



# A fast airplane boarding strategy using online seat assignment based on passenger classification



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## ABSTRACT

The minimization of the turnaround time, the duration which an aircraft must remain parked at the gate, is an important goal of airlines to increase their profitability. This work introduces a procedure to minimize of the turnaround time by speeding up the boarding time in passenger aircrafts. This is realized by allocating the seat numbers adaptively to passengers when they pass the boarding gate and not before. Using optical sensors, an agility measure is assigned to each person and also a measure to characterize the size of her/his hand-luggage. Based on these two values per passenger and taking into account additional constraints, like reserved seats and the belonging to a group, a novel seat allocation algorithm is introduced to minimize the boarding time. Extensive simulations show that a mean reduction of the boarding time with approximately 15% is achieved compared to existing boarding strategies. The costs of introducing the proposed procedure are negligible, while the savings of reducing the turnaround time are enormous, considering that the costs generated by inactive planes on an airport are estimated to be about 30 \$ per minute.

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## 1. Introduction

Airlines only generate profit when their airplanes are flying, therefore a common issue in airline industry is the minimization of the time they spend at the airports. This time, usually referred to as *turnaround time* (TAT), requires special attention. Several different ground operations are performed during TAT. Most of them can take place simultaneously, others, such as passengers boarding, cannot start until other processes, such as fueling, cleaning and catering, have been successfully completed. The boarding process plays an important role with respect to the TAT, since it is on its *critical path* Steiner and Philipp (2009). In this case, a substantial reduction of the boarding time can reduce the TAT by approximately the same amount.

This topic has been previously investigated by many authors. An

overview of their study can be found in Mas et al. (2013). Many strategies have been simulated under several assumptions for finding the strategy which minimizes the total boarding time through the minimization of passenger interferences. Since each of the mentioned studies focused on different components of boarding delay, the authors do not agree on the best overall approach. On the other hand, the problem of practical implementation of these strategies has not been studied in deep in the previous literature.

In this paper we present a novel technique based on passengers classification which results in a new strategy for reducing boarding time. Our work has been influenced by Jason H. Steffen who, in Steffen (2008), presented an optimum boarding method that works only if passengers are placed in a specific position in the boarding line that depends upon their ticketed seat location. In addition, Steffen method does not consider all the variables that come into play in a real boarding scenario, such as reserved seats and passengers who travel in group, making it inconvenient to implement in reality, as well as incompatible with passengers satisfaction and thus with airline plans.

The approach presented in this paper extends Steffen method

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both making the boarding faster and allowing a streamlining of the gate infrastructure. This is achieved by assigning seats to passenger based on their hand-luggage, as considered also in Milne and Kelly (2014), and on their agility. Moreover, our algorithm takes into account the constraints created by passengers with reserved seats and it is also able to handle passenger groups.

Our study is addressed to solve real implementation issues of the presented technique by designing a new seat allocation algorithm based on real data recorded at the airport gates. The proposed system is based on cameras and makes use of computer vision algorithms in order to detect hand-luggage and to estimate people agility, which constitute two input parameters for the seat allocation algorithm. We performed various simulations using Mathworks® MATLAB for validating it in different relevant scenarios. The results of our simulations reveal a significant reduction of the boarding time with respect to other algorithms and therefore a considerable cost saving. What has to be pointed out too, is that our approach does not require gate modifications or training of the groundcrew in order to be applied.

This paper is organized as follows. In this section we provide an overview of the existing boarding strategies highlighting advantages and drawbacks of their practical implementation. In Section 2 the theory behind the developed boarding strategy is presented: the algorithm, as well as the evaluation of the parameters on which it depends, are explained in detail. Section 3 is dedicated to the simulations and its results. Section 4 concludes the paper and reports future work that has been planned to do.

1.1. State of the art

Several passenger boarding strategies have been investigated in order to board passengers as fast as possible. Among these, the commonly adopted ones by most of the airlines are reported below and depicted in Fig. 2:

Ferrari and Nagel (2005) present a survey on the different boarding strategies that are currently used by companies. It also proposes ways to model passengers, bin occupancy, seating and disturbances. In McFadden and Nyquist (2008) boarding strategies are discussed too. They also present an overview on the airlines and on their most adopted boarding procedures. As discussed also later, in their work there is also an analysis of the financial impact of the TAT.

Both the WilMA method and the reverse pyramid method eliminate seat interferences (within a given seats row) and aisle interferences. Bazargan (2007), starting from the reverse pyramid model, proposed a mixed integer linear program approach which attempts to further minimize the total interferences among the passengers.

Conventional wisdom would suggest the back-to-front boarding as the fastest. This strategy is actually employed very often and, besides the arrangements that have to be made at the gate, is not even the optimal method. Studies on airplane boarding use a variety of approaches: van Landeghem and Beuselinck (2002) found that there is much room for improvements over traditional back-to-front boarding (even the random boarding can be faster than many traditional methods). Later studies van den Briel et al. (2005) also confirmed that traditional methods are not optimal. Since each of the mentioned studies focused on different components of

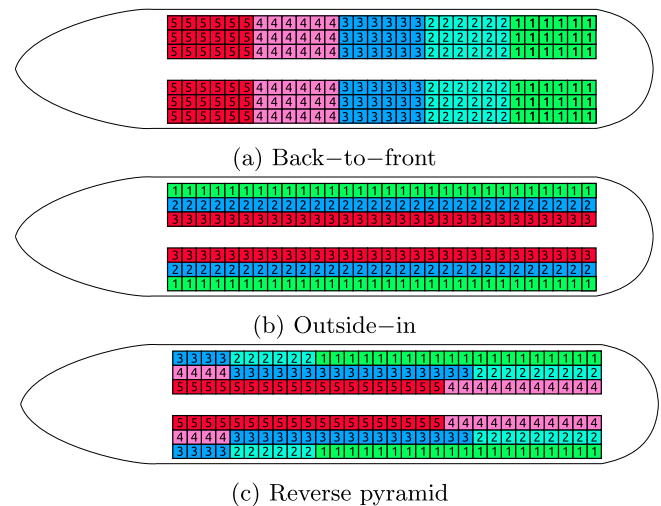


Fig. 2. Most popular boarding methods.

- **Back-to-front:** it consists in boarding first class firstly. Then, passengers are called in groups to board the aircraft, following the sequence from back to front (Fig. 2a).
- **Outside-in:** it is also called *WilMA*, acronym of Window-Middle-Aisle. First class passengers are boarded first. Then, passengers in window seats are boarded, then middle seats, and finally aisle seats (Fig. 2b).
- **Reverse pyramid:** it is a hybrid approach between the traditional back-to-front and the outside-in boarding strategies derived using a nonlinear model including all the different interferences that could possibly occur during boarding van den Briel et al. (2005) (Fig. 2c).
- **Rotating zone:** it consists in boarding passengers sitting in the middle of the aircraft last. Thus, passengers are grouped into zones and board the aircraft first in the front, then in the back, then front again, then back, and so on.
- **Random boarding** this strategy does not specify any condition to board passengers and the aircraft is boarded in one zone randomly. First class passengers are also boarded firstly. Then, passengers board the airplane in a first-come first-serve basis.

boarding delay, there is not a generally accepted method. A different approach was given by Jason H. Steffen who, in Steffen (2008), defined an optimal sequence to board assuming that the time that a passenger requires to load her/his luggage is the dominant reason of delay. However, as already mentioned, Steffen method does not consider all the variables that come into play in a real boarding, making it inconvenient to implement in reality.

In this paper we overcome these limitations, while guaranteeing a faster boarding in every situation, still allowing passengers to reserve a seat or to stay with their families or in a group of friends.

Also, after experiencing the advantages of the proposed method, the number of passengers that will choose their seats could significantly decrease, allowing the algorithm to reach its maximum performances.

1.2. Main contributions

The main contributions of the presented work are:

- Extension of the Steffen method by using a seat allocation algorithm based on real parameters,
- Use of computer vision techniques for obtaining in real-time the desired input parameters for the algorithm.

The application of computer vision in the airports is not a new subject: Schreiber and Rauter (2012) used cameras to count people; Vaddi et al. (2013) proposed a vision based surveillance system; Spreeuwes et al. (2012) a face recognition system for automatic border control, with real tests at Schiphol airport, which has become state of the art nowadays. Our method, however, makes

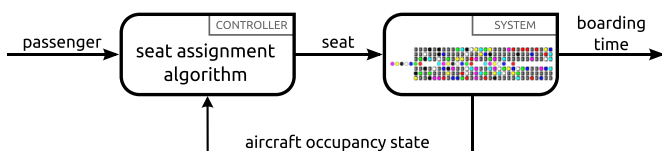
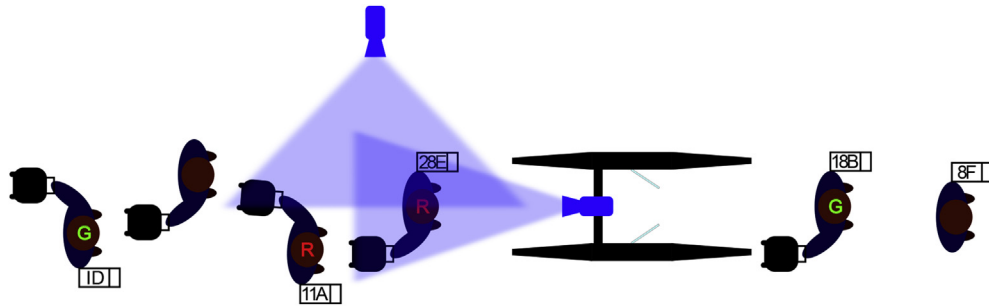


Fig. 1. Control scheme of the presented boarding method.



**Fig. 3.** Top view of an airport gate. Before passing through the gate, passengers have their ticket either empty or containing information related to their reserved seat or the group they belong. In the case passengers have a reserved seat (identified with a red “R” in the figure) the seat number is already on the ticket. For passengers belonging to groups (depicted with a green “G” in the figure), instead, only the group ID is on the ticket. The information on the ticket will be used by the proposed algorithm to assign the best available seat. After having passed the gate, all passengers are depicted with the seat number printed on their respective ticket. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

use of computer vision techniques in order to speed up boarding and to allow to save both time and money.

Simulations are used to analyze and test the proposed boarding strategy. They require different parameters, such as the estimation of the passenger agility and of the size of their hand-luggage, an ID referring to groups of passengers and the handling of reserved seats. Once these quantities, in terms of particular coefficients, are available, simulations can be started. They can show the current boarding time as well as the boarding percentage in real-time. The simulation environment allows to load the seating plan configuration of a single-aisle aircraft with 30 rows and 6 seats per row, with a single entrance, at the front. Simulations take into account the time required to sit, which is influenced by the passenger coefficients, i. e., by the size of the hand-luggage and by their agility. A considerable number of simulations has been performed in order to consider every possible scenario. The results of these simulations is shown in terms of mean and variance of the boarding time. By using these quantities, a comparison with existing boarding method is considered.

A closer look on the resulting boarding controller is shown in Fig. 1. It describes the intrinsic nature of the controller of being dependent on both real-time physical parameters and previous allocated seats Fig. 3.

## 2. Theory of the algorithm

In this section the theory underlying the proposed seat allocation algorithm is presented. First, in Subsection 2.1, the methods that have been used to retrieve important parameters for the algorithm are explained. Then, in Subsection 2.2, the use of these parameters for the proposed seats allocation approach is presented.

### 2.1. Passenger classification

Passenger classification has the objective of providing an *agility* coefficient, from now on indicated by  $\alpha$ , and a *hand-luggage* coefficient, referred to as  $\beta$ , to the seat allocation algorithm.

The challenge is to obtain these parameters in a way which is as simple and robust as possible, since they have to be calculated in real-time and used to evaluate the optimal passenger seat.

A computer vision algorithm is responsible to extract these parameters from images. The processing software performs the shape recognition of both the passenger and her/his luggage. The used object detector has been introduced by Viola and Jones (2001) for face recognition and improved by Lienhart and Maydt (2002). It classifies images making use of simple rectangular features based on Haar basis functions Papageorgiou et al. (1998). In order to compute these features in a rapid way, in Viola and Jones (2001) the *integral image*,

an intermediate representation for the image, is introduced. To train the classifier, a variant to the *AdaBoost* learning algorithm is used.

A people detection system that uses a feature-based detector is described in Papageorgiou et al. (1998). A different approach for people detection, based on HoG (Histogram of Oriented Gradients), is introduced in Gao et al. (2014). A comprehensive overview of people detection techniques is presented in Dollar et al. (2012).

The steps to obtain information from images are listed below and explained more in detail in the following:

1. Feature-based classifier training, which is performed off-line;
2. Use of the trained algorithm to classify an input image;
3. Two-dimensional geometric figure generation;
4. Computation of  $\alpha$  and  $\beta$ .

Before recognizing shapes, a feature-based classifier is trained with respect to the shapes that it has to detect. Given a feature set and a training set of *positive* and *negative* images, a machine learning algorithm is used to obtain a classification function. The training set of positive examples has to come from a real scenario. For a more efficient and refined training procedure, in our case the images will be recorded using cameras mounted in the designed positions at the gate in the airport. The labeling procedure now takes place. The goal is that of obtaining a training database of hundreds of sample views depicting objects of interest, i. e., passengers and luggage. The negative examples which have to be included in the training database must not contain any shape of the objects of interest.

After the training, the classifier can be applied to the input image. It gives as outputs the region of interest of the classified object.

Viola and Jones (2001) trained a cascaded classifiers to detect frontal faces with a set of 4916 positive examples. The non-face subwindows come instead from 9544 images which were manually inspected and found to not contain any faces. The frontal face classifier constructed yielded a detection rate of 95% in testing phase. Similar results can be founded in Dollar et al. (2012) for people classification. Therefore, in the present case, after a training procedure conducted in the airports a similar detection rate is expected. Recording data in the airports to train a passenger classifier can be against the law in several countries. However, this recording phase can be performed only in those countries that agree with it. Once the classifier has been trained with the discussed method, the resultant algorithm can be used everywhere without significant modifications. As far as the online video recording is concerned, the images required by the classifier are needed only for a short time period (order of milliseconds) after which they can be safely deleted. Note that training can be done not only with images, but also with videos (Dollar et al. (2012)).

After the shape recognition, the proposed algorithm generates

2D geometric figures for body and luggage (rectangles), that contain the detected shapes (see Fig. 4). After this stage, the agility and hand-luggage coefficients have to be calculated. In the following the procedures used for these calculations will be explained.

2.1.1. Agility coefficient

Since there is not a universal accepted definition of agility, different measures have been defined in order to compute it. It has been defined as the ability to change direction rapidly Bloomfield et al. (1994); Clarke (1959), or the ability to change direction rapidly and accurately Barrow and McGee (1971); Johnson and Nelson (1979). More recently some authors have given a definition of agility including whole-body change of direction but also rapid movement and direction change of limbs Baechle and Earle (2008); Draper and Lancaster (1985). Chelladurai (1976) proposed to include in the concept of agility an appropriate recognition of the perceptual and decision-making components that are involved in many sports. Other authors have considered the agility as any dynamic sport action that involves a change in body position Fulton (1992); Draper and Lancaster (1985). Young et al. (2002) stated that the two main components of agility are the change of direction

speed and perceptual and decision-making components. Sheppard and Young (2006) defines the agility as a rapid whole-body movement with change of velocity or direction in response to a stimulus. Although the last definitions are more detailed, in order to make the agility detection simpler, the developed idea is to quantify the agility by means of an index related both to the modulus and the direction of the velocity vector applied to the Center Of Gravity (CoG) of people during motion. In particular, the variation over time of both the modulus and the direction of the velocity vector is considered. As a first estimate, we can consider the people CoG coincident with the center of the rectangle surrounding the body shape. In order to relate the index  $\alpha$  with the acceleration vector modulus and the variation of the velocity vector direction, three images are needed. To detect the velocity vector in space, two cameras (frontal and lateral) are needed. The first one gives images with information in the plane  $xy$ , the second one in the plane  $yz$  (see Fig. 5). The axes  $xyz$  are those of the common reference system adopted for both cameras.

The frontal camera follows the CoG in the image plane: the coordinates  $x_i$  and  $y_i$  representing the center of the rectangle in the  $xy$  plane vary little in the three shots (see Fig. 6), and their change is also due to the perspective transformation. More important for detecting the agility is the role of the lateral camera (see Fig. 7): it detects the velocity in the  $z$ - direction, the most significant contribution to the velocity vector. Eq. (1) shows the calculus of the two velocity vectors,  $i$  and  $i+1$ , which can be obtained from the three images:

$$\mathbf{v}_{i,i+1} = v_{x_{i,i+1}} \hat{\mathbf{i}} + v_{y_{i,i+1}} \hat{\mathbf{j}} + v_{z_{i,i+1}} \hat{\mathbf{k}} = \frac{x_{i+1} - x_i}{\Delta t} \hat{\mathbf{i}} + \frac{y_{i+1} - y_i}{\Delta t} \hat{\mathbf{j}} + \frac{z_{i+1} - z_i}{\Delta t} \hat{\mathbf{k}}, \quad i = 1, 2. \tag{1}$$

For each photo,  $\Delta t$  is the time interval between consecutive shots (which is always the same),  $\hat{\mathbf{i}}$ ,  $\hat{\mathbf{j}}$  and  $\hat{\mathbf{k}}$  are the axis unit vectors. Since during the timestep  $\Delta t$  all the image processing takes place, it is on the order of 100 ms. Therefore there are no numerical problems in the calculation of the velocity vector components which is robust enough. The coordinates  $x_i$  come from the frontal camera, while  $y_i$  and  $z_i$  from the lateral one. Note that, if the two cameras are placed at the same distance from the passenger to detect, as  $\Delta t$  decreases, the coordinates  $y_i$  obtained from the frontal and the lateral one tend to coincide.

Eq. (2) computes the norm of each velocity vector:



Fig. 4. Shape detection of passenger and luggage.

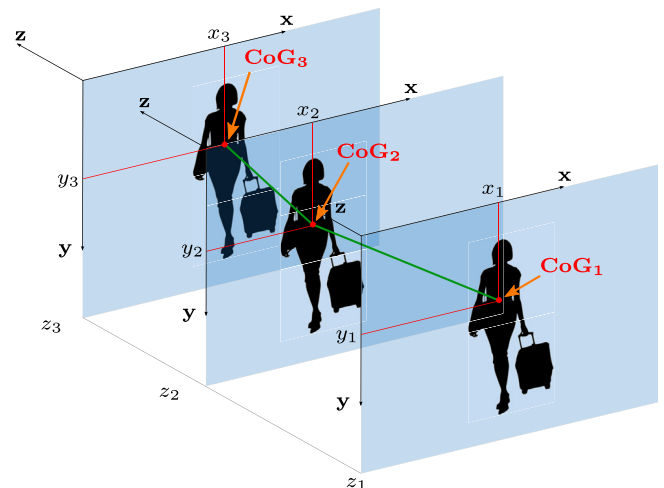


Fig. 5. Passenger CoG in three consecutive shots.



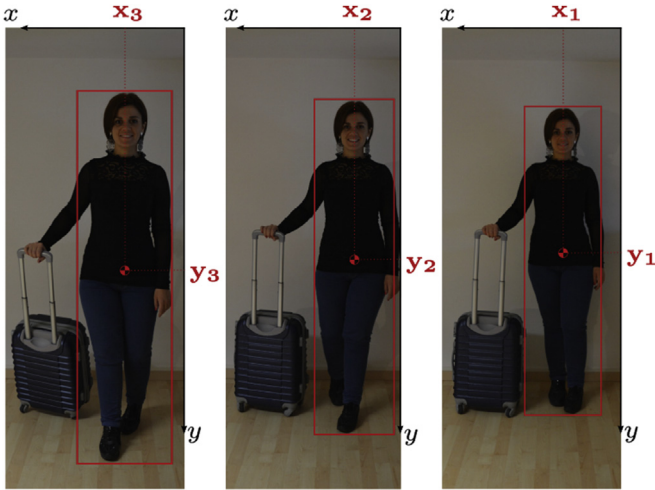


Fig. 6. Passenger CoG in the xy plane (shots from frontal camera).

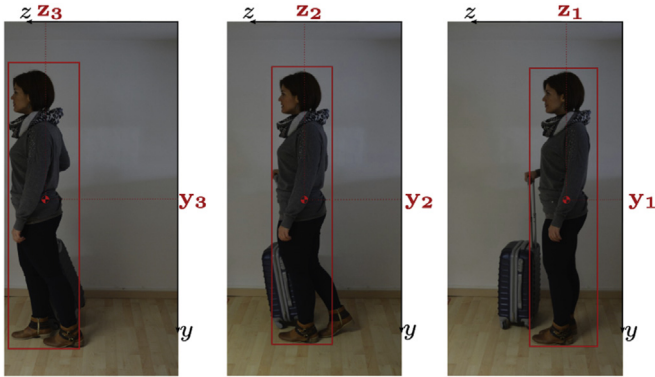


Fig. 7. Passenger CoG in the yz plane (shots from lateral camera).

$$|\mathbf{v}_{i,i+1}| = \sqrt{(v_{x_{i+1}})^2 + (v_{y_{i+1}})^2 + (v_{z_{i+1}})^2}, \quad i = 1, 2. \quad (2)$$

Remembering the evaluation of the direction cosines of a generic vector, Eq. (3) computes  $\theta_x$ ,  $\theta_y$  and  $\theta_z$ , the angles between each velocity vector and the  $x$ ,  $y$  and  $z$ -axis.

$$\begin{cases} \theta_{x_{i+1}} = \cos^{-1} \frac{v_{x_{i+1}}}{|v_{i,i+1}|}, \\ \theta_{y_{i+1}} = \cos^{-1} \frac{v_{y_{i+1}}}{|v_{i,i+1}|}, \\ \theta_{z_{i+1}} = \cos^{-1} \frac{v_{z_{i+1}}}{|v_{i,i+1}|}, \end{cases} \quad i = 1, 2. \quad (3)$$

These three angles are used to capture the changes in the orientation of the velocity vector with respect to the reference system of Fig. 5. Starting from Eq. (1), Eq. (4) computes the resulting acceleration vector, while Eq. (5) its norm:

$$\mathbf{a} = a_x \hat{i} + a_y \hat{j} + a_z \hat{k} = \frac{v_{x_2} - v_{x_1}}{\Delta t} \hat{i} + \frac{v_{y_2} - v_{y_1}}{\Delta t} \hat{j} + \frac{v_{z_2} - v_{z_1}}{\Delta t} \hat{k}, \quad (4)$$

$$|\mathbf{a}| = \sqrt{(a_x)^2 + (a_y)^2 + (a_z)^2}. \quad (5)$$

Starting from Eq. (3), Eq. (6) computes a vector  $\hat{\theta}$  whose components are associated with the rate of variation of the direction of

the velocity vectors:

$$\hat{\theta} = \theta_x \hat{i} + \theta_y \hat{j} + \theta_z \hat{k} = \frac{\theta_{x_2} - \theta_{x_1}}{\Delta t} \hat{i} + \frac{\theta_{y_2} - \theta_{y_1}}{\Delta t} \hat{j} + \frac{\theta_{z_2} - \theta_{z_1}}{\Delta t} \hat{k}. \quad (6)$$

In order to obtain a scalar value useful to compute the desired agility index, the norm of  $\hat{\theta}$  is computed in Eq. (7):

$$|\hat{\theta}| = \sqrt{(\theta_x)^2 + (\theta_y)^2 + (\theta_z)^2}. \quad (7)$$

The resulting agility index  $\alpha$  is shown in Eq. (8), where  $\tilde{a}$  represents the normalized acceleration norm (see Eq. (5)) and  $\tilde{\theta}$  the normalized speed of variation norm (see Eq. (7)) of the velocity directions of the selected passenger:

$$\alpha = \frac{\tilde{a} + \tilde{\theta}}{2}. \quad (8)$$

These scalar values forming the index are normalized with respect to ideal parameters coming from tests on young athletic people, assumed as reference for agility.

### 2.1.2. Hand-luggage coefficient

Also for the evaluation of the hand-luggage coefficient a geometric measure is employed.

The calculus of the parameter  $\beta$  is shown in Eq. (9)

$$\beta = \frac{\tilde{A}}{A}, \quad (9)$$

where  $\tilde{A}$  is the area of the rectangle that encloses the luggage shape, normalized with respect to the maximum area ( $550 \times 350$  mm) which represents the maximum allowable cross-section of hand luggage for most airlines.

If the passenger is detected without luggage, this parameter is set to 0, while if two pieces of luggage are detected for a single passenger, it is set to 1 anyway.

### 2.2. Seat assignment algorithm

The algorithm is based on a dynamic seat assignment and it focuses on four elements, evaluated for each passenger:

- passenger agility, indicated by  $\alpha$  as in Eq. (4);
- hand-luggage coefficient related to the luggage size, represented by  $\beta$  as in Eq. (5);
- group ID and group dimension, if the passenger belongs to a group
- reserved seat, if the passenger has got one.

A value of  $\alpha$  close to 0 means that the passenger has low agility, whereas  $\alpha$  close to 1 means high agility. The value of  $\beta$  is referred to a *handLuggageCoefficient*, which can assume values between 0 and 1 and represents the maximum luggage size allowed. Similarly to what has been defined for  $\alpha$ ,  $\beta$  equal to 0 means that the passenger does not have any luggage and  $\beta$  equal to *handLuggageCoefficient* means that the passenger carries the largest luggage size allowed.

Using these parameters, in the following the different parts which build up the algorithm will be explained separately. In Fig. 8 there is an overview on the algorithm and its subroutines. The ticket of each passenger contains information such as the reserved seat, if the passenger has got one, and a group identifier (group ID), in case the passenger belongs to a group. This information are used by the seat assignment algorithm and is taken as a constraint in the procedure that will be described below.

First of all, if the passenger has a reserved seat, that seat, of

course, will be assigned. In the other case the interactive allocation here proposed comes into play.

2.2.1. Groups handling

At first the algorithm checks if the passenger belongs to any group, making use of the information reported on her/his ticket. If so, if there is already at least another member of the same group on board, the passenger will be assigned to a seat next to her/his fellow traveler. In case none of the passengers belonging to her/his group is already on board (i. e., she/he is the first of the group), the algorithm will find the number of the required seats together, according to the group size, as more in the back of the airplane as possible. This choice is dictated by the fact that, since usually people belonging to the same group board together, the interference with other passengers behind them will be as little as possible if they are going to sit in the back of the plane. When the occupancy state of the plane is high there may not be a sufficient number of seats together, so the algorithm will divide the group into sub-groups in order to allow as many passengers as possible to seat next to each other (see pseudocode in Appendix A). If there is no space even for the subgroup, an individual seat to each of the group members will be assigned.

2.2.2. Normal cases

When the passenger does not belong to any group, the assignment will be made depending on the parameters of  $\alpha$  and  $\beta$ . In particular to the passengers whose  $\alpha$  is higher than a maximum threshold the algorithm will assign the next seat in the Steffen sequence as more in the back of the airplane as possible, as shown in Fig. 9a.

Whereas to the passengers whose  $\alpha$  is lower than a minimum threshold the next seat in the Steffen sequence as more in the front of the airplane as possible will be assigned, as depicted in Fig. 9b.

The maximum and the minimum thresholds have been obtained based on simulation and on a tuning procedure. The values which have been used are:

- 0.75 for the maximum threshold
- 0.25 for the minimum threshold.

If the value of  $\alpha$  is between the two boundaries, the algorithm will take into account also the value of  $\beta$  and the assignment will follow the same logic explained for  $\alpha$ . If even  $\beta$  is between the two boundaries the seat assigned to the passenger will be the next one in the Steffen sequence.

Table 1 summarizes the explained procedure. A pseudo-code of the explained procedure is reported in Appendix A.

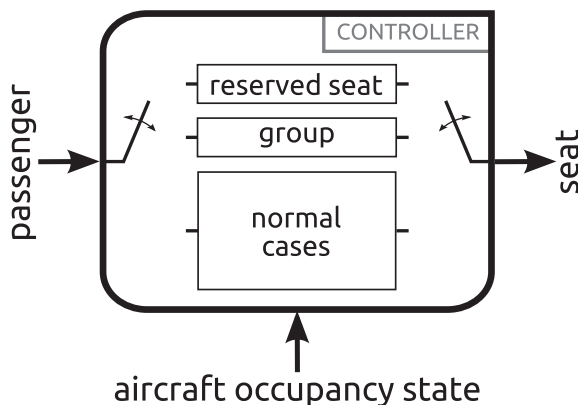


Fig. 8. Overview of the seat assignment algorithm block of Fig. 1.

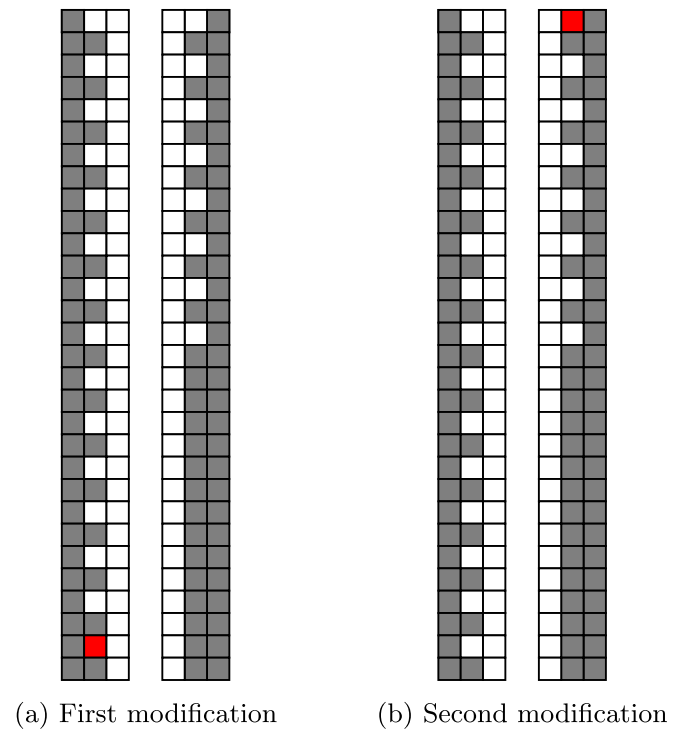


Fig. 9. Modifications to the Steffen method.

3. Simulation and results

This section is intended to report the outcomes of different simulation tests that have been carried out using the proposed algorithm. The main objective of these simulations is that of comparing the presented approach to other existing ones and, in particular, to the most used ones.

Moreover, since during this preliminary work computer simulations have been used to validate the devised boarding strategy, the results of these simulations are compared with those obtained by other authors in their works, in which real tests are taken into consideration. Furthermore, simulations have been extensively used and shown to be a valid method to compare different aircraft boarding strategies as discussed in Dangelmaier et al. (2013) and in Marelli et al. (1998). Finally, in Mas et al. (2013) a study on the simulations of different aircraft boarding strategies is conducted and the most efficient one is proposed.

3.1. Simulation model

Fig. 10 is a snapshot of the seating plan of the aircraft considered in the simulations. Here the boarding time as well as the percentage of boarded passengers are shown. This was developed to visualize the boarding procedure and to have in this way a visual feedback of how the algorithm performs in the different cases presented in the performed simulations.

In order to simulate the boarding of the passengers into the

Table 1  
Logic for the seat assignment.

$\alpha$	$\beta$	Seat assignment logic
<0.25	–	find the seat on the closest local maximum
>0.75	–	find the seat on the closest local minimum
0.25–0.75	<0.25	find the seat on the closest local maximum
0.25–0.75	>0.75	find the seat on the closest local minimum
0.25–0.75	0.25–0.75	assign the next seat in the sequence

plane, a kinematic model of the passenger has been developed.

The kinematics of the passenger has been divided into three parts:

- walking
- hand-luggage storing
- sitting.

This three components depend all on the passenger parameters and on the airplane state, therefore each passenger can be represented by the three indexes  $\alpha$ ,  $\beta$  and  $\gamma$ . As already introduced in Section 2, the parameters  $\alpha$  and  $\beta$  are the indexes of agility and of amount of hand-luggage, respectively, whereas the parameter  $\gamma$  represents the state of the hand-luggage compartment relative to the seat assigned to the passenger.

In fact, unlike the seat assignment algorithm, the boarding simulation takes into account also the influences of the time to store the hand-luggage and that required to sit. In order to do so, the boarding simulation routine makes use of two subroutines that retrieve and update the state of the hand-luggage compartment. The state of each of these compartments is represented by the  $\gamma$  parameter associated with it. In Fig. 11 the hand-luggage compartments used in simulation are shown. Next to each of them there is also the corresponding value that the parameter  $\gamma$  assumes. The walking speed of the passenger has been supposed to be linear with respect to the agility parameter, hence the following expression for its value holds:

$$v = v_{\min} + \alpha(v_{\max} - v_{\min}), \tag{10}$$

where  $v_{\min}$  and  $v_{\max}$  are the minimum and the maximum values of the walking speed.

The same assumption has been made for the sitting time, leading to the following equation:

$$T_{\text{sit}} = T_{\text{sit},\min} + \alpha(T_{\text{sit},\max} - T_{\text{sit},\min}), \tag{11}$$

where  $T_{\text{sit},\min}$  and  $T_{\text{sit},\max}$  are the minimum and the maximum values of the sitting time. The expression in Eq. (11) is the component of the sitting time calculated taking into account the agility of the passenger. An additional component takes into account the occupancy of the row where the passenger has to sit. In this way the sitting time increases linearly with the number of passengers that occupy the row where the current passenger has to sit.

Both Eq. (10) and Eq. (11) are linear and go from a minimum to a maximum value. Table 2 reports these values. As regards the time required to store the hand-luggage, Eq. (12) is the function relating this time to the parameters  $\alpha$ ,  $\beta$  and  $\gamma$ :

$$T_{\text{store}} = \left( \frac{T_{\text{store},\min}}{T_{\text{store},\max}} + (1 - \alpha)\beta(1 + 4\gamma) \right) T_{\text{store},\max}, \tag{12}$$

which was derived based on experiments and expert knowledge.

As can be seen, this kinematic model is fully parametric, therefore it offers the possibility of being adjusted and refined

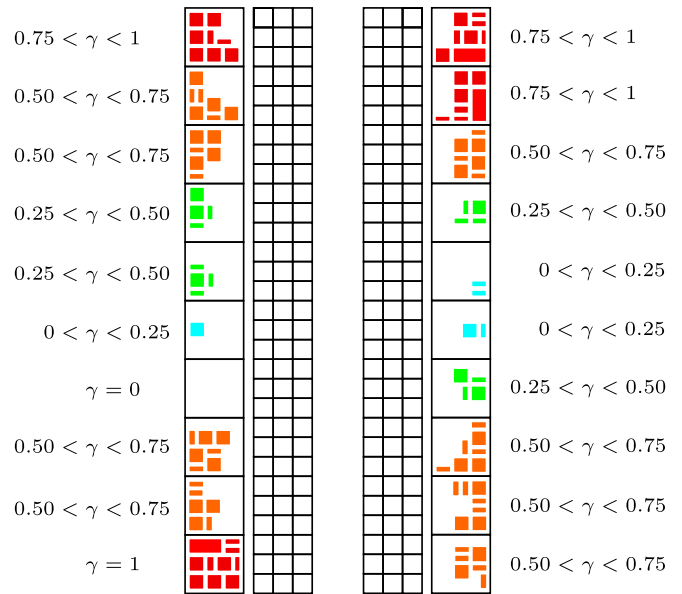


Fig. 11. Overview on the hand-luggage compartments with the associated values of parameter  $\gamma$ .

Table 2

Minimum and maximum values for the walking speed and for the sitting time.

	Minimum value	Maximum value
Walking speed [m/s]	0.5	2
Sitting time [s]	1	10

according to the results of experimental tests. Another important reason to perform these experimental tests is that of determining the weights of the different parts that build up the kinematic model of the passenger. In fact, from Eq. (10) and Eq. (11) is clear that the agility parameter of the passenger influences in the same linear way both the walking speed and the time required to sit. Performing the experimental tests is then a mean to refine the optimization process done on the seat assignment algorithm. The pseudo-code in Appendix A shows how the agility parameter determines the assignment of the seat. Moreover, from the boarding simulation based on this assignment algorithm it is possible to analyze how the agility influences, through the walking speed and the time to sit, the boarding time.

The three expression of the kinematics of the passenger have been used as a basis for the simulation tests. In order to simulate scenarios as close to the real ones as possible, Gaussian probability distributions have been considered for the characteristic parameters of the passenger and her/his hand-luggage. This has been done conservatively since the algorithm is expected to work even better if the distributions are uniform. The considered airplane model is single-aisle with 30 rows and 6 seats per row. This configuration is similar to the Boeing 737 or the Airbus A320, for instance. This choice has been made due to the fact that this kind of aircraft is one

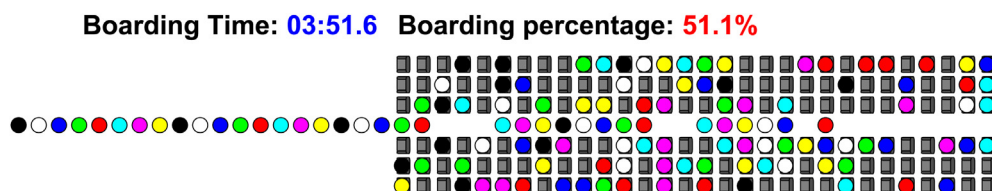


Fig. 10. Snapshot of the simulation environment.

of the best-selling single-aisle aircraft and it is used both for short-range flights and for intercontinental segments. Further simulations have been performed considering smaller and bigger aircrafts and it has been found out that the benefits generated by the proposed strategy increase with the size of the aircraft.

The simulations have been performed using Mathworks® MATLAB as a development and simulation environment.

### 3.2. Outcomes

Fig. 12 shows the boarding times of 1000 simulations run on the described airplane model. The actual number of simulation is 250,000. It has been reduced in this figure since the represented first 1000 values already contain all the statistical information of the whole simulation data set. The mean and variance, in fact, differ by less than 1% from those obtained using the whole data set. As can be noticed from Fig. 12, the average boarding time, plotted in bold, is 466 s, i. e., 7 min 46 s. In Fig. 13 a comparison between the proposed method and the Steffen method Steffen (2008) is shown.

Comparing the mean values, always depicted in bold, the application of the Steffen method results in a boarding time of 546 s, i. e., 9 min 6 s. This means that the proposed boarding method is capable of reduction of about 15%. The comparison with the random method is reported in Fig. 14. This comparison is of great importance since the random method is the most used one for the flight segments of the considered aircraft model.

The simulations on the boarding method presented in this paper has been useful also to study the influence of various factors on the boarding time. In fact, even though the proposed approach is able to handle cases in which passengers have reserved seat and/or belong to groups, Fig. 15 shows the boarding time as a function of the parameter  $\beta$ , proportional to the allowed maximum quantity of hand-luggage. This is presented to emphasize one of the most critical parts in the boarding phase, i. e., the hand-luggage storing.

Whereas the boarding time is not influenced much by passengers with reserved seat or by passengers traveling in groups, the dependence on the amount of hand-luggage is clear.

### 3.3. Cost saving

In our work, we have not overlooked to study the economic aspect of saving time. We start from the results obtained in the previous sections, and give them an economic significance, that highlights even more how our method is an innovative idea and permit to tackle not only wasted time. Inactive planes represent a significant problem in terms of cost, estimated to be about 30\$ per minute McFadden and Nyquist (2008), so we have compared our method to the random boarding, that is the most used boarding procedure for the type of aircrafts that we have considered. To load a plane with random boarding 1000 s on average are necessary. The

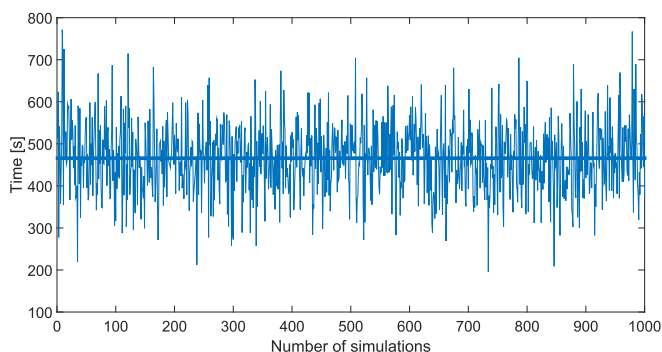


Fig. 12. Simulation results.

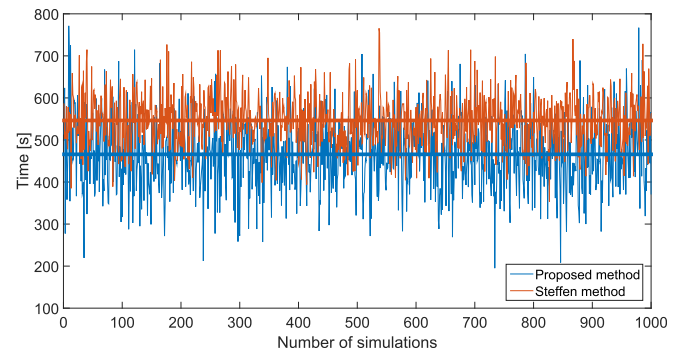


Fig. 13. Comparison with the Steffen method.

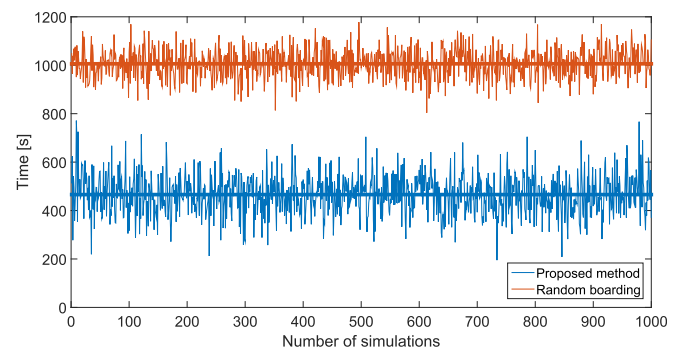


Fig. 14. Comparison with the random method.

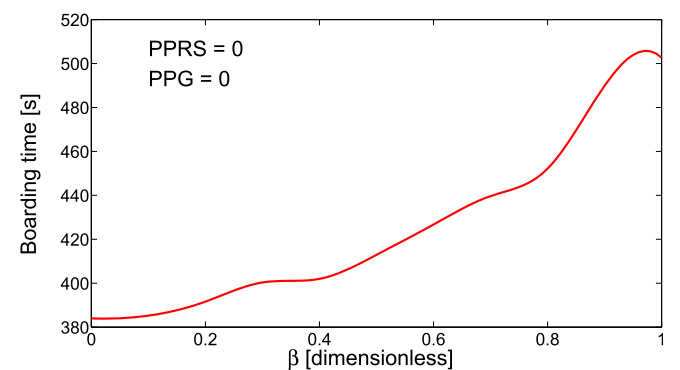


Fig. 15. Boarding time as a function of  $\beta$ .

simulations show that our method can board the same aircraft in 466 s on average. The difference of 534 means that 267\$ can be saved for each flight.

Considering the case of the Frankfurt Airport, out of its 469,026 annual flights Fraport (2014), the flights that are served by aircrafts similar to those used for our simulation approximately are 393,860 per year. Assuming that only the 50% of these flights use jet bridge for passenger boarding, our novel boarding method would result in the significant saving of 52,580,310\$ per year.

## 4. Conclusions

In this paper, a novel strategy for speeding up the boarding into an airplane has been presented. The proposed approach contributes to the minimization of the *turnaround time* which turns into a significant cost saving.

Firstly, the reported work has been compared with others in this field, such as Steffen (2008); Milne and Kelly (2014), and it has been



found out that none of the considered boarding strategies has imposed itself as the best.

The work in this paper extended Steffen method, which has been demonstrated to be among the fastest ones. The extension makes it both faster and feasible for practical implementation.

Using simulations, it has been showed that by assigning passengers seats based on the amount of luggage they carry and their agility the boarding time can be drastically reduced. And, by taking into account reserved seats and passenger groups the presented approach is also attractive for airlines.

The proposed method makes use of cameras and shape recognition algorithms to estimate passenger agility and hand-luggage dimensions.

A large number of simulations has been performed in order to estimate mean and variance of the boarding time, in every possible combination of the involved parameters. The simulations considered a fully-loaded single-aisle airplane. The passenger model has been developed taking into account the walking speed, the time to sit and the time to store the hand-luggage.

The simulation showed that the proposed method is 15% faster than Steffen method and from a minimum of 12% to a maximum of 14% faster compared to the method proposed by Milne and Kelly.

Furthermore, the presented approach does not even influence luggage weight distribution in the plane, which remains evenly allocated. This is due to the use of Gaussian distributions in the characteristic parameters of the passengers, that are both the hand-luggage size and the agility. Since these components have opposite effects on the hand-luggage weight distribution, the Gaussian distribution of them allows an even allocation of the luggage in the cabin.

#### 4.1. Future scopes

One of the next steps will be that of implementing the developed algorithm on an embedded microcontroller. This step will be useful to deal with the problems of limited computational and memory resources of embedded systems (especially for computer vision algorithms) and evaluate, in this way, the hardware requirements.

After this implementation, real data will be collected during different tests sessions. These are meant to estimate the model parameters and their statistics. The estimation of these quantities, using an analysis of variance (ANOVA), will be used to evaluate the influence of the corresponding parameters on the boarding time given used the proposed approach.

#### Acknowledgments

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#### Appendix A. Pseudocode

The pseudo-code presented in this section is intended to explain more in detail how the procedure of the assignment of the passenger seat works. All the functions and the symbols used in the pseudocode refer to those used in Section 2 during the explanation of the theoretical part.

This seat assignment procedure needs to be called only if the passenger does not have a reserved seat, in which case the chosen seat is immediately assigned and the aircraft state is updated.

In the following algorithm, the dot operator, in an Object-Oriented fashion, is used to access a property of an object. For instance, *somePassenger.alpha* represents the agility parameter relative to the considered passenger.

---

#### Algorithm Seat assignment

---

**Require:** *passenger*, *aircraftState*

**Ensure:** *passengerSeat*

```

1: agilityLowThreshold  $\leftarrow$  0.25
2: agilityHighThreshold  $\leftarrow$  0.75
3: handLuggageLowThreshold  $\leftarrow$  0.25
4: handLuggageHighThreshold  $\leftarrow$  0.75
5:  $\alpha \leftarrow$  passenger.alpha
6:  $\beta \leftarrow$  passenger.beta
7: if passenger  $\in$  group of  $N$  people then
8:   groupSeats  $\leftarrow$  find( $N$  seats together in the aircraftState) // it returns true if there are  $N$  seats together in the current occupancy grid map of the aircraft (represented by the variable aircraftState), otherwise it returns false
9:   if groupSeats then
10:    passengerSeat  $\leftarrow$  first seat of the  $N$  selected seats
11:    return passengerSeat
12:   else
13:    groupSeats  $\leftarrow$  find ( $\lceil \frac{N}{2} \rceil$  seats together in the aircraftState)
14:    if groupSeats then
15:      split group into 2 subgroups
16:      reassign group ID to the passengers
17:      passengerSeat  $\leftarrow$  first seat of the  $\lceil \frac{N}{2} \rceil$  selected seats
18:      return passengerSeat
19:    else
20:      remove passenger from group
21:      update group properties
22:    end if
23:  end if
24: end if
25: if passenger  $\notin$  group then
26:   if  $\alpha \leq$  agilityLowThreshold then
27:    passengerSeat  $\leftarrow$  next seat on the Steffen sequence as more in the front as possible // see Fig. 9b
28:   else if  $\alpha \geq$  agilityHighThreshold then
29:    passengerSeat  $\leftarrow$  next seat on the Steffen sequence as more in the back as possible // see Fig. 9a
30:   else // agilityLowThreshold  $<$   $\alpha$   $<$  agilityHighThreshold

```

```

31:  if  $\beta \leq \text{handLuggageLowThreshold}$  then
32:      passengerSeat ←
          next seat on the Steffen se-
          quence as more in the front as
          possible // see Fig. 9b
33:  else if  $\beta \geq \text{handLuggageHighThreshold}$  then
34:      passengerSeat ←
          next seat on the Steffen se-
          quence as more in the back as
          possible // see Fig. 9a
35:  else //  $\text{handLuggageLowThreshold} < \beta < \text{hand-}$ 
          LuggageHighThreshold
36:      passengerSeat ←
          next seat on the Steffen se-
          quence
37:  end if
38:  end if
39: end if
40: return passengerSeat

```

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