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Transportation Research Procedia 5 (2015) 211 – 220

Transportation Research Procedia

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SIDT Scientific Seminar 2013

# A metaheuristic approach to solve the flight gate assignment problem

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**Abstract**

In the past decades, the increase of civil air-traffic and the corresponding growth of airports have highlighted the importance of the gate scheduling as a key activity in airport operations. To solve this problem, different mathematical models for flights assignment to gates can often be found in technical literature. In this work we propose a method based on the Bee Colony Optimization (BCO) to find an optimal flight gate assignment for a given schedule. This metaheuristic represents an interesting methodology in the field of Swarm Intelligence for its capability to solve high level combinatorial problems with fast convergence performances. The proposed methodology includes a multicriteria analysis considering two main objectives: minimization of passenger total walking distance and remote gate usage. Results of the comparison with the Milano-Malpensa airport schedule highlight the effectiveness of the proposed method.


Peer-review under responsibility of the Società Italiana dei Docenti di Trasporti (SIDT).

*Keywords:* Air transport; Flight gate assignment; Bee Colony Optimization; Metaheuritstics; Multicriteria analysis

## 1. Introduction

Gate scheduling is a key activity in airport operations; it is concerned with flight assignment to terminal or ramp positions, called gates. With the increase of civil air-traffic and the corresponding growth of airports in the past decades, the complexity of the task has increased significantly. Flight schedule defines the time frame for processing

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Peer-review under responsibility of the Società Italiana dei Docenti di Trasporti (SIDT).
doi:10.1016/j.trpro.2015.01.013

a flight and the subset of gates to which it can or should be assigned, taking into account, e.g. aircraft-gate size compatibility, access to governmental inspection facilities for international flights etc.

In the Flight Gate Assignment Problem (FGAP), the main objective is to find feasible flight-to-gate assignments which minimizes total passenger walking distances including distances between connecting flights. The typical distances in airports considered are: (i) the distance from check-in to gates for embarking or originating passengers, (ii) the distance from gates to baggage claim areas (check-out) for disembarking or destination passengers, and (iii) the distance from gate to gate for transfer or connecting passengers. The main input for gate scheduling is a flight schedule with flight arrival and departure times and additional detailed flight information, including pairwise links between successive flights served by the same aircraft, the type of aircraft, the number of passengers, the cargo volume, and the origin or destination of a flight, classified e.g. as domestic or international.

In the next section, a brief analysis of previous works presented in literature is proposed. In section 3, the flight gate assignment problem and the objective function are described. In section 4 the method based on the Bee Colony Optimization (BCO) is explained to understand how it could be considered effective in solving the FGAP. In section 5, we have considered the case of Milano-Malpensa international airport to test the proposed method, then the results of the sensitivity analysis are reported. Finally, in section 6, some concluding remarks are given.

## 2. Literature review

Mathematical models for flights assignment to gates can often be found in technical literature. A detailed survey is given by Dorndorf et al. (2007). Exact algorithms are rarely used for assigning flights to gates because they often have little practical relevance. Babic et al. (1984) minimize the walking distance of passengers using the branch and bound algorithm. The objective is to reduce the number of passengers who have to walk maximum distances—at the price that more passengers have to walk the minimum distances, compared to random aircraft position assignment. Contrary to this, Mangoubi and Mathaisel (1985) take into account transfer passengers. Moreover, they use the LP relaxation and greedy heuristics to solve the FGAP. Bihr (1980) uses 0–1 integer programming to solve the minimum walking distance gate assignment problem for fixed arrivals in a hub using a simplified formulation as an assignment problem. Wirasinghe and Bandara (1990) additionally integrate the cost of delays to minimize intra-terminal travel in terminal design process.

Most papers present heuristic approaches. Xu an Bailey (2001) propose a tabu search algorithm for a single slot FGAP with the objective function of minimizing the overall distances, that passengers have to walk in order to get connecting flights. The problem is formulated as a quadratic assignment problem and reformulated as a mixed 0–1 integer linear program. The algorithm exploits the special properties of different types of neighborhood moves, and creates effective candidate list strategies. Ding et al. (2004) study the case in which the number of flights exceeds the number of gates and they solve the problem using tabu search. The primary goals are to minimize the number of open (non-assigned) flights and the total connection times. A two-stage algorithm, which exploits both a greedy strategy to minimize the number of open flights and a tabu search metaheuristic improved by a new neighborhood search technique to minimize the total connection times, is proposed to solve the problem. Drexl and Nikulin (2008) study a very similar problem and optimize their multicriteria objective using simulated annealing. Modelling 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 heuristic.

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 continuous flights assigned to the same gate in order to absorb the stochastic flight delays. Yan and Chang (1998) develop a multi-commodity network flow model. Moreover, they use Lagrangian relaxation with sub-gradient optimization and some heuristics to solve the FGAP. Yan and Huo (2001) formulate a dual objective 0–1 integer programming model for the aircraft position allocation. The first objective tries to minimize passenger walking time while the second objective aims at minimizing passenger waiting times. 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 try to 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. When gate idle times are distributed uniformly among the gates, the probability that the delayed departure time will still be earlier than the arrival of the next flight is maximized. Bolat (2000) proposes mathematical models and (optimal and heuristic) procedures to provide solutions with minimum dispersion of idle time periods for the FGAP.

The aircraft gate reassignment problem occurs when the departure of an incoming aircraft is delayed. Gu and Chung (1999) propose a genetic algorithm which efficiently calculates minimum extra delayed time schedules that are at least as effective as solutions generated by experienced gate managers. Bard et al. (2001) propose an integral minimum cost network flow model is introduced. This model aims at reconstructing airlines schedules in response to delays by transforming the routing problem into a time-based network in which the overall time horizon is divided in discrete periods. The transformation is polynomial with respect to the number of airports and flights. An optimum of the new model corresponds to the optimal solution of the original problem under some slight conditions.

Other authors focus on the design of so called rule-based expert systems. An expert system uses production rules to produce assignments, but the number of factors to be taken into account is large. Therefore, the most crucial task is to identify all the rules, order them by importance and list these rules 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 implemented at a major hub of Denver Stapleton airport. Srihari and Muthukrishnan (1991) use a similar approach for solving the FGAP and also describe how to apply sensitivity analysis.

From a practical point of view, it is even more important to develop simple expert systems that make use of mathematical programming techniques (branch and bound, dynamic programming, local search). Such an integration would help to create a gate scheduling system with the desired flexibility property. For example, 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 BCO algorithm because based on a solution *improvement* approach that could not be 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 BCO algorithm is based on a solution *construction* approach that always generates feasible solutions and improves them over iterations. The proposed approach can increase the efficiency of the optimization procedure and improve convergence capabilities.

## 3. Problem formulation

There are different classes of decisions for which airline and airport management is responsible: crew scheduling, disruption management, airline fleet assignment, aircraft scheduling and rotation, ground operations scheduling and some others that can be modelled as traditional machine scheduling problems. Nevertheless, one of the most important and most complicated airport management topics is flight gate scheduling.

The primary purpose of flight-to-gate assignments in airports is to assign aircrafts to gates to meet operational requirements while minimizing inconveniences to passengers. Planners seek to minimize distances passengers have to walk to departure gates, baggage belts and connecting flights since this is a key quality performance measure of any 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. Such bus connection may increase connection time and can hardly be regarded as desirable if our main goal is to minimize total passenger walking distance and connection time.

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

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

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

where:
*N* is the number of flights;
*M* is the number of gates, including remote gates;
$f_{j,o}$ is the number of passenger from flight j to the baggage claim area;
$f_{o,j}$ is the number of passenger from check-in area to flight j;
$f_{j,r}$ is the number of passenger from flight j to flight r;
$w_{i,o}$ is the walking distance between gate i and baggage claim area;
$w_{o,i}$ is the walking distance between check-in area and gate i;
$w_{i,k}$ s the walking distance between gate i and gate k;
$Y_{i,j}$ is a binary value representing the association of gate i to flight j.

- 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*):

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

To evaluate a single objective, a decision variable *p* is introduced to weight each criteria. Thus, the resulting optimization problem is:

$$min\ [p \cdot TWD + (1-p) \cdot RG] \tag{3}$$

This 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 can not be assigned to a small gate. A large gate has the flexibility to accommodate various size of aircraft where as 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:

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

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

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

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 Bee Colony Optimization metaheuristic to solve this problem.

## 4. The Bee Colony Optimization approach

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 problem.

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. 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 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 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,..., m).
The following is the pseudo-code of the Bee Colony Optimization, while figure 1 shows the flowchart related to a single iteration of the algorithm.

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1. *Initialization*. Determine 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.

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In this work, BCO is used to find an optimal path through an artificial network that represents the decision space (Fig. 2). The network is composed by 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 $Y_{i,j}$ in the problem formulation (eqs. 1-2). During a single iteration, each bee finds partial solutions and choses the next node through a roulette wheel selection. All the partial solutions are identified observing the constraints of the optimization problem and the associated fitness value is given by the objective function (3). 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.

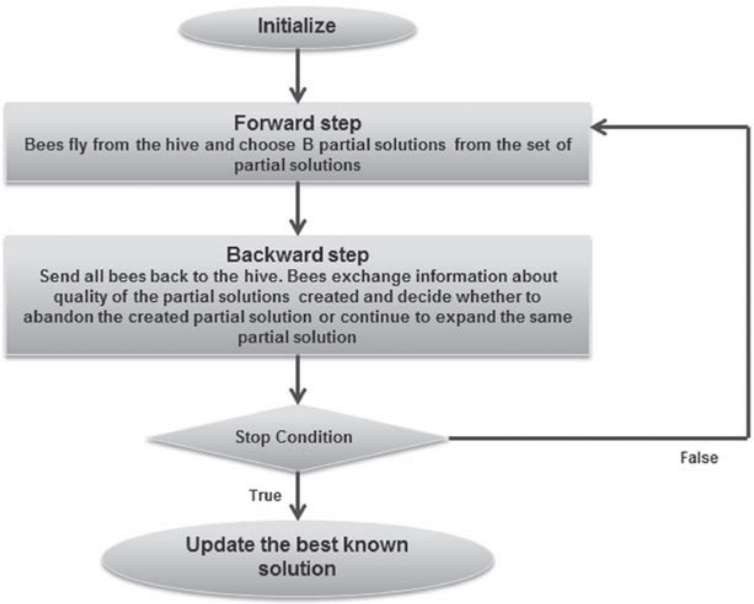


Fig. 1. Flowchart of a single iteration of the Bee Colony Optimization algorithm.

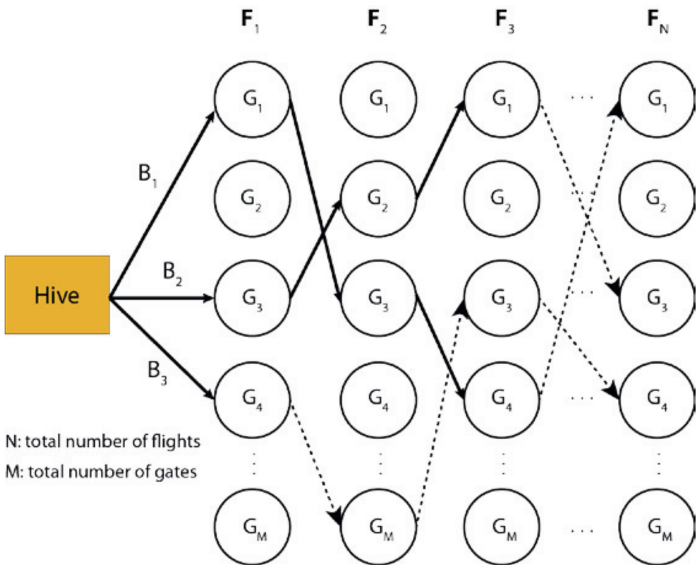


Fig. 2. The artificial network of the decision space

## 5. Application and results

The Milano-Malpensa international airport, in the following called Malpensa, has been considered to evaluate the outcomes of the proposed method. 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. Figure 3 shows the Milano-Malpensa airport map. 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 $p$ values after the Bee Colony Optimization process (Fig. 4, 5). Table 1 reports in detail the obtained results in terms of FG (flights to fixed gates) and TWD (total walking distance) for the considered $p$ values. Thus, a sensitivity analysis has been made in order to highlight the role of the variable $p$ in the decision making process.

We can observe that, as $p$ value increases, it gives more importance to the minimization of TWD which decreases up to 40% for $p$=1 (Fig. 4). On the other hand (Fig. 5), the number of flights associated to fixed gates (FG) decreases (RG increases). Thus, a decision should be made in the interval [0.9, 1.0] where we have a significant variation in the objective functions.

Finally, we have to point out how the solutions found by BCO are almost always better than the objective values related to actual scheduling in Malpensa. As a matter of fact, the total walking distance is always lower than the actual values in Malpensa (red line in figure 4), while the number of flights assigned to fixed gates is greater than Malpensa (87, red line in figure 5) up to $p$=0.98.

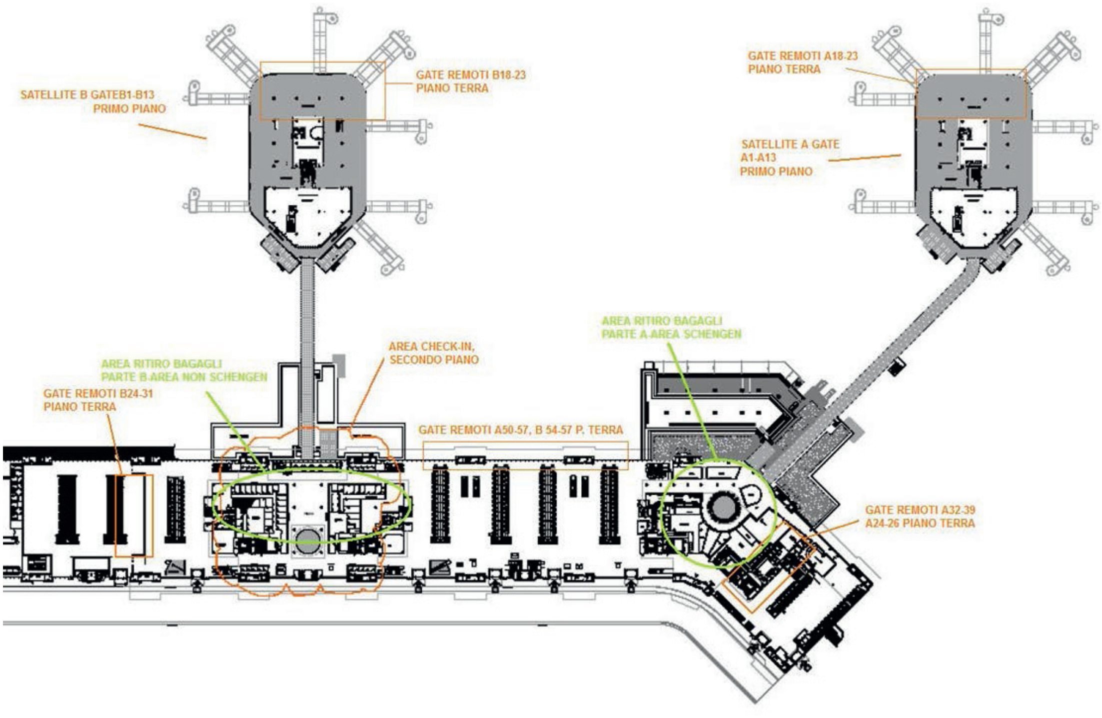


Fig. 3. Milano-Malpensa airport map

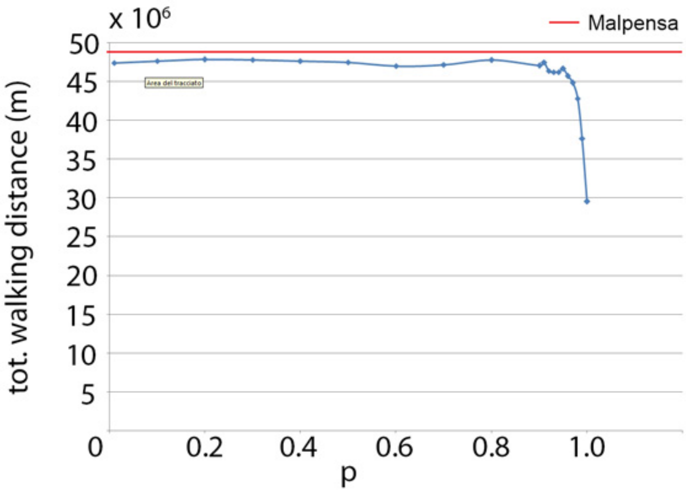


Fig. 4. Resulting total walking distance obtained for different *p* values compared to Milano-Malpensa scheduling (red line).

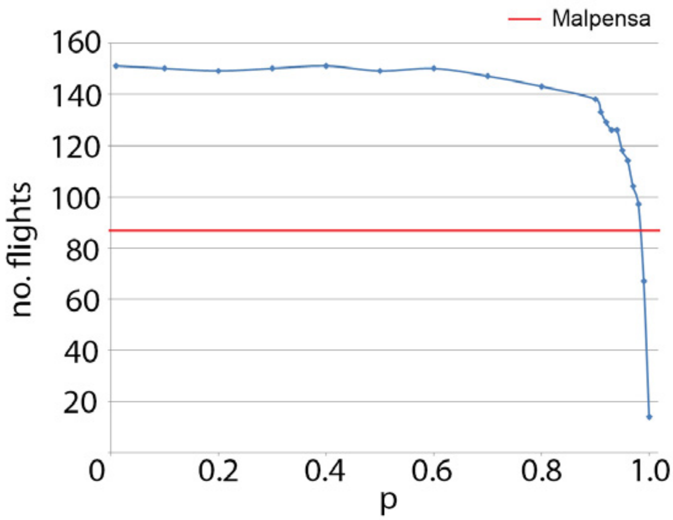


Fig. 5. Resulting number of flights assigned to fixed gates obtained for different *p* values compared to Milano-Malpensa scheduling (red line).

Table 1. Results of the optimization procedures for different *p* values.

| *p* | FG | TWD (m) | *p* | FG | TWD (m) |
|---|---|---|---|---|---|
| 0.01 | 151 | 47382080 | 0.91 | 133 | 47424940 |
| 0.10 | 150 | 47593585 | 0.92 | 129 | 46321019 |
| 0.20 | 149 | 47808824 | 0.93 | 126 | 46204800 |
| 0.30 | 150 | 47771220 | 0.94 | 126 | 46198760 |
| 0.40 | 151 | 47630673 | 0.95 | 118 | 46617243 |
| 0.50 | 149 | 47459193 | 0.96 | 114 | 45658507 |
| 0.60 | 150 | 46967739 | 0.97 | 104 | 44804043 |
| 0.70 | 147 | 47116671 | 0.98 | 97 | 42756548 |
| 0.80 | 143 | 47727154 | 0.99 | 67 | 37603348 |
| 0.90 | 138 | 47009585 | 1.00 | 14 | 29498658 |

## 6. Conclusions

In this paper we have presented a metaheuristic approach based on the Bee Colony Optimization (BCO) to solve the flight gate assignment problem. This method has shown good capabilities in solving high-order combinatorial problems, like overall combinations in flight assignment to a gate. A dual criteria problem has been considered in order to minimize the total walking distance and the number of flights assigned to remote gates, subject to compatibility constraints. Results highlight the effectiveness of the proposed method when compared to the actual Milano-Malpensa flight scheduling. A multicriteria analysis has been carried out to show how the solutions found by BCO are almost always better than the Malpensa ones. Concluding, the proposed method can be considered as a good tool to support decision-making in flight scheduling. Further developments cover the adaptation of the method to the dynamic gate assignment problem considering more constraints related to airline companies' preferences and agreements. Moreover, more criteria can be considered to better evaluate the quality of the assignment.

## References


Babic O., Teodorovic D., Tosic V., 1984. Aircraft stand assignment to minimize walking. Journal of Transportation Engineering 110:55–66.

Baron P., 1969. A simulation analysis of airport terminal operations. Transportation Research;3:481–91.

Bihr R., 1980. A conceptual solution to the aircraft gate assignment problem using 0–1 linear programming. Computers & Industrial Engineering;19:280–4.

Bolat A., 2000. Models and a genetic algorithm for static aircraft gate assignment problem. Journal of the Operational Research Society;52:1107–20.

Cheng Y., 1997. A knowledge-based airport gate assignment system integrated with mathematical programming. Computers & Industrial Engineering;32:837–52.

Cheng, C-H., Ho, S. C., Kwan, C-L., 2012. The use of meta-heuristics for airport gate assignment. Expert System with Application 39:12430–12437

Ding H., Lim A., Rodrigues B., Zhu Y., 2004. New heuristics for the over constrained airport gate assignment problem. Journal of the Operational Research Society;55:760–768.

Dorndorf U., Drexl A., Nikulin Y., Pesch E., 2007. Flight gate scheduling: state-of-the-art and recent developments. Omega 35:326–334.

Dorndorf U., Jaehn F., Pesch E., 2008. Modelling robust flight gate scheduling as a clique partitioning problem. Transportation Science 42:292–301.

Drexl A., Nikulin Y., 2008. Multicriteria airport gate assignment and Pareto simulated annealing. IIE Transactions 40:385-397.

Gosling G., 1990. Design of an expert system for aircraft gate assignment. Transportation Research;24A:59–69.

Hamzwawi S., 1986. Management and planning of airport gate capacity: a microcomputer-based gate assignment simulation model. Transportation Planning and Technology;11:189–202.

Hassounah M, Steuart G., 1993. Demand for aircraft gates. Transportation Research Record;1423:26–33.

Hu, X., Di Paolo, E., 2009. An efficient genetic algorithm with uniform crossover for the multi-objective airport gate assignment problem. In C.K. Goh, Y.S. Ong, & K.C. Tan (Eds.). Studies in Computational Intelligence 171: 71–89.

Mangoubi R, Mathaisel D., 1985. Optimizing gate assignments at airport terminals. Transportation Science;19:173–88.

Milano-Malpensa Airport Regulations , 2010. From: http://www.milanomalpensa2.eu/it/download?_fname=/AssetsProtected/contentresources_2/mmo/486/C_2_mmo_1287_file.pdf&_ofname=RegScaloMXP2.1%20mag.%20%2710-%20allegati.pdf

Srihari K, Muthukrishnan R., 1991. An expert system methodology for aircraft-gate-assignment. Computers & Industrial Engineering;21:101–5.

Teodorovic D., Dell'Orco M., 2005. Bee Colony Optimization – A Cooperative learning approach to Complex Transportation Problems. Advanced OR and AI Methods in Transportation, pp. 51-60.

Teodorovic D., Lucic P., Markovic, G., Dell'Orco M., 2006. Bee Colony Optimization: Principles and Applications. Neural Network Applications in Electrical Engineering, pp. 151 – 156.

Wirasinghe S., Bandara S., 1990. Airport gate position estimation for minimum total costs—approximate closed form solution. Transportation Research;24B:287–97.

Xu J., Bailey G., 2001. The airport gate assignment problem: mathematical model and a tabu search algorithm. In: Proceedings of the 34th Annual Hawaii International Conference on System Sciences, IEEE. p. 3032.

Yan S., Chang C., 1998. A network model for gate assignment. Journal of Advanced Transportation;32:176–89.

Yan S., Huo C., 2001. Optimization of multiple objective gate assignments. Transportation Research;35A:413–32.

Yan S., Shieh C.-Y., Chen M., 2002. A simulation framework for evaluating airport gate assignments. Transportation Research;36:885–98.