Check-in Counters Management: The Case Study of Lisbon Airport

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Abstract: In this paper the problem of assigning check-in counters to flights in a Zone of Lisbon airport is addressed at an early stage. Real traffic scenario and simulation of passengers behaviour and characteristics are considered. The aim is to minimize an objective function that takes into consideration the managing cost of opening check-in counters and the passengers' cost of waiting to be served by the check-in operator. This latter cost function has been modelled by considering the International Air Transport Association level of service perceived by the passengers. Since the performances depend on the passengers' behaviour and characteristics, simulation is used to compute the value of the objective function. Two optimization heuristic procedures have been tested and their results compared.

1 INTRODUCTION

Airport land side processes involve several types of resources and services whose performance affect the costs of the airport management and of the airlines, but also the passengers' satisfaction.

In this paper a first step of a more complex study for solving the problem of assigning check-in counters to flights is proposed. The aim is to minimize the check-in counters opening costs and the passengers discomfort due to the waiting time in line. Authors study the real case of Lisbon airport, where real air traffic is considered and realistic passenger flow is simulated.

Several authors have addressed problems concerning Check-in opening optimization (Appelt et al., 2007), (Hsu et al., 2012). Models and solution approach are different. Real scenarios have been represented by mean of linear programming models to plan the check-in operations (Stolletz, 2010) and to optimize associated costs (Al-Sultan, 2016). A combination of linear programming and simulation have been addressed to optimizing the costs and performing a certain service level (Araujo and Repolho, 2015). Simulation constitutes a valid instrument to model passengers specific characteristics and to represent stochastic passengers behaviour that constitute the input of an optimization approach ((Adacher et al., 2017), (Mota and Alcaraz, 2015), (Mota, 2015)). Many authors address the problem of customer satisfaction by considering service quality indicators modeled in different cost functions ((Manataki and Zografos, 2009), (Caot et al., 2003), (Ju et al., 2007), (Bruno and Genovese, 2010), (Parlar et al., 2013), (Suárez-Alemán and Jiménez, 2016)).

In this paper authors combine simulation and optimization techniques to solve the problem of assigning check-in counters to the flights in a given time interval, optimizing costs, by considering passengers discomfort and by introducing cost coefficients that depend on levels of service. The levels of service depend on the length of the queues in terms of waiting time and are derived by the International Air Transport Association standards (IATA, 2014). Simulation provides the cost objective function value after modeling and processing passengers characteristics and behaviour. At this first stage, optimization algorithms are very simple. Results output by a greedy algorithm, completed by a local search procedure, and by a genetic algorithm have been compared. The former easily suites the bicriteria aspect of the problem (and of the objective function), the latter is implemented in several simulation tools and allows the solution to avoid local minima.

The paper is organized as follows: Section 2 presents the problem description. In section 3 the two heuristic procedures are briefly described. In Section

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4 tests are described and results are reported and analyzed. Section 5 is dedicated to the conclusion and to the description of the future development of the study.

2 PROBLEM DESCRIPTION

The problem of assigning the check-in counters of a Zone of the Lisbon airport is addressed. The airport is formed by two terminal areas, the second is dedicated to the domestic flights and the check-in area is composed by four Zones in which 107 counters are located (see Figure 1).

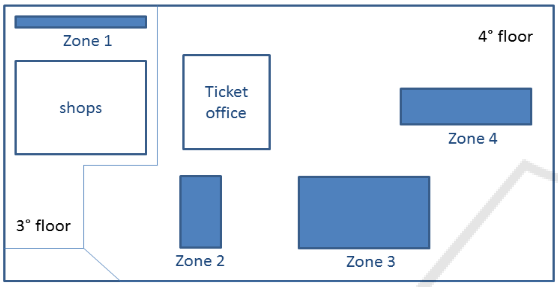


Figure 1: Layout of check-in area.

This paper focuses on the optimization of Zone 3, hosting 58 check-in counters, but the same model and solution approach can be easily extended to the whole area. The problem consists in assigning a set of check-in counters C to a set of flights F in a given time interval T, optimizing costs. The time interval is assumed to be discrete and divided in time slots, each of 15 minutes. Total costs are given by the costs of opening the check-in counters plus the cost of passengers' discomfort that depends on the length of the queues. The objective function is reported below, where

- C_1 represents the unit cost of opening a check-in counter in a time slot,
- $C_2(w_p)$ represents the cost of the discomfort of passenger p,
- w_p is the waiting time (minutes) in line for passenger p,
- y_{ct} is equal to one if the check-in counter c is open in the time slot t.

$$OF = \min\{\sum_{c=1}^{|C|}\sum_{t=1}^{T} C_1 y_{ct} + \sum_{p=1}^{|P|} C_2(w_p)\}$$

The decision variable is x_{fct} and it is equal to 1 if the flight f is assigned to the check-in counter c for the slot time t.

Table 1: Levels of service and corresponding waiting times (min).

Level of Service	A	B	C	D
Max waiting time	10	25	40	60

$$x_{fct} = \begin{cases} 1 & \text{if flight } f \text{ is processed by check-in} \\ & \text{counter } c \text{ in the time slot } t \\ & \text{for f = 1} \ldots |F|\text{, c = 1} \ldots |C|\text{, t = 1} \ldots T \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

When all flights have been assigned it is possible to calculate w_p and y_{ct}. w_p is calculated by simulation, while y_{ct} is calculated by the relation below:

$$y_{ct} = \begin{cases} 1 & \text{if } \sum_{f=1}^{|F|} x_{fct} \geq 1, \\ 0 & \text{otherwise.} \end{cases}$$

Constraints can be summed up as follows:

- the number of check-in counters is limited to C_{max}
- each flight must be processed by at least one check-in counter
- if a flight f is processed by a check-in counter c in a time slot t ($x_{fct} = 1$) the check-in counter c must be active in the time slot t ($y_{ct} = 1$)
- the check-in operation for a flight must last 120 minutes (8 consecutive slots)
- the check-in operation for a flight must be completed 20 minutes before the take-off
- each passenger that arrives by 20 minutes before the take-off must be processed
- the length of the queue for the check-in operation is limited by the space dimension (no more than 45 people can wait in a queue)

C_2 is neither constant, nor linear: it is a waiting time-dependent step function that will be described in Section 4. An additional aspect is represented by the level of service of a solution. The level of service has been standardized by the International Air Transport Association (IATA) and can be defined as Excellent (A), High (B), Good (C) and Adequate (D). In Table 1 the relation between the levels of service and the maximum waiting time (in minutes) in line are reported.

The objective function value is calculated by simulation, since it depends on the passengers arrivals, on their distribution in the lines and on their characteristics, such as the number of luggage that affect the check-in operator service time.

As already mentioned while listing the constraints, each flight f must be processed by a check-in counter for 120 minutes (8 time slots). This time interval can be denoted by τ_f.

3 HEURISTICS

In this section the description of two heuristic procedures is provided. A greedy heuristic with a local search algorithm is presented. It is very fast and easily addresses the simultaneous minimization of operational costs and of passengers' discomfort costs. A basic genetic algorithm has been implemented to test the procedure embedded in several simulation tools. Its performance have been compared to the results obtained by a standard genetic algorithm. Both the procedures are sketched below.

3.1 Greedy Heuristic + Local Search

Before briefly describing the main steps of the heuristic procedure, the definition of set X_f is provided. Given a flight f the set X_f is formed by all the flights f' of the same airline, such that τ_f and $\tau_{f'}$ overlap. The heuristic can be summed up in the steps in Algorithm 1. It is composed by two phases, the first implementing the greedy procedure and the second executing the local search procedure. The greedy phase tries to assign a set of check-in counters for each flight, so that the maximum length of the queue is under a tolerable threshold. The local search phase tries to improve the solution.

3.2 Genetic Heuristic

This heuristic is a standard genetic algorithm, whose main steps are reported in Algorithm 2. After generating the initial population of cardinality S, by a random assignment of the check-in counters to all the considered flights, a cyclic subroutine selects two parents that will generate the new population, till the stop criteria are met. The probability of each individual to be selected for the reproduction is proportional to their Fitness value. In such way the best individuals have a higher probability to transmit their genetic inheritance. The two operators that generate the new population from the parents are:

- The Crossover operator combines the genetic inheritance of the parents to generate new individuals. Each children is composed by two parts, each one belonging to one of the two parents. The CR is the rate of crossover. Each crossover operation generates two children.

Algorithm 1: Greedy heuristic and Local search.

Given the F ▷ Set of flights
Given $|C|$ ▷ Total number of the check-in counters
Given K ▷ K is the maximum length of the queue
$C_{ass} = 0$ ▷ Counter: it counts the number of assigned check-in desks ▷ **Greedy heuristic phase**
Order F with respect to the increasing departure times
for (each $f \in F$) **do**
  Generate X_f; ▷ X_f is the set of all the flights $f' \in F$ of the same airline, such that τ_f and $\tau_{f'}$ overlap
end for
for (each $f \in F$) **do**
  Assign to f a check-in counter list CKC_f, one every K passengers;
  $C_{ass} = C_{ass} + |CKC_f|$; ▷ Total number of check-in counters assigned till f
  while ($C_{ass} > |C|$) **do**
    Remove a check-in counter from the list
    of a previous flight f' such that $f' \in X_f$
    and $|CKC_{f'}| \geq 2$;
    $C_{ass} = C_{ass} - 1$;
  end while
  Construct CKC ▷ Form CKC from all the CKC_f assigned and modified till now
end for
▷ **Local search phase**
Fix L ▷ L is the maximum number of iterations
for ($l \leq L$) **do**
  Select randomly a flight f such that $|CKC_f| \geq 2$;
  Remove a check-in counter from $|CKC_f|$;
  Assign it to a flight in X_f;
  Construct CKC;
end for
Return the best CKC.

- The Mutation operator changes casually one or more components of a individual. The mutation operator is applied only with a certain probability, called mutation rate MR. The number of children that are generated by the mutation operator depends on the number of individuals generated by the crossover operator. The new population will have the same cardinality of the initial one (S).

Algorithm 2: Genetic heuristic.

Given I ▷ I is the maximum number of iteration of the algorithm
Given RC ▷ CR is the rate of crossover
Generate $P = \{p_1, p_2, \dots p_S\}$ ▷ The initial population of feasible solutions of cardinality S
for $(i \leq I)$ **do**
    for $(s \leq S)$ **do**
        Compute $Fitness(p_s)$ ▷ The Fitness function is the objective function of the problem
        Select the two parents p_m and p_f in P with the best Fitness function values
        Update p^* ▷ p^* is the individual with the best Fitness function value
        CC = Crossover (p_m, p_f, CR); ▷ CC set of individuals derived from the Crossover
        M = Mutation (MR) ▷ M set of individuals derived from the Mutation
        $P = CC \cup M$
    end for
    $i = i + 1$
end for
Return p^*

4 RESULTS AND ANALYSIS

4.1 Instances Definition

This section presents the problem parameters, the instances assumptions and the analysis of the results. In order to simulate the passenger flow it is necessary to introduce the following assumptions:

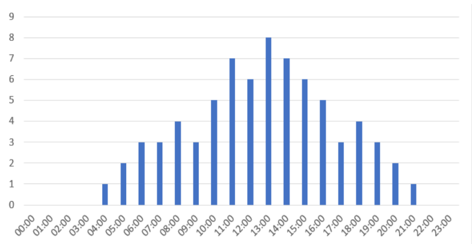


Figure 2: Daily arrival distribution.

- Discretization of the problem: the time horizon T is divided into intervals with constant duration t. The problem becomes a discrete problem, and all the parameters and variables are referred to each interval t. The simulation time is divided into time slots, each of 15 minutes.
- Flights distribution: the distribution of the flights in a day is shown in Figure 2. The trend reported reproduces the daily performance of the Lisbon Airport, the peak of arrivals is between 11 am and 16 am. Different numbers of flights are daily considered for the tests (73 to model low traffic, 105 for medium traffic and 130 for high traffic).
- Arrivals distribution: check-in service demand can be expressed in terms of passengers arrival, represented by stochastic variables. The passengers arrival distribution is shown in Figure 3 that depicts the arrival pattern in the time interval before the flight departure. Two different cases are tested. The first represents an homogeneous distribution of passengers per flight: the passengers are characterized by a Gaussian distribution ($\mu = 60, \sigma = 20$); the second models an heterogeneous distribution: the passengers are characterized by a Gaussian distribution ($\mu = 60, \sigma = 40$).
- Passenger types: two types of passengers are here considered: *business*, travelling alone and with at most one baggage; *tourist* travelling alone or in groups up to 2 people carrying one or two luggage each. 20% of the passengers are business passengers while 80% are tourist passengers (30% with one luggage and 50% with two luggage).
- Service time: service time represents the time needed to process the passenger. At the Check-in counter, the processing time depends on the number of bags. No bags needs 1 minute, one bag needs 1.5 minute and 2 bags need 2 minutes to be processed.

The maximum number of Check-in counters that can be opened is 58.

Considering the quality service given by the IATA, the unit costs to evaluate the objective function are fixed:

- the managing cost of a single check-in counter is equal to $C_1 = 20$ euro/slot;
- the cost for the passengers' waiting time w_p has been set to the following step function:

$$C_2 = \begin{cases} 0 & \text{if } w_p \leq 10 \\ 15 & \text{if } 11 \leq w_p \leq 25 \\ 25 & \text{if } 26 \leq w_p \leq 40 \\ 40 & \text{if } 41 \leq w_p \leq 60 \\ 80 & \text{if } w_p \geq 61 \end{cases} \qquad (2)$$

This cost function is a result of the simulation tests. It guarantees a balanced distribution of the costs in the two terms related to the check-in counters opening and passengers' discomfort. This issue is verified in the following analysis of the solution costs, that are similar with respect to the two heuristic procedures, and balanced with respect to the two cost items.

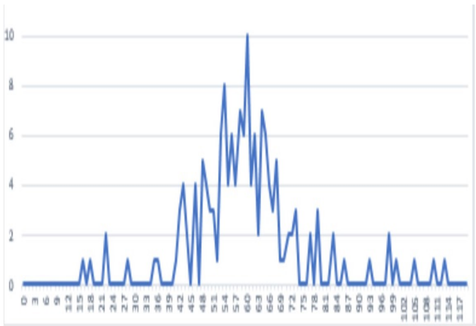


Figure 3: Passengers arrival distribution.

4.2 Time and Cost Analysis

In this section a comparison between the two proposed heuristics is shown. For the Greedy heuristic, K has been set to 35 and represents the threshold that takes into consideration an acceptable level of service. On the basis of test bed, the configuration below was adopted for the genetic algorithm: Number of iterations 50, Population Size 20, Crossover Rate $CR \in [0.4; 0.8]$, Mutation Rate 0.1. The results reported in the following are the mean values calculated on 10 different runs with the same probability distribution of the simulation parameters.

The following notation can be introduced:

- GRL stands for Greedy heuristic plus local search;
- GEN stands for Genetic heuristic;
- HET stands for heterogeneous distribution for passengers;
- HOM stands for homogeneous distribution for passengers
- HT-MT-LT mean High, Medium and Low traffic.

In all cases the two heuristics give the best performances when the arrivals are homogeneously distributed.

In Figure 4 and in Figure 5 the maximum and the average waiting time generated by the two heuristics are reported. As for the maximum waiting time the two heuristics present the same trend. When the average waiting time is considered the *GRL* gives the best performances. This is due to the fact that the greedy heuristic only focuses on the customer satisfaction opening a new check-in counter when the queue becomes too long with respect to the fixed threshold oh 35 people. The total costs are optimized by the local search.

In Figure 6 the trend of the check-in costs is reported. Here the *GEN* optimizes the managing costs since the *GRL* considers especially the passengers satisfaction. The *GEN* gives better performances and its

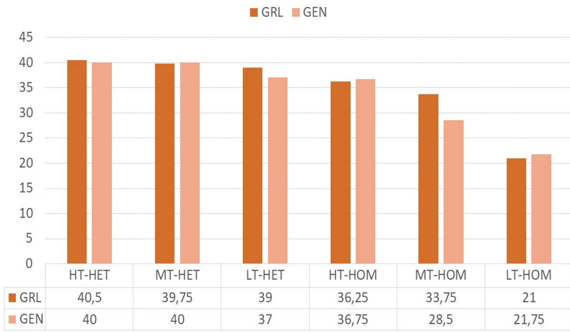


Figure 4: Max waiting time (minutes).

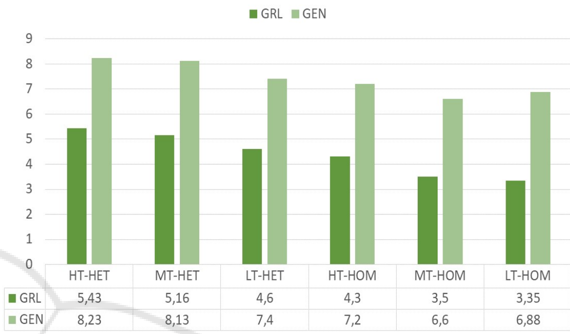


Figure 5: Average waiting time (minutes).

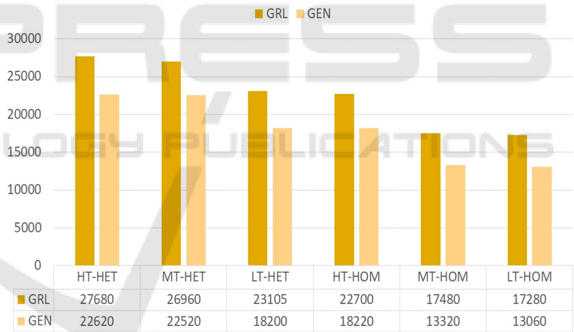
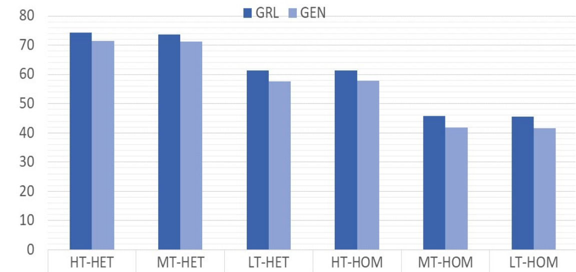


Figure 6: Cost of opening check-in counters.

improvement is around $20\% - 30\%$ for all cases when considering all the flights of a day.

In Figure 7 the total cost trend is shown and is represented in thousands of euros. The Genetic heuristic gives better performances and these results confirm its ability to jump out of local minima and to solve complex problems. Considering the total cost the improvement of *GEN* respected to the *GRL* is around $3\% - 9\%$ for all cases when considering all the flights in a day.

In Figure 8, 9 and 10 the level of service of the solutions is reported with reference to the heterogeneous passenger distribution. The trend of the solutions is similar when considering the homogeneous case. As highlighted before, the *GEN* gives the best perfor-



	HT-HET	MT-HET	LT-HET	HT-HOM	MT-HOM	LT-HOM
GRL	74,39	73,61	61,39	61,38	45,75	45,5
GEN	71,42	71,15	57,7	57,94	41,71	41,64

Figure 7: Objective function values (K).

mances in terms of total costs but when the level of service is considered the *GRL* output optimizes passengers' satisfaction. In all cases more the 55% of the solution is Excellent (A), instead for the *GEN* solution quality is High (B).

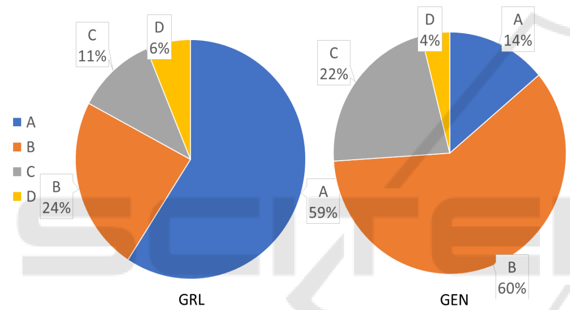


Figure 8: Level of service for High traffic and heterogeneous passenger distribution.

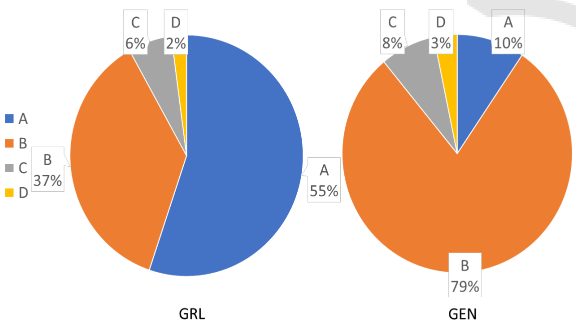


Figure 9: Level of service for Medium traffic and heterogeneous passenger distribution.

5 CONCLUSION AND FUTURE RESEARCH

In this paper authors address the problem of optimizing costs of opening and assigning check-in counters to a set of flights in a given time interval. Besides the classical cost term due to the check-in counters opening operations, the objective function models the passenger discomfort costs integrated with the level of service performed. The real case of the Lisbon airport has been considered. In this preliminary phase two heuristic procedures have been tested and costs and waiting times have been compared. The future of this study will model other aspects of the airport and of the passengers and will consider more performing optimization techniques.

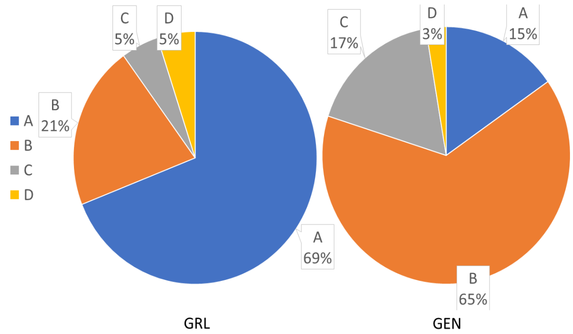


Figure 10: Level of service for Low traffic and heterogeneous passenger distribution.

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