Journal of Air Transport Management 54 (2016) 52–60

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Symmetrical design of strategy-pairs for enplaning and deplaning an airplane

Sheng-Jie Qiang [a], Bin Jia [a,*], Rui Jiang [a], Qing-Xia Huang [a], Essam Radwan [b], Zi-You Gao [a], Yu-Qing Wang [a,c]

[a] MOE Key Laboratory for Urban Transportation Complex Systems Theory and Technology, Beijing Jiaotong University, Beijing 100044, China
[b] College of Engineering and Computer Science, University of Central Florida, Orlando, FL 32816, USA
[c] School of Mechanical and Automotive Engineering, Hefei University of Technology, Hefei 230009, China

ARTICLE INFO

Article history:
Received 15 April 2015
Received in revised form
25 January 2016
Accepted 22 March 2016

Keywords:
Airplane management
Enplaning/deplaning
Strategy
Cellular automaton

ABSTRACT

Enplaning and deplaning processes are two main activities that passengers experience in an airplane. They are also the main factors contributing to the airplane turn time. Thus, both processes need to be carefully considered when designing a new strategy. The main contribution of this paper is twofold. Firstly, we propose a symmetrical design of deplaning strategies to match three typical grouped enplaning strategies (back-to-front, windows-to-aisle and reverse pyramid), in which the groups are organized in a LIFO (Last In First Out) manner. Secondly, we present an integrated cellular automaton model to describe the dynamic characteristics of passengers in the enplaning and deplaning processes. Numerical evaluation results indicate that the proposed windows-to-aisle and reverse pyramid strategies perform better in the following aspects: (i) the total operation time decreases; (ii) the two strategies are less sensitive to the load condition, e.g., luggage distribution and cabin occupancy rate; (iii) passengers' satisfaction is enhanced since both individual waiting time and processing time lower down; (iv) the two strategies are fairer for the passengers since the difference among the groups remarkably shrinks.

1. Introduction

Due to the rapid civil aviation growth, the competition pressure increases among airlines. Therefore, airlines need to continually optimize their operations with the goal of maximizing their efficiency and profitability. One of the most promising ways is to reduce the airplane turn time, i.e., the time to unload an airplane after its arrival and to prepare it for departure again. A significant saving could be achieved by reducing the enplaning and deplaning time, since they are the main contributions to an airplane's turn time. A successfully designed strategy-pairs for enplaning and deplaning is expected to perform satisfactorily to meet the needs of the three principal users: the airlines, airport operators and the passengers.

Airlines make every effort to minimize the time that their flights stay on the ground. Nyquist and McFadden (2008) pointed out that for each minute an active airplane stays on the ground, the airline needs to spend US $30. Thus, each minute saved in the turn time of a flight can accumulate to produce considerable annual savings. Reduction of airplane turn time can also benefit the airport operators in three aspects: firstly, it could reduce the flight delays caused by imbalances between demand and capacity by scheduling more flights (Ball et al., 2010). Secondly, it improves the passengers' experience at airport terminals and consequently increases level of service of the airport; thirdly, it makes a more efficient utilization of the equipment on ground. For passengers, they are concerned about their own waiting time, and individual enplaning and deplaning time. Passengers generally prefer shorter enplaning and deplaning time. A reduction in total enplaning and deplaning time implies a reduction of the average individual enplaning and deplaning time for passengers.

Efforts have been made to reduce the enplaning time, and most of them are based on simulation works. Marelli et al. (1998) reported a discrete event simulation model and evaluated different enplaning scenarios and airplane interior configurations. Van Landeghem and Beuselinck (2002) discussed various enplaning strategies via computer simulation to study to what extent enplaning time can be reduced. Results have shown that the choice

* Corresponding author.
E-mail address: bjia@bjtu.edu.cn (B. Jia).

http://dx.doi.org/10.1016/j.jairtraman.2016.03.020

of enplaning strategies highly influences the enplaning time, both totally and individually. Ferrari and Nagel (2005) evaluated robustness of strategies with three disturbances: early or late enplaning of passengers, dimensions of airplane, and the occupancy level of the airplane. Steffen (2008, 2012) presented the most time-saving strategy by applying a Markov Chain Monte Carlo optimization algorithm. Tang et al. (2012) explored the dynamic properties of passengers' motions in enplaning process with consideration of passengers' individual properties. Milne and Kelly (2014) and Qiang et al. (2014) emphasized the importance of luggage storage space and passengers were assigned to seats based on the number of luggage they carried.

Apart from the simulation studies, new strategies are also proposed by using linear or nonlinear programming approaches, based on a basic assumption that a minimization of the number of interferences leads to a minimal enplaning time (Bazargan, 2007; Soolaki et al., 2012). Moreover, physicists have analyzed the impact of passenger sequential disorder on the scaling behavior of airplane enplaning time, in the context of a particle system with distinguishable particles on a substrate (Frette and Hemmer, 2012; Brics et al., 2013; Baek et al., 2013). Bachmat et al. (2009) used space-time geometry and random matrix theory to analyze the relation between the efficiency of various airline enplaning strategies and interior airplane design parameters.

Comparing with enplaning studies, the topic of deplaning is relatively new. To our knowledge, there are only a few papers discussing this process. For instance, Yuan et al. (2007) proposed a deplaning model and developed a new inside-out deplaning strategy for midsize and large airplanes. Wald et al. (2014) studied how to minimize the deplaning time by using deplaning group assignments. Unique features of deplaning process have been taken into account, e.g., the retrieving of carry-on bags and the interferences of passengers.

Nevertheless, we would like to point out that present studies investigated enplaning and deplaning separately. Therefore, potential optimization might be achieved by considering the enplaning and deplaning processes integratedly. Moreover, in present studies, little attention has been paid to the individual experience of passengers. Motivated by the above facts, this paper proposes a cellular automaton model to study the enplaning and deplaning processes in an integrated way. A symmetrical design of deplaning strategies to match three typical enplaning strategies has been presented. In particular, the individual experience of passengers has been evaluated.

The remainder of the paper consists of four sections. Section 2 surveys the common practically used enplaning strategies, and proposes the matched deplaning strategies for each of enplaning strategies. Section 3 presents a cellular automaton model integrating both enplaning and deplaning processes. Section 4 performs extensive evaluation of the proposed strategies from the perspective of airlines and passengers. Finally, section 5 summarizes the research findings and makes outlooks for future research.

2. Strategies

Fig. 1 illustrates the four typical enplaning maps, including the random, back-to-front (BF), windows-to-aisle (WA) and reverse pyramid (RP). These strategies are employed by major airlines and their rules are summarized as follows.

(1) Random: Each passenger has an assigned seat, and enters into the airplane in an unstructured manner (see Fig. 1a). Examples of usage are American Airlines and US Airways.
(2) Back-to-Front: Passengers are divided into several groups and enplane in a back to front order, and passengers are essentially random in each group (see Fig. 1b). This strategy is widely used in, e.g., Delta, American Airlines, Spirit Airlines and Frontier Airlines.
(3) Windows-to-Aisle: United Airlines lets passengers enplane in an order of windows first, followed by the middle and aisle seats enplaning last. Within each group the passengers are essentially random (see Fig. 1c).
(4) Reverse Pyramid: US Airways (America West) used a hybrid method between the traditional back-to-front and outside-in enplaning strategies. Passengers enplane in a V-like manner with back windows and middle boarding first, followed by back aisle and front aisle (see Fig. 1d).

Since no airline adopts a deplaning strategy, passengers leave the airplane without any organization. Therefore, passengers with rear seats will wait for a long time to deplane. It will be unfair for them if they have suffered a long waiting time when enplaning. An ideal order should be that passengers are organized as enplaning first and deplaning later. Furthermore, it has been proved by Wald et al. (2014) that a structured deplaning strategy may reduce the deplaning time. Based on these facts, we proposed a series of matching structured deplaning strategies by considering their enplaning strategies. Passengers are divided into groups according to their enplaning orders and deplane with a basic principle that the first enplaning group will be the last to leave, much like a "stack" system. The rules are summarized respectively as follows.

(1) Front-to-Back: Passengers are divided into several groups and deplane in a front to back order.
(2) Aisle-to-Windows: Passengers with aisle seats deplane first; once those ones have fully deplaned, passengers with middle seats deplane, followed by passengers with window seats.
(3) Pyramid: Passengers deplane in a pyramid manner with front aisle and back aisle first, followed by middle and back windows.

The proposed strategies are listed by comparing with the originals, see Table 1.

3. Integrated simulation framework

This section develops an integrated simulation framework which captures inherent benefits of strategies without complicating the model with unsubstantiated assumptions. The airplane model is simple, describing a typical narrow body, single aisle airplane with 150 seats, divided into 25 rows and 6 seats per row, just like airplanes of the Airbus 320 family or the Boeing 737. For simplicity, we assume that passengers do not know each other, thus they enplane and deplane individually. We further assume that passengers do not try to overtake other passengers, which is reasonable in a narrow cabin aisle.

The cabin is represented by a rectangular array comprised of a set of cells, see Fig. 2. Each cell represents a space, either seat or aisle, which can be occupied by only one passenger at a time. The size of the cell is 0.8 m in length (0.4 m of the length of seat and 0.4 m of leg room in the front of seat) and 0.4 m in width. The seats are indicated by letters from A to F and the rows are numbered from 1 in the front to 25 in the rear of airplane.

3.1. Passenger enplaning model

Enplaning starts when the first passenger starts to check his ticket and ends when the last passenger is seated. Activities that influence passengers' experiences in enplaning include lining up in front of the gate, ticket validation, walking in the cabin, stowing of

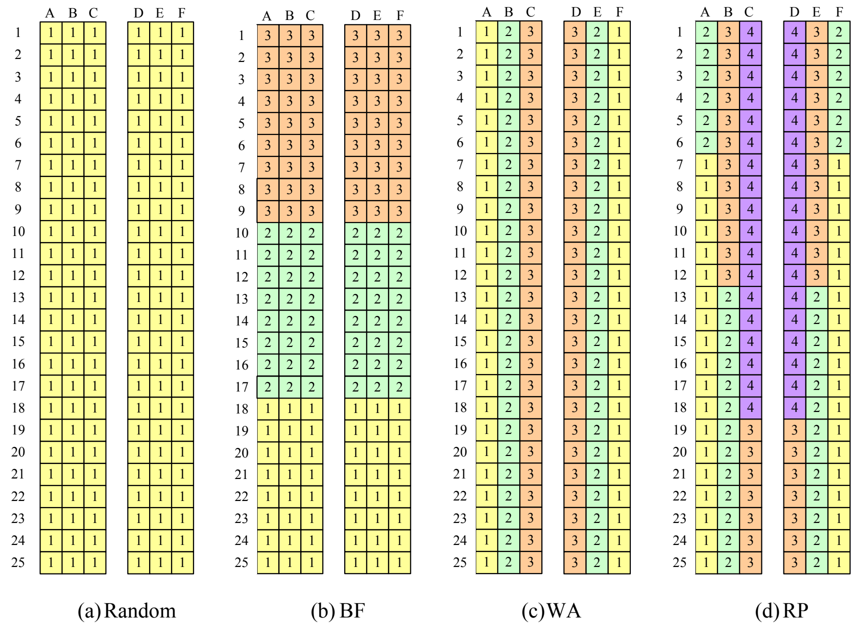


Fig. 1. Schematic representation of the common used enplaning strategies. The number denotes the boarding order. 1 means boarding first, followed by 2, 3 and 4.

Table 1
Summary of various strategies.

	Original	Proposed
Random	No group, both enplaning and deplaning are random, see Fig. 1a	_
BF	Grouped, enplaning in a back to front manner: 1 → 2→3, see Fig. 1b; deplaning randomly (**O-BF**)	Grouped, enplaning in a back to front order: 1 → 2→3; deplaning in a reverse manner: 3 → 2→1, see Fig. 1b (**P-BF**)
WA	Grouped, enplaning in a windows to aisle manner: 1 → 2→3, see Fig. 1c; deplaning randomly (**O-WA**)	Grouped, enplaning in a windows to aisle order: 1 → 2→3; deplaning in a reverse manner: 3 → 2→1, see Fig. 1c (**P-WA**)
RP	Grouped, enplaning in a reverse pyramid manner: 1 → 2→3 → 4, see Fig. 1d; deplaning randomly (**O-RP**)	Grouped, enplaning in a reverse pyramid manner: 1 → 2→3 → 4; deplaning in a reverse manner: 4 → 3→2 → 1, see Fig. 1d (**P-RP**)

carry-on luggage and settling into his seat. The dynamics of passenger movement arise from interferences occurs when a passenger blocks another passenger. Two types of interferences, aisle and seat related, are identified.

Aisle interference happens when a passenger is blocked by another one in front of him in the narrow aisle. The most time-consuming component identified is when a higher row passenger is blocked by a lower row passenger. Two factors contribute to luggage storage time t_i^{store} of passenger i: the number of luggages already in the luggage bin and the number of luggages carried by himself, indicated by N_e and N_i respectively. We assume, as proposed in Qiang et al. (2014)

$$t_i^{store} = \alpha + \frac{\beta N_i}{[(\gamma+1)-(N_e+N_i)]}, \tag{1}$$

when $N_i \geq 1$.

In Eq. (1), γ is the capacity of luggage rack corresponding to the half-rows, α is the basic time to deal with luggage and β is the correction coefficient. According to Van Landeghem and Beuselinck (2002), parameters α, β and γ equal to 2, 11 and 6 respectively. Moreover, passengers are randomly assigned 0, 1 or 2 pieces of luggage with percentages of λ, θ and $1-\lambda-\theta$ respectively. An example of normal enplaning condition is listed in Table 2.

Another common disturbance is caused by seat interference. It occurs when passengers seated close to the aisle block other passengers to be seated in the same half-row, see Fig. 3. Those

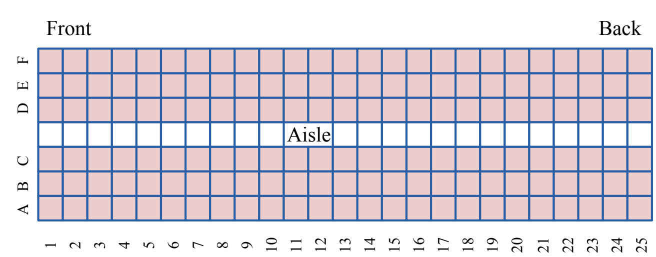


Fig. 2. Schematic illustration of airplane cabin in cellular space.

interfering passengers have to get out of their row and then sit down again after the new passenger sits. Additional time is needed in the aisle before the passenger sits down. We denote the additional time as t_i^{seat}, which depends on the number of interfering passengers M_i. Their relationship is expressed in Eq. (2) as proposed by Ferrari and Nagel (2005)

$$t_i^{seat} = \lfloor t_p(1+2M_i) \rfloor, M_i \geq 1. \tag{2}$$

Table 2
A normal luggage distribution.

Enplaning condition	Luggage distribution		
	λ	θ	$1-\lambda-\theta$
Normal	20%	60%	20%

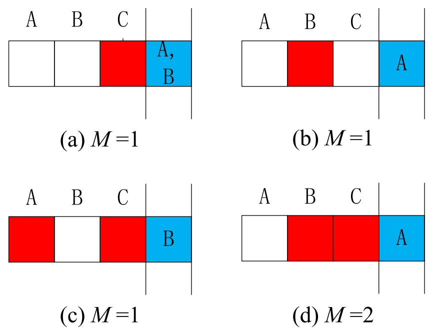


Fig. 3. Number of interfering passengers M in the half-row during enplaning process. Situation in the other half-row with seats D, E and F is similar.

Where, t_p is the time needed for an interfering passenger to get up from the seat and step into the aisle or back of the seat, which is set as 1.5 time steps in the model. $\lfloor x \rfloor$ denotes the maximum integer that is not larger than x.

From time step $t \to t+1$, the parallel update rules of passenger enplaning are adopted as follows.

Procedure 1. (passenger entry).

With a ticket validation time T_{ticket}, the 1st passenger queuing outside of the airplane will have his ticket validated. A validated passenger can enter the airplane if the first cell in cabin aisle is vacant.

Procedure 2. (passenger movement).

The update of passenger i' s motion depends on whether he has reached his assigned row or not.

(1) If he has not reached his assigned row, do the following two steps:

Step 1: Moving in the aisle according to three restrained rules.
(R1) acceleration or deceleration

$$v_i(t+1) \leftarrow \min\{v_i(t)+1, gap1_i(t), v_{max}\} \quad (3)$$

(R2) randomization

$$\delta(t+1) < P_s \Rightarrow v_i(t+1) \leftarrow \max\{0, v_i(t+1)-1\} \quad (4)$$

(R3) passenger movement

$$x_i(t+1) \leftarrow x_i(t) + v_i(t+1) \quad (5)$$

Where x_i^t and v_i^t are the position and velocity of passenger i at time t, respectively. The velocity is updated in R1 and R2, and the position of passenger i is updated in R3. R1 shows that each passenger attempts to walk as fast as possible within the velocity limit v_{max} (cells per time step), in which $gap1_i(t)$ is the number of empty cells ahead of passenger i. Since a passenger has to stop at his assigned row even if the gap to the preceding passenger is larger than zero, $gap1_i(t)$ is thus defined as:

$$gap1_i(t) = \min\{x_{\text{head}1}(t) - x_i(t) - 1, X(s_i) - x_i(t)\}. \quad (6)$$

Where $x_{\text{head}1}(t)$ is the location of the preceding passenger in front of passenger i at time step t. The first term in the right of Eq. (6) is the distance gap to the preceding passenger. The second term indicates the distance to his target row, where $X(s_i)$ denotes the location of the target seat s_i of passenger i.

Furthermore, the model also introduces stochasticity in rule R2. This rule captures natural speed fluctuations due to human behavior or varying external conditions. At each time step $t+1$, a uniformly distributed random number $\delta(t+1) \in [0,1]$ is generated. This number is then compared with a randomization parameter $P_s \in [0,1]$ (called the slowdown probability).

Step 2: Determine whether stop or not.

If $x_i(t+1) = X(s_i)$, then passenger i has reached his assigned row. In such a case, he will stand still to dispose his luggage and then deal with seat interference, thus $v_i(t+1) = 0$. The total time that passenger i must stay at the aisle is t_i^{total}, which is defined as

$$t_i^{total} = t_i^{\text{store}} + t_i^{seat}. \quad (7)$$

(2) If passenger i is at his assigned row, then we check t_i^{total},

If $t_i^{total} > 0$, then the passenger will keep up staying in the aisle but $t_i^{total} = t_i^{total} - 1$. His velocity and position will not change in this condition, so $v_i(t+1) = 0$ and $x_i(t+1) = x_i(t)$.

If $t_i^{total} = 0$, the passenger will sit in his assigned seat and finishes his enplaning process.

3.2. Passenger deplaning model

It is assumed that there is no seat interference in deplaning, because in most cases passengers in the same half-row will leave in sequence from aisle seat to window seat. If a passenger manages to move from his seat into the aisle, he will occupy the corresponding aisle cell for a period of time known as an “aisle delay”. Passengers behind the delayed passenger will remain “stuck” until the passenger has finished retrieving his belongings. Once the aisle delay is completed, he will move in the aisle until leaves the airplane.

To make the model simple, we suppose that passengers begin to deplane once the cabin door is opened. A set of parallel rules are applied to all passengers in the cell from time step $t \to t+1$, as explained below.

Procedure 1. (passenger leaves his seat to the aisle).

Passenger i will wait for opportunity to step into the aisle. The willingness of passenger to leave his seat is defined with a probability of $P_w = 0.8$. If he manages to step into the aisle, then he will retrieve his luggage. The total time for luggage retrieving (in simulation time steps), indicated by t_i^{retrieve}, is presented in Eq. (8) with a linear manner

$$t_i^{\text{retrieve}} = \tau N_i. \quad (8)$$

Where, τ is the time needed for a passenger to retrieve one piece of luggage, 2 time steps in simulation. During the luggage retrieving process, the passenger's motion is updated by $x_i(t+1) = X(s_i)$ and $v_i(t+1) = 0$.

Procedure 2. (passenger movement). The motion of passenger i is updated depending on whether he has finished retrieving his luggage. We check t_i^{retrieve},

(1) If $t_i^{\text{retrieve}} > 0$, then passenger i continues retrieving his luggage and $t_i^{\text{retrieve}} = t_i^{\text{retrieve}} - 1$. No changes occur for his velocity and position, so, $v_i(t+1) = 0$ and $x_i(t+1) = x_i(t)$.
(2) If $t_i^{\text{retrieve}} = 0$, then passenger i has finished retrieving his luggage. In this case, he will move according to the following steps.

(R1) acceleration or deceleration

$$v_i(t+1) \leftarrow \min\{v_i(t)+1, gap2_i(t), v_{max}\} \tag{9}$$

(R2) randomization

$$\delta(t+1) < P_s \Rightarrow v_i(t+1) \leftarrow \max\{0, v_i(t+1)-1\} \tag{10}$$

(R3) passenger movement

$$x_i(t+1) \leftarrow x_i(t) - v_i(t+1) \tag{11}$$

These rules are similar to passenger enplaning rules in Eqs. (3)–(5). One difference is the definition of $gap2_i(t)$. Two factors are considered: the gap to the preceding passenger at time step t and the distance to the cabin door (the location of which is zero). Thus, $gap2_i(t)$ can be defined as:

$$gap2_i(t) = \min\{x_i(t) - x_{head2}(t) - 1, x_i(t)\}, \tag{12}$$

where $x_{\mathrm{head2}}(t)$ is the location of the passenger in front of passenger i.

Procedure 3. (passenger leaving) If $x_i(t+1) = 0$, then passenger i has exited and then he will be removed from the simulation.

Due to the usage of parallel dynamics, it is possible that two or three passengers choose the same destination cell in update procedure 1 and 2. For example, a passenger in the aisle wants to advance, at the same time a seated passenger also wants to move to that aisle cell. Such situations will be called conflicts. As shown in Fig. 4, there are four kinds of conflicts in deplaning process. As in Wald et al. (2014), we resolve this problem by using a probabilistic method and an equal chance to occupy the cell is set for passengers involved in the conflict.

3.3. Simulation procedure

Below are the three steps for passengers enplaning and deplaning in one experimental condition.

Initialization: Passengers are waiting outside of airplane and each of them has a seat number; Assign number of luggages to passengers according to the carry-on luggage number distribution.

Enplaning: Passengers start to enplane according to a selected strategy; and the dynamics of passenger flow are updated by the model described in sub-section 3.1. This process lasts until all of the passengers have seated themselves.

Deplaning: Passengers will deplane with a matched strategy without any delay after enplaning ends. The behavior of passenger follow the rules in sub-section 3.2 and this process ends when the last passenger leaves the airplane.

The simulations are carried out with 10,000 replications for each experimental condition tested. In our model, T_{ticket}=2 passengers move with v_{max}=1 as used by Ferrari and Nagel (2005). Note that, Van Landeghem and Beuselinck (2002) used a triangular distribution to describe the row-to-row time, with a modus value 2.4 s. Therefore, one time step of our simulation corresponds to 2.4 s in absolute time.

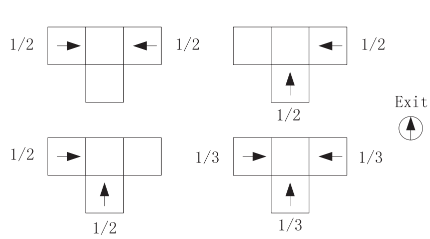


Fig. 4. Four types of conflicts in the deplaning process.

4. Evaluation of the proposed strategies

4.1. Validation

The motion trails of passengers in the cabin aisle under four strategies are plotted in Fig. 5. To make a clear trajectory, we only show trails of 30 passengers. Specifically, we show trails of the 1st, 5'th, 10'th …. and the 145'th passengers. As shown in Fig. 5, we conclude the following findings:

4.2. Total time

The total operation time can be reduced by using an efficient strategy. We define T_{total} as the total time and it includes the total enplaning time and the total deplaning time, denotes as T_{en} and T_{de} respectively. The total enplaning time is defined as the time interval from the time that the first passenger starts to enplane to the time that all passengers have seated themselves. The total deplaning time is defined as the time interval from the time that the cabin door opens to the time that all passengers leave the airplane.

Results of the seven scenarios are presented in Table 3. Note that if no strategy is adopted in deplaning process, the most time-saving strategy is the O-RP and O-WA, followed by the Random, and the O−BF is the worst. This conclusion is in accordance with other researches discussing the enplaning time, e.g., Van Landeghem and Beuselinck, 2002, Ferrari and Nagel, 2005. Note as well that the deplaning time will be reduced if we organize passenger's deplaning process, and this will finally lead to a reduction of total time. For example, a reduction of 3.28% is achieved for the proposed P-WA strategy than the original used O-WA strategy and this number is about 2.88% for the P-RP strategy. The structured front to back strategy worsens the deplaning process, which performs even worse than the random deplaning strategy. This is reasonable, because passengers in the second and the third group must wait until passengers in their prior group totally left, and this makes the deplaning intermittent.

Apart from the mean total time, the variability of total time is also an important index to evaluate strategies since airlines need to have a reliable schedule. Fig. 6 shows distribution of total time in the strategies. One can see that P-WA and P-RP perform better than other strategies. Both the mean total time and the variance of total time are smaller in the two strategies than in other strategies.

4.3. Individual time and other related characteristics

Total time is clearly important for airlines, since it determines the airplane turn time. However, passengers are more susceptible to their personal experiences. To evaluate the individual experience, we examine the following three indexes: waiting time, actual processing time and conflict index.

A passenger i must wait outside of the airplane for a time of $WT_{en,i}$ before he begins to validate his ticket. After the ticket validation, he will process in the cabin until gets seated. We define this time interval as his actual enplaning time $AT_{en,i}$, which includes the time that the passenger validates his ticket, moves in the cabin aisle, disposes his luggage and deals with seat interferences. Similarly, the waiting time $WT_{de,i}$ and actual deplaning time $AT_{de,i}$ are defined in deplaning process. $WT_{de,i}$ denotes the time interval from the start of deplaning to the time passenger i has managed to step into cabin aisle. $AT_{de,i}$ consists of the luggage retrieving time and the time passenger i moves in the aisle until he exits the airplane.

In addition, we define $ET_{en,i}$ as the ideal enplaning time, which includes the ticket validation time, time of moving freely in aisle (equals to the distance) and the minimum luggage disposing time

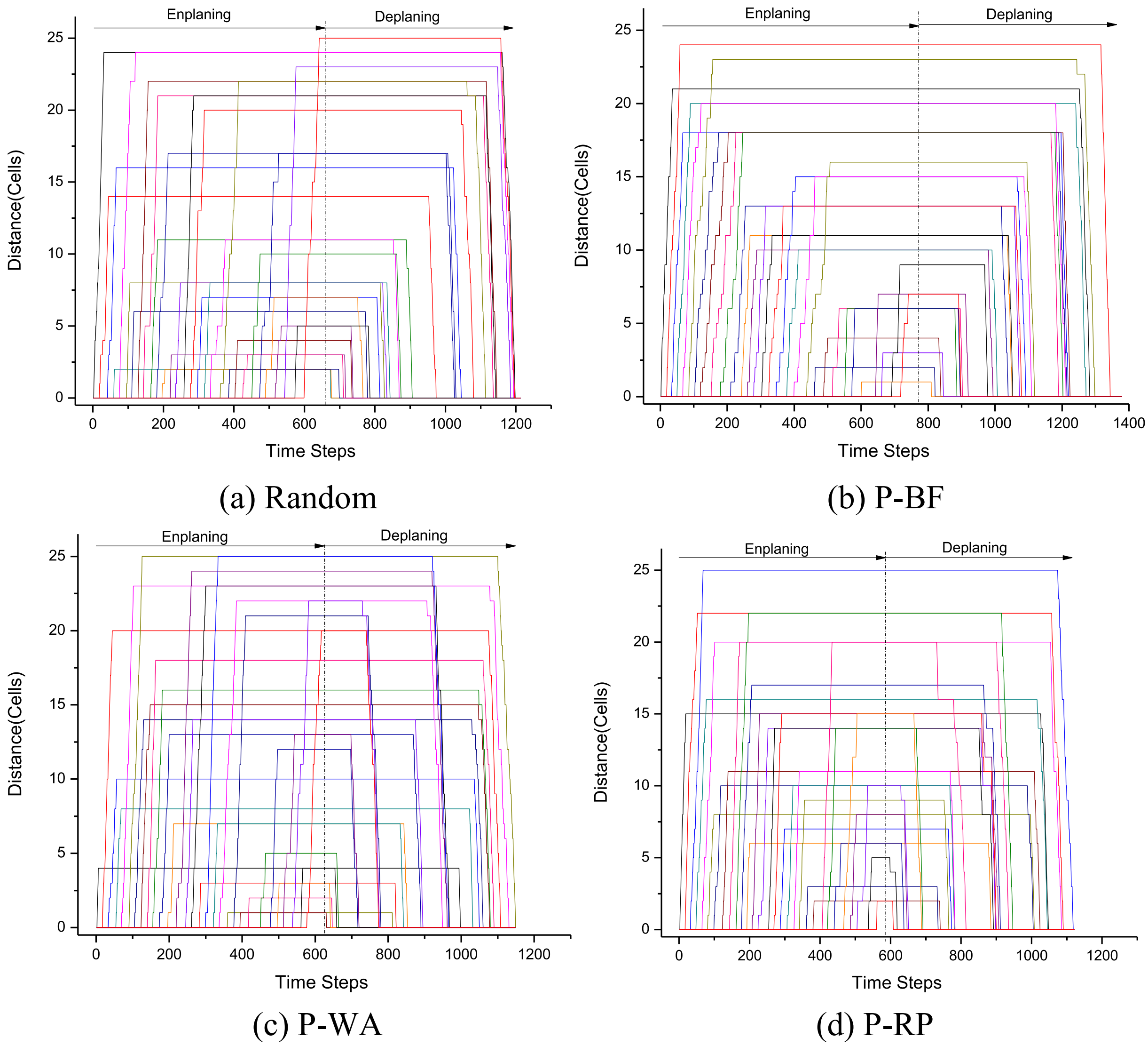


Fig. 5. The motion trails of 30 passengers in the cabin aisle. Enplaning time and deplaning time are given in simulation time steps and the distances are counted by cells.

(a) The model can qualitatively describe each passenger's motion trail during the airplane enplaning and deplaning processes. Passengers must wait outside of the gate before entering. After the passenger enters the aisle, he will move in a following manner until he is seated. A “stop and go” like pattern exists, which is caused by the seat or aisle interferences or a randomization slow down.

(b) The differences between the strategies can be easily distinguished by the trails of passengers. For the typical random strategy, passengers enplane randomly and deplane in a front to back way, see Fig. 5a. This always benefits passengers seating in the front of airplane, because they always leave quickly if no extra instructions are imposed. Symmetrical patterns exist for the three proposed strategies as shown in Fig. 5b, c and d. One can see that the aim of the design has been achieved, i.e., passengers' enplaning and deplaning roughly obey the rule “last in first out”.

Table 3
Comparison with 100% load factor.

	Random	O-BF	P-BF	O-WA	P-WA	O-RP	P-RP
T_{en}	27.304	28.956	28.953	23.932	23.936	23.592	23.590
T_{de}	21.926	21.922	23.596	21.922	20.416	21.924	20.613
T_{total}	49.230	50.878	52.549	45.854	44.352	45.516	44.203
			3.28%		−3.28%		−2.88%

(no luggage in the bin overhead). Similarly, we define $ET_{de,i}$ as the ideal deplaning time which includes the luggage retrieving time and the time of moving freely in aisle to the cabin door.

The difference between actual time and ideal time indicates the degree of conflicts. Specifically, we define the conflict index (CI_i) of passenger i for enplaning ($CI_{en,i}$) and deplaning ($CI_{de,i}$) as follows

$$CI_{en,i}(CI_{de,i}) = \frac{Actual\ time - Ideal\ time}{Actual\ time} = \frac{AT_{en,i}(or\ AT_{de,i}) - ET_{en}(or\ ET_{de,i})}{AT_{en,i}(or\ AT_{de,i})}. \tag{13}$$

A perfect enplaning or deplaning strategy would have CI equaling 0. Increasing values of CI would be associated with an increasingly bad strategy, since passenger would suffer from conflicts frequently.

All involved indexes are also averaged over all passengers. So, we obtain their mean values as follows: $WT_{en} = \frac{1}{N}\sum_{i=1}^{N} WT_{en,i}$, $WT_{de} = \frac{1}{N}\sum_{i=1}^{N} WT_{de,i}$, $AT_{en} = \frac{1}{N}\sum_{i=1}^{N} AT_{en,i}$, $AT_{de} = \frac{1}{N}\sum_{i=1}^{N} AT_{de,i}$, $CI_{en} = \frac{1}{N}\sum_{i=1}^{N} CI_{en,i}$, $CI_{de} = \frac{1}{N}\sum_{i=1}^{N} CI_{de,i}$, where N is the number of passengers.

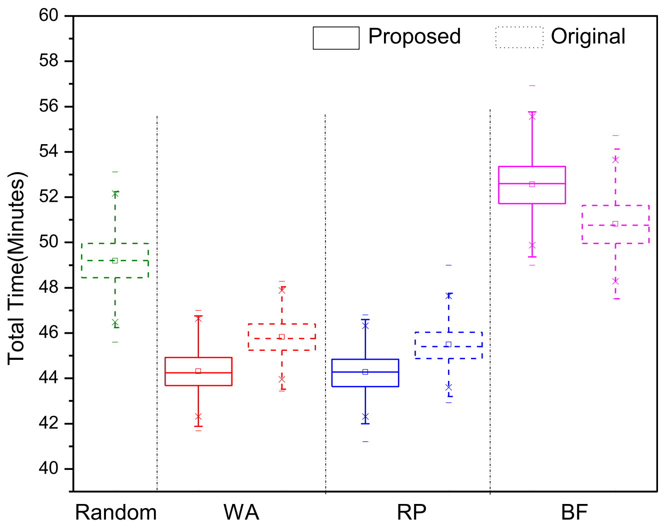


Fig. 6. Total time comparison under 100% load factor.

Table 4 shows the mean values of three individual experience indexes. Here $WT = WT_{en} + WT_{de}$, $AT = AT_{en} + AT_{de}$, $CI = (CI_{en} + CI_{de})/2$. Note that the proposed P-WA and P-RP strategies are superior in two aspects than the originals: firstly, they reduce the average individual waiting time by 1.77% (P-WA) and 2.23% (P-RP) respectively; secondly, they quicken the deplaning process and this lead to a reduction of total processing time by 9.67% and 16.95%. However, they fail to reduce the conflict index and even make them worse, about 18.94% and 17.91% higher than the originals. It is reasonable as the passengers spread along the whole aisle for the P-WA and P-RP strategies when deplaning. There is a high probability that the passenger who is in the rear of the aisle will meet the conflicts frequently. For the proposed P–BF strategy, a strict front to back deplaning order will largely reduce the processing time and this will lead to a reduction of total processing time by 25.95%. However, the reduction for individual processing time could not balance the increase of waiting time, nearly 2 min more than the original BF strategy. This is why the proposed BF is not time-efficient.

4.4. Impartiality between groups

Impartiality means that there is no obvious difference among the groups for a strategy. It is annoying that passengers in a group will suffer a longer waiting time or processing time than in other groups. The three index (waiting time, actual processing time and conflicts index) are calculated for each group and the results are plotted in Fig. 7.

It can be easily seen that significant differences exist among groups in the original strategies, e.g., the O-WA strategy (Fig. 7b) and the O-RP strategy (Fig. 7c). Usually, passengers with a large group index number will have a bad experience, suffering a longer waiting and processing time and a higher conflict index. We would like to mention that both the O-WA and the O-RP strategy spread their passengers in the aisle in the deplaning process, and this will take passengers in the rear of airplane a long time to deplane. One exception is the O–BF strategy (Fig. 7a), because passengers in the front rows can easily get off, like a front-to-back procedure. The outstanding advantage for the proposed strategies is that they can reduce the difference largely in the waiting time, processing time and the conflict index. However, one drawback is that it will increase the conflict index.

4.5. Sensitivity

4.5.1. Effects of luggage distribution

Sensitivity to the luggage distribution and variation over replication should be as small as possible in a well performed strategy. We also investigated the effect of an increased luggage leveland the results are shown in Fig. 8. We can see that the luggage number distribution has a significant impact on the total time. As the number of luggage increases, passengers will spend much more time to deal with their luggage. We also see that the performances of each strategy are quite different. The proposed P-WA and P-RP strategies behave better, as they show smaller sensitivity to the change of luggage number distribution.

4.5.2. Effects of occupancy rate

To find out how the efficiency of strategies depends on the airplane occupancy rate, we evaluate these strategies under different occupancy rates between 10% and 100%. As shown in Fig. 9, the performance of various strategies changes nearly linearly with the cabin occupancy rate. Remarkable differences exist between the strategies if the cabin occupancy rate exceeds 50%. It can be seen that the proposed P-WA and P-RP strategies work slightly more efficiently than others. When occupancy rate is under 40%, there are no significant differences between the strategies. In such a case, a random strategy is quite a good choice regarding its easy and customer-friendly implementation.

5. Conclusions

In this paper, we have proposed an integrated simulation model to study the enplaning and deplaning process, which are two main contributions to the airplane turn time. Three matched strategy-pairs have been studied. It was shown that the proposed

Table 4
Individual performance of three overall measures under 100% load factor.

Strategies	Waiting Time (Min)			Actual time (Min)			Conflicts Index		
	WT_{en}	WT_{de}	WT	AT_{en}	AT_{de}	AT	CI_{en}	CI_{de}	CI
Random	11.796	8.417	20.213	1.424	2.434	3.858	0.423	0.392	0.408
O-BF	12.920	8.415	21.335	1.899	2.435	4.334	0.539	0.391	0.465
P-BF	12.919	10.261	23.180	1.898	1.311	3.209	0.539	0.352	0.446
			8.64%			−25.95%			−4.08%
O-WA	10.796	8.412	19.208	1.185	2.433	3.618	0.326	0.391	0.359
P-WA	10.790	8.077	18.867	1.185	2.083	3.268	0.326	0.527	0.427
			−1.77%			−9.67%			18.94%
O-RP	10.739	8.418	19.157	1.197	2.434	3.631	0.334	0.392	0.363
P-RP	10.741	8.321	18.731	1.197	1.818	3.015	0.335	0.521	0.428
			−2.23%			−16.95%			17.91%

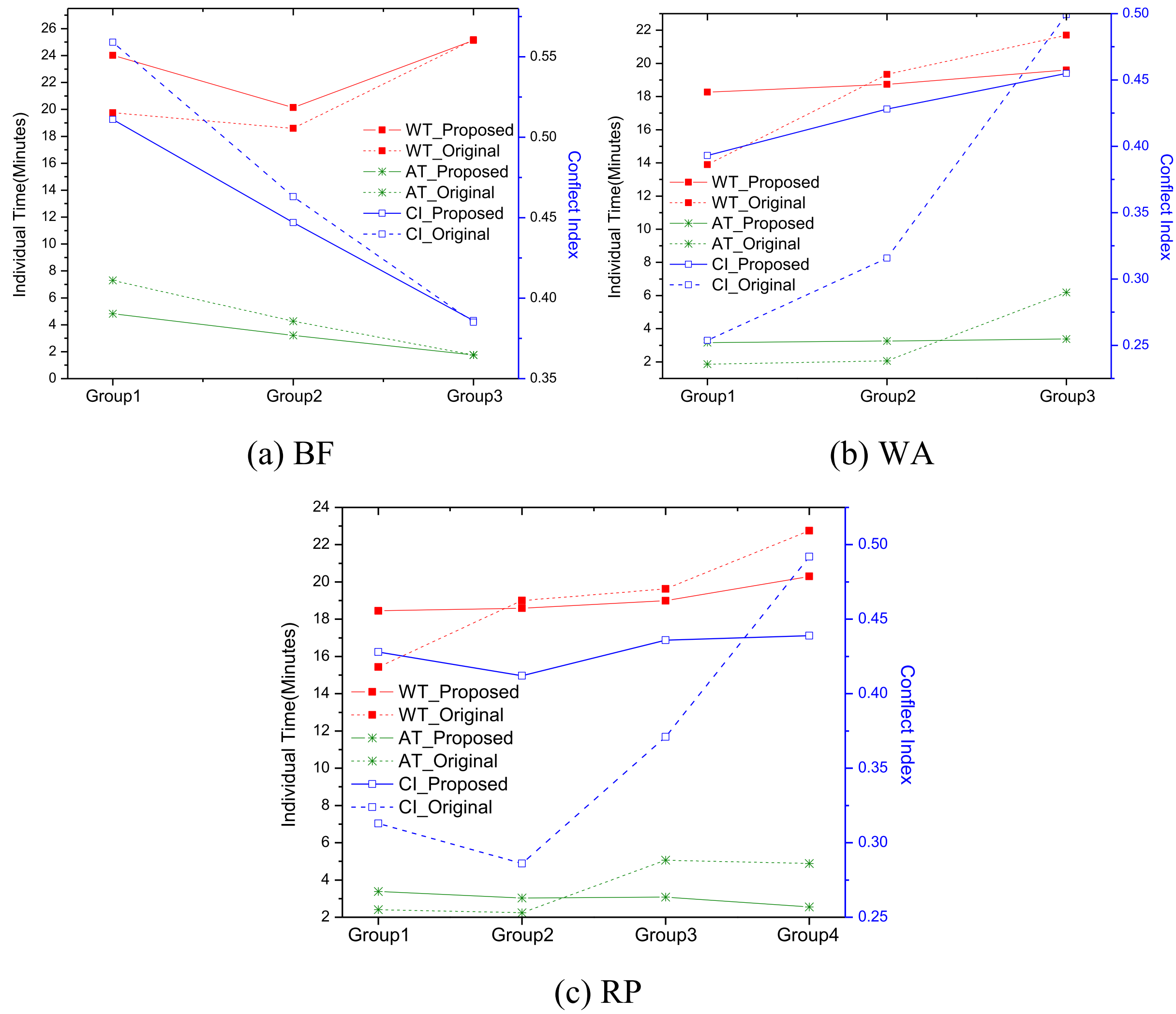


Fig. 7. Differences between groups for the three grouped strategies.

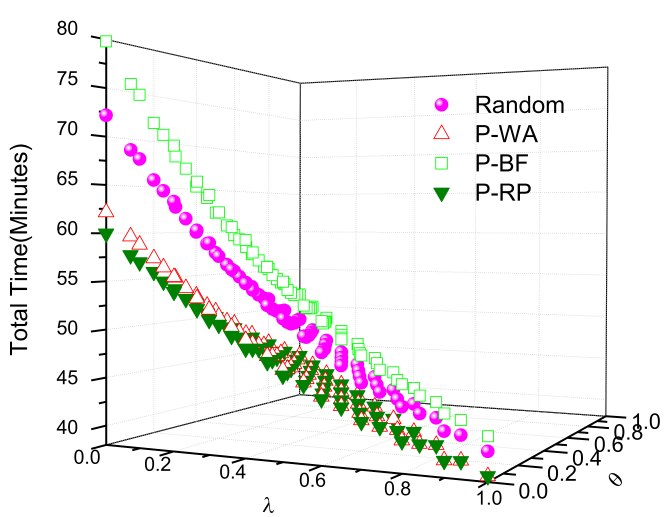
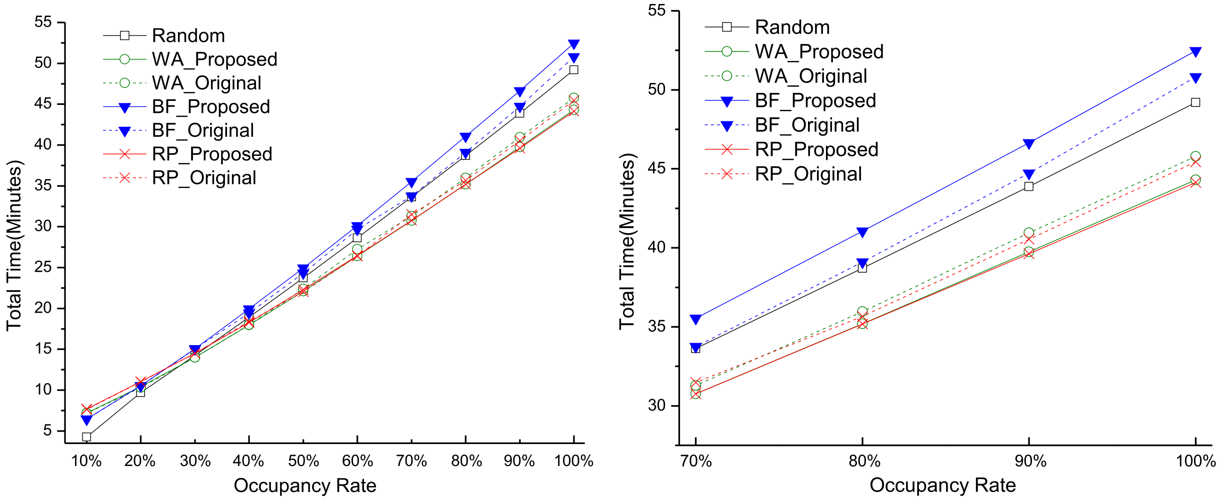


Fig. 8. Sensitivity of the luggage number distribution for total time with λ and θ the percentage of 0, 1 pieces of luggage respectively.

windows-to-aisle and reverse pyramid strategies perform better than the original strategies without deplaning strategy. Simulations show that the mean total operation time can be reduced by 3.28% and 2.88%, respectively, in the proposed P-WA and P-RP strategy. Suppose the current mean total operation time is 45 min, the proposed P-WA would enable an airline with 1000 flights per day to save 16 million dollars per year. Due to reduction of mean total time, it is easy to understand that both individual waiting and processing time decrease in the two strategies, which improves experience of passengers. Moreover, it has been shown that the two strategies are fairer for passengers in different groups since difference among the groups remarkably decreases.

A feasible approach to implement the proposed P-WA and P-RP strategies is using the “call-off” system. This has been widely used in the grouped enplaning strategy, the same idea can be used in deplaning process. Furthermore, airlines can apply a bonus to the passenger's credit card for complying with the deplaning strategy. The deplaning bonus could be printed on the boarding pass, with the idea that passengers need to wait longer than those in the first or second group to deplane. If the average deplaning bonus is $X, then the airlines could add $X to the price of a ticket and they don't lose money from the practice.

Actually, the proposed P-WA and P-RP strategies can be further improved. Note that in the two strategies, a group is permitted to deplane if and only if passengers in the prior group have totally left the airplane. As a result, a gap will appear between groups. In fact,



(a) (b)

Fig. 9. Sensitivity of the occupancy rates for total time, where (a) is the whole graph and (b) is the partial graph.

this deplaning strategy can be relaxed. Passengers in a group should be allowed to deplane when the queue of passengers in the prior group becomes small. In this way, the deplaning time can be further reduced, since no gap appears between groups.

Acknowledgments

This work is financially supported by the National Basic Research Program of China (2012CB725400), China National Science Funds for Excellent Young Researchers (71222101), the National Natural Science Foundation of China (71471012, 71390332) and the Fundamental Research Funds for the Central Universities (T15JB00130). The authors would like to thank the anonymous referees for their helpful comments and valuable suggestions.

References

Bachmat, E., Berend, D., Sapir, L., Skiena, S., Stolyarov, N., 2009. Analysis of airplane boarding times. Operations Res. 57 (2), 499–513.
Baek, Y., Ha, M., Jeong, H., 2013. Impact of sequential disorder on the scaling behavior of airplane boarding time. Phys. Rev. E 87 (5), 052803.
Ball, M., Barnhart, C., Dresner, M., Hansen, M., Neels, K., Odoni, A., Peterson, E., Sherry, L., Trani, A., Zou, B., 2010. Total Delay Impact Study. Technical Report. National Center of Excellence for Aviation Operations Research.
Bazargan, M., 2007. A linear programming approach for aircraft boarding strategy. Eur. J. Operational Res. 183 (1), 394–411.
Brics, M., Kaupužs, J., Mahnke, R., 2013. Scaling behavior of an airplane-boarding model. Phys. Rev. E 87 (4), 042117.
Ferrari, P., Nagel, K., 2005. Robustness of efficient passenger boarding strategies for airplanes. J. Transp. Res. Board 1915, 44–54.
Frette, V., Hemmer, P.C., 2012. Time needed to board an airplane: a power law and the structure behind it. Phys. Rev. E 85 (1), 011130.
Marelli, S., Mattocks, G., Merry, R., 1998. The Role of Computer Simulation in Reducing Airplane Turn Time. Boeing Aero Magazine 1.
Milne, R.J., Kelly, A.R., 2014. A new method for boarding passengers onto an airplane. J. Air Transp. Manag. 34, 93–100.
Nyquist, D.C., McFadden, K.L., 2008. A study of the airline boarding problem. J. Air Transp. Manag. 14, 197–204.
Qiang, S.J., Jia, B., Xie, D.F., Gao, Z.Y., 2014. Reducing airplane boarding time by accounting for passengers' individual properties: a simulation based on cellular automaton. J. Air Transp. Manag. 40, 42–47.
Steffen, J.H., Hotchkiss, J., 2012. Experimental test of airplane boarding methods. J. Air Transp. Manag. 18, 64–67.
Steffen, J.H., 2008. Optimal boarding method for airline passengers. J. Air Transp. Manag. 14, 146–150.
Soolaki, M., Mahdavi, I., Mandavi-Amiri, N., Hassanzadeh, R., Aghajani, A., 2012. A new linear programming approach and genetic algorithm for solving airline boarding problem. Appl. Math. Model. 36, 4060–4072.
Tang, T.Q., Wu, Y.H., Huang, H.J., Caccetta, L., 2012. An aircraft boarding model accounting for passengers' individual properties. Transp. Res. Part C 22, 1–16.
Van Landeghem, H., Beuselinck, A., 2002. Reducing passenger boarding time in airplanes: a simulation based approach. Eur. J. Operational Res. 142, 294–308.
Wald, A., Harmon, M., Klabjan, D., 2014. Structured deplaning via simulation and optimization. J. Air Transp. Manag. 36, 101–109.
Yuan, B., Yin, J., Wang, M., 2007. Star: (saving time, adding revenues) boarding/deboarding strategy. UMAPJournal 371.