach that always generates feasible solutions and improves them over iterations. The BCO was first applied to transportation problems by Teodorovic et al. (2005, 2006). This work is an extension of a previous study by Marinelli et al. (2015).

3. Problem description

Airline and airport managements are responsible for different tasks: crew scheduling, disruption management, airline fleet assignment, aircraft scheduling and rotation, ground operations scheduling. Planners seek to minimize distances that passengers have to walk to reach departure gates and connecting flights, since this is a key quality performance measure for an airport. Aircraft stands at the terminal and off-pier stands on the apron are often simply referred to as “gates’’. As the gate assignment is a type of job-shop scheduling problem, its complexity increases exponentially as constraint size changes (e.g. number of flights, available gates, aircrafts, flight block time, etc.). The NP-hard characteristic of the problem implies that there is no known algorithm for finding the optimal solution within a polynomial-bounded amount of time. When an aircraft arrives at the airport, it can be either assigned to the fixed terminal gates or, in particular conditions, it can be assigned to a remote terminal gate. All the fixed gates are usually equipped with passenger bridges, whereas passengers from flights assigned to remote gates can be transported to the terminal building by transfer busses. The connection through the busses increases the connection time, so the main objective is minimizing total passenger walking distance and connection time.

Let us consider the following notation:

Nomenclature

N	number of flights
M	number of gates, including remote gates
$f_{j,o}$	number of passengers from flight j to the baggage claim area
$f_{o,j}$	number of passengers from check-in area to flight j
$f_{j,r}$	number of passengers from flight j to flight r
$w_{i,o}$	walking distance between gate i and baggage claim area
$w_{o,i}$	walking distance between check-in area and gate i
$w_{i,k}$	walking distance between gate i and gate k
$Y_{i,j}$	binary value representing the association of gate i to flight j
$Y_{k,r}$	binary value representing the association of gate k to flight r

In this work, the flight gate assignment problem is considered as composed of two main criteria:

- Minimization of total walking distance (TWD), including respectively the distance that a passenger walks to reach departure gates, baggage claim area and connecting flights:

$$min\ TWD = \sum_{i=1}^{M}\sum_{j=1}^{N} f_{o,j}\cdot w_{o,i}\cdot Y_{i,j} + \sum_{i=1}^{M}\sum_{j=1}^{N} f_{j,o}\cdot w_{i,o}\cdot Y_{i,j} + \sum_{i=1}^{M}\sum_{k=1}^{M}\sum_{j=1}^{N}\sum_{r=1}^{N} f_{j,r}\cdot w_{i,k}\cdot Y_{i,j}\cdot Y_{k,r} \qquad (1)$$

- Minimization of the number of flights assigned to remote terminal gates (*RG*), corresponding to the maximization of the number of flights assigned to fixed gates (*FG*):

$$min\ RG = \sum_{i \in RG} \sum_{j=1}^{N} Y_{i,j} \quad (2)$$

To evaluate a single objective function, a weight p is introduced for each criterion. Thus, the resulting optimization problem is:

$$min\ Z = p \cdot TWD + (1-p) \cdot RG \quad (3)$$

The decision variables of the problem are $Y_{i,j}$ and $Y_{k,r}$ as they represent the assignment of flights to gates. The optimization problem is subject to the following constraints:

1. compatibility between gate and airplane: a small aircraft can be assigned to a big gate, but a large aircraft cannot be assigned to a small gate. A large gate has the flexibility to accommodate various sizes of aircraft whereas a small gate is more limited. The compatibility is usually provided by the airport regulations;
2. every flight j must be assigned to exactly one gate including remote gates:

$$\sum_{i=1}^{M} Y_{i,j} = 1\,, \quad 1 \leq j \leq N;$$

3. prevent schedule overlapping of two flights if they are assigned to the same gate:

$$t_{i,j}^{dep} < t_{i,z}^{arr} \quad if\ Y_{i,j} = 1\ and\ Y_{i,z} = 1\,, \quad 1 \leq i \leq M, \quad 1 \leq j,z \leq N$$

where $t_{i,j}^{arr}$, $t_{i,z}^{dep}$ are respectively the arrival and departure time of flights j and z associated to gate i.

In the next section, we present the proposed methodology based on the fusion of two metaheuristics, Biogeography-Based and Bee Colony Optimization metaheuristics, to solve this problem.

4. The proposed methodology

In this paper, we present an extension of a previous study by Marinelli et al. (2015) where a metaheuristic approach based on the Bee Colony Optimization (BCO) was proposed. Now we extend that approach proposing a new hybrid methodology (B-BCO) obtained by fusing BCO and the Biogeography-Based Optimization (BBO).

4.1 Biogeography-Based Optimization (BBO)

Biogeography-based Optimization (BBO), originally introduced by Simon (2008), is a population-based evolutionary algorithm (EA) based on the biogeography. The biogeography is the science of the geographical distribution of biological organisms over space and time.

In nature, these concepts bring a balance between different ecosystems. In other words, nature tends to improve the overall stability of different geographical regions. The BBO algorithm uses these concepts to improve the habitat suitability index (HIS) of all habitats, which results in evolving the initial random solutions for a particular problem. The BBO algorithm starts with a random set of habitats. Each habitat has different individuals that correspond to the number of variables of a particular problem. In addition, each habitat has its own immigration, emigration, and mutation rates.

In the habitats with high HSI there is a high number of species; they are characterized by a high rate of emigration and have a low rate of immigration. The species that migrate to the habitats with a high number of species, tend to die because there is too much competition for resources from other species.

The maximum possible immigration rate occurs when there are zero species in the habitat. Increasing the number of species, the habitat becomes more crowded and, therefore, able to accommodate a number of lower species, thereby decreasing the rate of immigration.

However, species diversity is correlated with HSI, so when more species arrive at a low HSI habitat, the habitat's HSI will tend to increase. The immigration rate λ and the emigration rate μ are functions of the number of species in the habitat. The maximum possible immigration rate I occurs when there are zero species in the habitat. S_{max} is the largest number that the habitat may contain; not being able accommodate new species, it has a rate of immigration zero. If there are no species in the habitat, then the emigration rate is zero.

With the increase in the number of species in the habitat, the habitat becomes ever more crowded, therefore of the representative species leave the habitat and increases the rate of emigration (Fig. 1).

In BBO, λ_k is the probability that a given independent variable in the k-th candidate solution will be replaced (Eq. 4); that is, λ_k is the immigration probability of x_k. If an independent variable is to be replaced, then the emigrating candidate solution is chosen with a probability that is proportional to the emigration probability μ_k (Eq. 5).

$$\lambda_k = I\left(1 - \frac{k}{n}\right) \tag{4}$$

$$\mu_k = \frac{E \cdot k}{n} \tag{5}$$

where *n* is the number of individuals in each habitat.

To see how the proposed method works, a flow-chart of the BBO is reported in figure 2 and a conceptual picture of the migration between the habitats is shown in Fig.3.

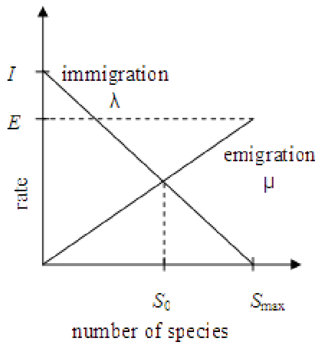

Fig.1 - Species model of a single habitat

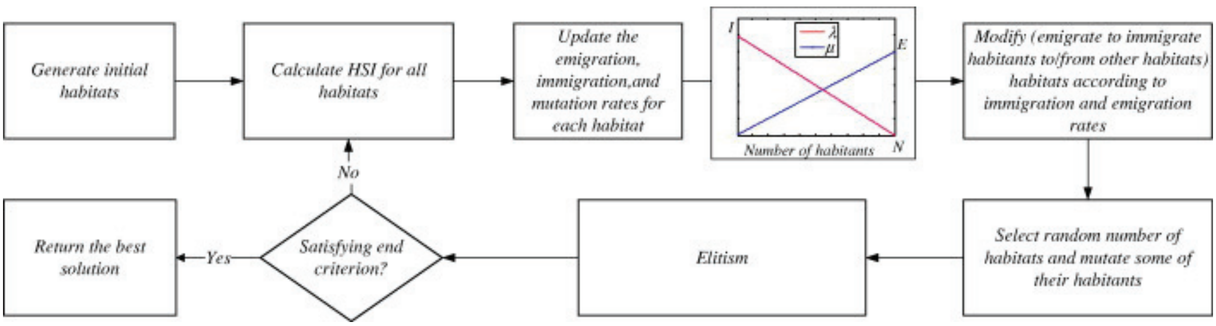

Fig.2 - General steps of the BBO algorithm.

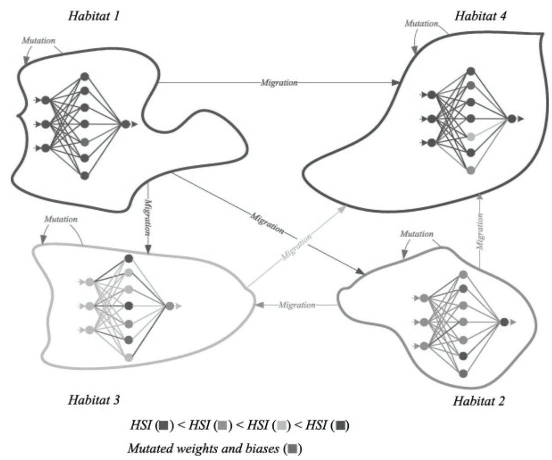

Fig.3 - Conceptual model of migration between habitats (BBO)

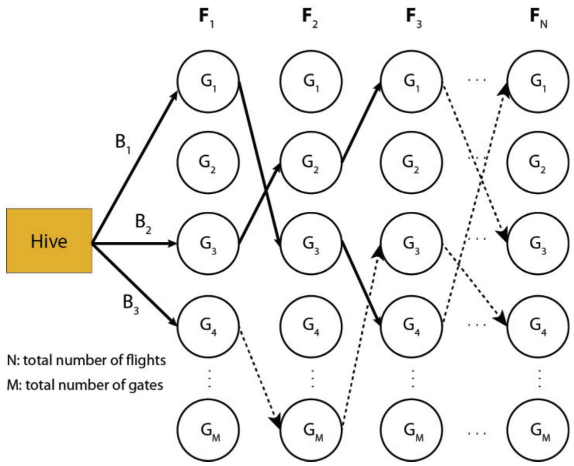

Figure 4. The artificial network of the decision space (BCO)

4.2 Bee Colony Optimization (BCO)

Various natural systems (social insect colonies) lecture us that very simple individual organisms can create systems able to perform highly complex tasks by dynamically interacting with each other. Within the Bee Colony Optimization (BCO) metaheuristic, agents that we call "artificial bees" collaborate in order to solve difficult combinatorial optimization problems. All artificial bees are located in the hive at the beginning of the search process. During the search process, artificial bees communicate directly. Each artificial bee makes a series of local moves, and in this way incrementally constructs a solution of the problem (fig.4). Bees are adding solution components to the current partial solution until they create one or more feasible solutions When flying through the space, artificial bees perform forward step or backward step. During a forward step, bees create various partial solutions. They do this via a combination of individual exploration and collective experience from the past. After that, they perform a backward step, i.e. they return to the hive. In the hive, all bees participate in a decision-making process. The search process is composed of iterations. Each iteration ends when one or more feasible solutions are created. Like Dynamic Programming, the BCO also solves combinatorial optimization problems in stages. Each of the defined stages involves one optimizing variable. Let us denote by $ST = \{st_1, st_2, \ldots, st_m\}$ a finite set of pre-selected stages, where m is the number of stages. By B we denote the number of bees to participate in the search process, and by I the total number of iterations. The set of partial solutions at stage st_j is denoted by S_j ($j = 1, 2, \ldots, m$). The following is the pseudo-code of the Bee Colony Optimization.

1. *Initialization*. Set the number of bees B, and the number of iterations I. Select the set of stages $ST = \{st_1, st_2, \ldots, st_m\}$. Find any feasible solution x of the problem. This solution is the initial best solution.
2. Set i = 1. Until i = I, repeat the following steps:
3. Set j = 1. Until j = m, repeat the following steps:
   Forward step: Allow bees to fly from the hive and to choose B partial solutions from the set of partial solutions S_j at stage st_j.
   Backward step: Send all bees back to the hive. Allow bees to exchange information about quality of the partial solutions created and to decide whether to abandon the created partial solution and become again uncommitted follower, continue to expand the same partial solution without recruiting the nestmates, or dance and thus recruit the nestmates before returning to the created partial solution. Set, $j := j + 1$.
4. If the best solution x_i obtained during the i-th iteration is better than the best-known solution, update the best-known solution ($x := x_i$).
5. Set i = i + 1

4.3 Biogeography-based Bee Colony Optimization (B-BCO)

The previous two metaheuristics has been fused to obtain the Biogeography-Based Bee Colony Optimization (B-BCO). In this model, the bees tend always to move to find a partial solution. With the introduction of the concepts of migration and immigration of BBO, bees along optimal partial routes may move from one habitat to another (migration operator).

Therefore, within each habitat develops BCO and thereafter takes the interaction between habitats through the BBO.

In this work, B-BCO is used to find an optimal path through an artificial network that represents the decision space. The network is composed of different habitats and for each habitat there are different layers (previously called 'stages') which represent the set of flights, temporally ordered according to a given schedule. Each node represents an association of a flight F_i to an available gate G_j in the airport, so it refers to variable $Y_{i,j}$ which are the decision variables of the problem.

All the partial solutions are identified observing the constraints of the optimization problem and the associated fitness value is given by the objective function. As a result, a path of the artificial network corresponds to a particular flight gate assignment found by a bee in the colony.

At the end of each iteration, all the solutions found are evaluated referring to the associated fitness value and the best assignment is saved. Thus, a new iteration starts searching for new solutions until the maximum number of iterations is reached. In the following the pseudo-code of the algorithm is reported.

Figure 5 shows the networks obtained for each habitat and the emigration operations between different habitats.

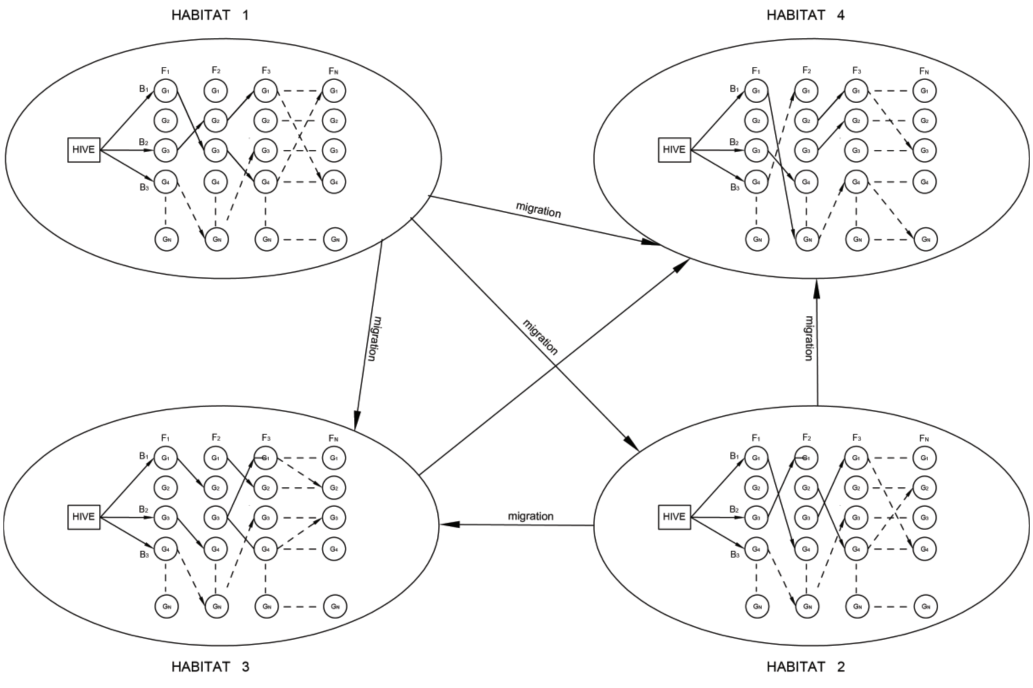

Fig.5 – The resulting artificial network for each habitat and between different habitats

1. *Initialization*. Set the number of bees B, the number of iterations I and number of habitats H. Select the set of stages ST = {st_1, st_2 ,…, st_m}. Find any feasible solution x of the problem. This solution is the initial best solution.
2. Set i = 1. Until i = I, repeat the following steps:
3. Set j = 1. Until j = m, repeat the following steps:
4. *For each habitat*
5. *Forward step*: Allow bees to fly from the hive and to choose B partial solutions from the set of partial solutions S_j at stage st_j.
6. *Get species count*: compute species number sorting bees from most fit to least fit
7. Calculate λ, μ of each bee in the habitat
8. *For each bee of in the habitat*
9. *If* rand < λ *then*
10. Select an emigrating bee with probability μ
11. *End if*
12. *End for each bee*
13. *Backward step*: Send all bees back to the hive. Allow bees to exchange information about quality of the partial solutions created and to decide whether to abandon the created partial solution and become again uncommitted follower, continue to expand the same partial solution without recruiting the nestmates, or dance and thus recruit the nestmates before returning to the created partial solution.
14. *End for each habitat*
15. Set j = j + 1.
16. If the best solution x_i obtained during the i-th iteration is better than the best-known solution, update the best-known solution ($x = x_i$).
17. Set i = i + 1.

5. Application and results

The Milano-Malpensa international airport, in the following called Malpensa, has been considered to evaluate the outcomes of the B-BCO method and compared to the BCO approach. Malpensa airport has two terminals, for international and domestic flights, and an area reserved for freight traffic called respectively Malpensa 1, Malpensa 2 and Malpensa Cargo. The airport is strategically important both for Italy and Europe. In 2012, the Malpensa airport was ranked second in Italy after Rome-Fiumicino airport for overall passenger traffic, with about 18.5 million passengers (on average 50 000 per day), and in the first place for freight traffic, with 414.317 tons.

We have taken into account the flight scheduling of May 2012. The database consists of 178 flights and 65 gates. The proposed approach has been applied considering the structure of the airport and, in particular, an additional constraint related to the assignment of a flight to international or domestic gates based on its origin/destination. The compatibility between gate and airplane has been determined according to Malpensa Airport Regulations (2010).

Results have been carried out in terms of optimal objective function values obtained for different values of *p* (Figs. 6, 7, 8). Table 1 reports in detail the obtained results for two models in terms of TWD (total walking distance), RG (flights to remote gates) and best objective function value Z* for the considered values of *p*. Thus, a sensitivity analysis can be carried out in order to highlight the role of the variable *p* in the decision-making process. We can observe that the solutions found by B-BCO are almost always better than the BCO solutions. As a matter of fact, the total walking distance is almost always lower (red line in Figure 6) than Malpensa and BCO resulting in an improvement of 5%. The number of flights assigned to remote gates is lower than the others (improvement of 6%) except for $p > 0.8$ where B-BCO tends to minimize the TWD (Figure 7). In terms of best objective function value Z* (Figure 8), the B-BCO outperforms the BCO approach with an improvement of 9%.

The resulting Pareto front is reported in figure 9. It is obtained considering the optimal solutions found by the B-BCO related to the two criteria (TWD vs. number of flights assigned to remote gates). As a result, the main range of *p* is the interval [0.8, 1] and it should be taken into account in the decision-making process to choose the best assignment.

Table 1. Comparison of the results obtained by BCO and B-BCO.

p	TWD (m)		RG (flights)		Z*	
	BCO	B-BCO	BCO	B-BCO	BCO	B-BCO
0,01	47458686	46704031	28	28	0,157	0,156
0,10	47326985	46284727	28	27	0,158	0,138
0,20	47412610	46345799	28	28	0,157	0,158
0,30	47346654	46142048	30	29	0,167	0,162
0,40	47531467	46368517	31	30	0,171	0,166
0,50	47476033	46853129	37	30	0,186	0,166
0,60	47159774	46652882	40	28	0,189	0,160
0,70	47256210	46318181	50	33	0,199	0,169
0,80	45257497	45813261	68	44	0,206	0,178
0,90	35979382	24810019	117	138	0,191	0,176
1,00	24411882	18695425	172	174	0,112	0,096
% improvement	**5%**		**6%**		**9%**	

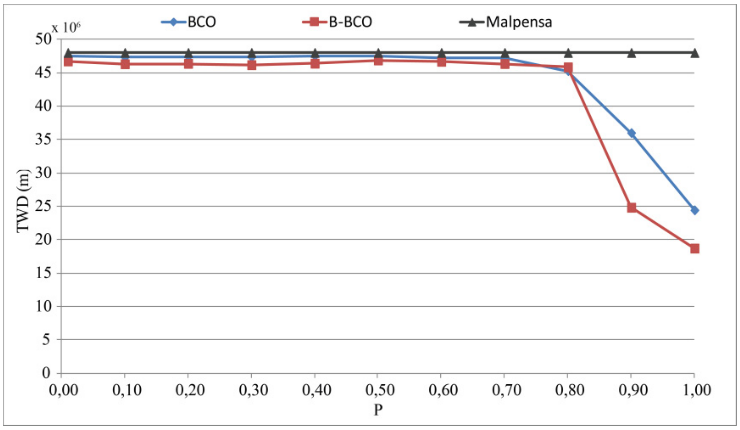

Fig. 6. Resulting TWD obtained by B-BCO (red line), BCO (blue line) and Malpensa (black line) for different values of *p*.

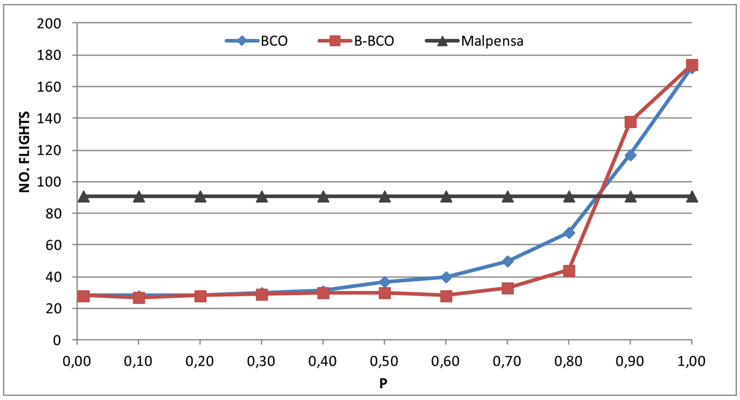

Fig. 7. Resulting number of flights assigned to remote gates (RG) obtained by B-BCO (red line), BCO (blue line) and Malpensa (black line) for different values of *p*.

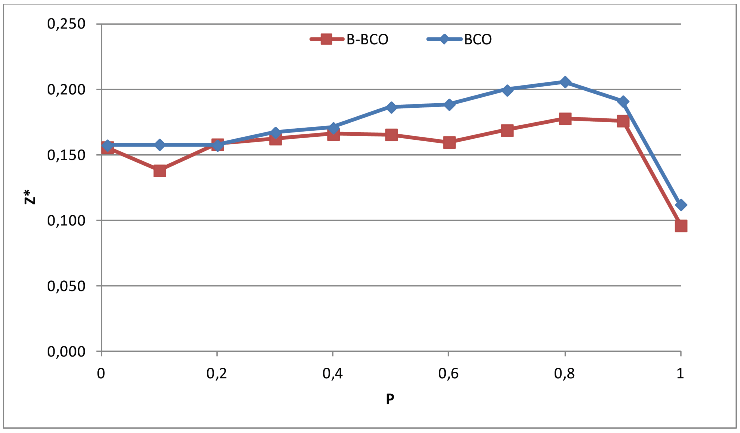

Fig. 8. Resulting best objective function value Z* found by BCO and B-BCO for different values of *p*.

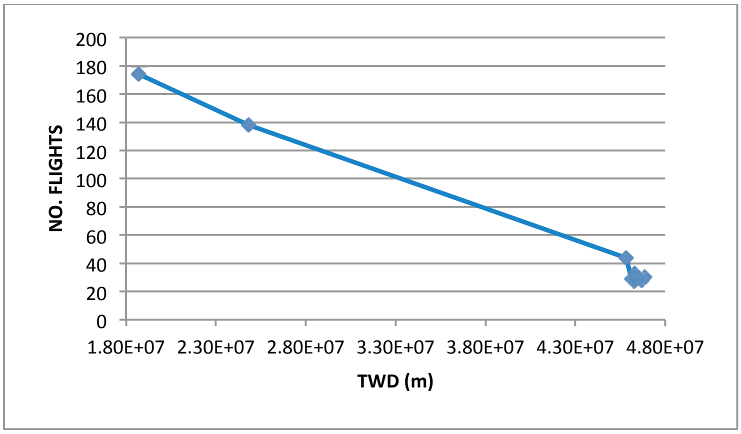

Fig. 9. The resulting Pareto front obtained by the optimal solutions found for different values of *p*.

6. Conclusions

In this paper, we have presented a hybrid metaheuristic approach based on the Bee Colony Optimization (BCO) fused with the Biogeography-Based Optimization (BBO) to solve the flight gate assignment problem (FGAP). The problem has been structured considering two criteria: minimization of the total walking distance and the number of flights assigned to remote gates, subject to compatibility constraints. Results obtained by the proposed B-BCO highlight the effectiveness of the method when compared to the BCO approach. As a matter of fact, B-BCO has better performances of the other metaheuristic. The multicriteria analysis has highlighted how the solutions found by B-BCO are better than BCO ones resulting in improvement of 9% in terms of best objective function value Z*. Concluding, the fusion of these two metaheuristics, known for their good capabilities in solving high combinatorial problems, results in a new strong optimization approach to solve the FGAP. Further developments will consider a more complex formulation of the problem with more criteria and constraints related to airline companies' preferences and agreements. Moreover, a comparison with other metaheuristics will be taken into account.

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