STAR: (Saving Time, Adding Revenues) Boarding/Deboarding Strategy

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Summary

Our goal is a strategy to minimize boarding/deboarding time.

- We develop a theoretical model to give a rough estimate of airplane boarding time considering the main factors that may cause boarding delay.

- We formulate a simulation model based on cellular automata and apply it to different sizes of aircraft. We conclude that outside-in is optimal among current boarding strategies in both minimizing boarding time (23–27 min) and simplicity to operate. Our simulation results agree well with theoretical estimates.

- We design a luggage distribution control strategy that assigns row numbers to passengers according to the amount of luggage that they carry onto the plane. Our simulation results show that the strategy can save about 3 min.

- We build a flexible deboarding simulation model and fashion a new inside-out deboarding strategy.

- A 95% confidence interval for boarding time under our strategy has a half-width of 1 min.

We also do sensitivity analyses of the occupancy of the plane and of passengers taking the wrong seats, which show that our model is robust.

Introduction

Airline boarding and deboarding has been studied extensively in operations research literature. U.S. domestic carriers lose $220 million per year in revenue for take-off delays [Funk 2003].

We examine strategies for boarding and deboarding planes with varying numbers of passengers, trying to minimize the boarding and deboarding time.

Literature Review

Marelli et al. [1998] designed a computer program called PEDS (Passenger Enplaning/Deplaning Simulation) that used a probabilistic discrete-event simulation to simulate boarding methods. PEDS predicted that it would take 22 min to board a Boeing 747-200. However, the paper did not lay out the boarding procedure.

Van Landeghem [2000] stated that the fastest boarding strategy is individually boarding by seat and row number, and the second fastest is a back-to-front "alternate half-row" boarding system, which was cited to take 15.8 min. He also proposed strategies with small numbers of boarding groups that are both faster and more robust against disturbances. A problem with the data is that only five replications were done for each boarding procedure tested [Pan 2006].

Later, van den Briel et al. [2003] showed that a reverse-pyramid boarding strategy could reduce airplane's turn time by 3-5 min compared to a traditional back-to-front boarding approach. The boarding time depends on events called "interferences."

Unfortunately, all of these researchers used simulation based on small or mid-size airplanes that do not extend to the much larger aircraft under development today. Our approach and results can be applied in all sizes of airplanes.

Basic Assumptions

- **First-class passengers board first.** Hence, our simulation considers only economy-class passengers.

- **Passengers do not try to pass other passengers in the aisle.** The aisles are narrow, so passengers have to wait to move until there are no "obstacles" in front of them.

- **A "call-off" system is used.** Passengers board in ordered groups; gate agents announce which group is to board.

- **A passenger does not take the wrong seat and does not walk past the row of the right seat.** Such mistakes inevitably delay boarding.

Reasons for Boarding Delay

Normal Delay

"Interference" is the main reason for boarding delay. Van den Briel et al. [2003; 2005] divide boarding interferences into two types:

- **Aisle interference:** Since the aisle is narrow enough to allow only one passenger to proceed forward, aisle interference occurs when a passenger stows luggage. To do this, the passenger must stand in the aisle for a moment, thereby acting as an "obstacle" for passengers behind.

- **Seat interference:** This kind of interference occur when a passenger is stalled by another one or two passengers sitting in the same half-row. Because of the limited space between contiguous rows, this passenger must ask these passenger already sitting in their seats to stand up and move into the aisle.

Abnormal Delay

Passengers take the wrong seats, or are late. These behaviors can hardly be avoided. Because of their complexity and variety, we don't take them into consideration. Our main objective is to reduce seat and aisle interference.

Theoretical Estimate Model

We consider boarding time as made up of two parts:

- Free boarding time t_{free}, the total time if all passengers board without any interference or delay.

- Interference time t_{inter}, the total interference time including aisle interference and seat interference.

So the total boarding time is

$$T_{\text{total}} = t_{\text{free}} + t_{\text{inter}}, \tag{1}$$

Free Boarding Time

We consider the passengers as a steady flow that pours into the plane at a rate of v_{flow} passengers per minute. So the free boarding time is

$$t_{\text{free}} = \frac{n}{v_{\text{flow}}}, \tag{2}$$

where n is the number of passengers.

Interference Time

Seat Interference

We assume that the times to get from the seat to the aisle and get back are the same, both denoted by t_S. Suppose that three passengers on the same side of a row are assigned to the same boarding group, passengers sitting in positions A (window), B (middle), and C (aisle). There are six equally likely kinds of seat interferences, corresponding to the boarding orders ABC, ACB, BAC, BCA, CAB, CBA. We calculate the interference time for each case. Take ACB as an example: The window-seat passenger boards first, followed by the aisle seat passenger; then the middle-seat passenger needs the aisle-seat passenger to get up and move to the aisle, the middle-seat passenger moves from the aisle to the seat, and the aisle-seat passenger and sits back down again. So the interference time is $3t_S$. The results are shown in **Table 1**.

Table 1.

Seat interference time by boarding order.

Boarding order	ABC	ACB	BAC	BCA	CAB	CBA
Seat interference time	0	$3t_S$	$3t_S$	$5t_S$	$6t_S$	$8t_S$

The average seat interference time for 3 passengers in the same half-row is

$$\bar{t}_S = \frac{25}{6}\, t_S.$$

With n passengers boarding, the total seat interference time is

$$t_{S:\text{inter}} = \bar{t}_S \cdot \frac{n}{3} = \frac{25}{6}\, t_S \frac{n}{3}. \tag{3}$$

Aisle Interference

Let $P_1, \ldots, P_n$ be the passengers in order in the queue, with corresponding row numbers $r_1, \ldots, r_n$. We say P_i *blocks* P_j if $r_i < r_j$. We use the number of blocking times as the number of aisle interference times, that is, when we calculate total interference times, we don't consider the situation that two or more blockings happen together. For example, for passengers $P_1, \ldots, P_5$ in rows 1, 4, 5, 2 and 3, P_1 blocks P_2, P_2 blocks P_3, and P_4 blocks P_5. But actually, after P_1 is seated, P_2 and P_4 can stow luggage simultaneously, and only P_3 and P_5 need to wait (two intervals of interference) to stow luggage. To simplify the calculations, we think of this as a total of three intervals of interference.

As a result, to calculate the aisle interference times, we need calculate only the number of instances of $r_i < r_{i+1}$. Since the order of passengers is random, the number i of aisle interference times is a random variable. We assume that every permutation is equally likely, so the average aisle interference time is

$$I = \frac{1}{n!} \sum i(r_1, \ldots, r_n),$$

where we sum over all permutations. The permutations can be divided into $n!/2$ pairs, each of which is the reverse of the other; together, each pair will have $(n-1)$ instances of $r_i < r_{i+1}$. Hence

$$I = \frac{n-1}{2}.$$

With t_L for the average time to stow luggage, the total aisle interference time is

$$t_{A:\text{inter}} = \frac{n-1}{2} \cdot t_L. \qquad\qquad \textbf{(4)}$$

From **(1)–(4)**, we get the total boarding time as

$$T = \frac{n}{v_{\text{flow}}} + \frac{25}{6} t_s \frac{n}{3} + \frac{n-1}{2} t_L.$$

Data Collection

Aircraft of Different Sizes

We base our computer simulations on three types of airplane of different sizes: Airbus A320 (small—124 seats), Airbus A300 (midsize—266 seats), Airbus A380 (large—555 seats).

Experimental Data

We could not collect the needed by experimenting or by interviewing airline executives. Fortunately, this work has already been done by van den Briel et al. [2003] as cited by Pan [2006]. They found the following average times:

- Get-on time (time between gate agent and gate—assuming one gate agent): 9.0 s.

- To advance one row: 0.95 s.

- Stowage: 7.1 s.

- Seat interference time: 9.7 s.

Cellular Automata Simulation Algorithm

In the cellular automata model of boarding analysis, each cell is designated as a passenger, a barrier, a road or a seat. The model restricts individual movements on the plane and computes total boarding time. Time, position, and passenger behavior are each discrete quantities. The passenger compartment

is specified as a grid of rectangular cells, while time is incremented using a convenient time step. During one simulation time step (STS), a passenger can move only one cell/row, and all cells representing passengers are processed once and in random order. The simulate iterates time steps and update passengers' state and position until all passengers sit down.

Call-off Function

Before passengers board the plane, they are usually divided by a gate agent into groups, often by consecutive rows, for boarding efficiency. We develop our call-off function with three steps:

1. Divide different seats into groups according to a specific strategy. For example, in implementing outside-in, we put seats in one column into a group.

2. Generate a random order number in each group.

3. Queue the groups consecutively.

Enplane Simulation Function

Simulation of the Next Passenger Boarding

The get-on time has an exponential distribution with mean that we estimate to be 10 STS.

Individual Behavior Judgments

What do passengers do in each time step?

- Stand still when there is an obstacle.

- Move forward by one cell toward the seat when there is free space in front.

- Stow luggage. This behavior needs a counter to record its STS because it requires more than one step.

- Seat interference when the passenger already seated must stand up and let other passengers move in. It also needs a counter.

Simulation Results and Analysis

We simulate common boarding strategies, including random, back-to-front, rotating-zone, outside-in, and reverse-pyramid [Finney 2006]. Back-to-front and rotating-zone allow us to choose the number of rows per group; we try 4, 6, and 8 to see how variation affects the strategies. Similarly, reverse-pyramid can also vary in layers, and we choose 2, 3, and 4 layers to analyze.

Simulation Results

We simulate each boarding strategy 100 times; the results are in **Table 3**.

Table 3.
Simulation results for strategies.

Strategy	Rows (or layers)	Average interference	Seat interference	Aisle
Random		24	72	52
Rows		32	72	55
Back-to-front #1	4	25	72	51
Back-to-front #2	6	25	72	52
Back-to-Front #3	8	25	73	53
Rotating #1	4	25	72	53
Rotating #2	6	25	73	54
Rotating #3	8	25	72	54
Outside-in		23	0	42
Reverse-pyramid #1	2	23	0	43
Reverse-pyramid #2	3	23	0	42
Reverse-pyramid #3	4	23	0	42

Analysis of the Simulation Results

- **The more rows in a group, the shorter the boarding time.** This is really unexpected! Usually, we think that if we divide the passengers into more groups before boarding in accordance with a boarding strategy, the passengers will be better organized and board the plane more efficiently. But to our surprise, our simulations run in the opposite direction. Take back-to-front as an example. When a group contains 8 rows, the boarding time is 24.6 min; but when there are 4 rows per group, the boarding time increases to 25.0 min. With the two extremes (i.e., one row per group vs. all the passenger as a group), the contrast is even more obvious: 32 min vs. 24 min.

  How could this happen? Through analysis of the simulation processes, we find that two or more interferences can happen at the same moment (**Figure 1**) without influencing the boarding process adversely. With more rows in a group, multi-interferences increase but boarding time decreases.

- **Dividing passenger groups according to their columns such as outside-in way and reverse-pyramid way avoids seat interference and reduces aisle interference.** This is easy to understand. If we divide the groups by rows, passengers in the same row get on the plane together, and try to stow their luggage at the same time. However, dividing the group by columns staggers the time when passengers stow luggage into the same overhead bin, which lead to a reduced number of aisle interference.

Optimal Strategy

Based on the above analysis, we draw the conclusion that dividing passenger groups by columns is more efficient than by rows. The two optimal strategies are outside-in (23.0 min) and reverse-pyramid (22.7 min). Although R-P takes a little less time, outside-in is easier to operate both for gate agents and also passengers. Considering this, *we choose outside-in as our boarding strategy*.

Cross-Validation between Theoretical and Simulation Models

We compare the results from the simulation with the results of our analytical mode, where we had total boarding time as

$$T = \frac{n}{v_{\text{flow}}} + \frac{25}{6}\, t_s\, \frac{n}{3} + \frac{n-1}{2}\, t_L.$$

Using parameter value estimates from van den Briel et al. [2003], we have

$$\bar{t_S} = \frac{25}{6}\, t_S = 9.7 \text{ s}, \qquad t_L = 7.1 \text{ s}.$$

We also estimate

$$\frac{1}{v_{\text{flow}}} = 4.5 \text{ s}^{-1}.$$

For the A320, we have $n = 126$, for which we calculate the total boarding time to be 23.2 min, a value that agrees closely with our simulation time.

Mid-size Planes

We extend our simulation model and boarding strategies to midsize aircraft such as the A300; outside-in takes 24.6 min, reverse-pyramid takes 24.4 min.

The A300 has two aisles in economy class, with most (although not all) rows in a 2–4–2 seat configuration. Correspondingly, we adjust our simulation algorithm. Since there are two aisles but only one boarding gate, we divide the passengers into two lines and assume that they don't get into the wrong aisle.

The two strategies are again comparable in average boarding time; again, considering simplicity, we recommend outside-in.

Large Planes

We extend our simulation model and boarding strategies to large aircraft such as the Airbus A380, with two decks and 555 seats in three classes.

Usually, the A380 opens two gates in front of the plane to let passengers board, one of which leads directly to the upper deck (where all business seats are located and a small portion of the economy seats) and the other goes to the main deck (where most economy seats are located).

Since seats in the upper deck are more spread out, it takes less time to board than the main deck. So we consider only the boarding process on the main deck, which is similar to that of a midsize plane, with two aisles and most rows with a 3–4–3 seat configuration. Both outside-in and reverse-pyramid take 26.8 min. We still recommend outside-in.

Luggage Distribution Control (LDC)

A Creative New Boarding Strategy

We offer a brand-new idea to reduce boarding time. During ticket-check time, the passengers are assigned numbers according to how many pieces of luggage they will take onto the plane. Although we do not completely control the order in which passengers board, we can control the distribution of passengers with different amounts of luggage.

A passenger in the last row of the plane blocks nobody when stowing luggage; a passenger in the front row blocks all other passengers behind. Let $P(r)$ denote the probability that a passenger in row r blocks other passengers behind; $P(r)$ is a decreasing function of r. The expected aisle interference time that this passenger causes is

$$t_{A:I} = P(r)t_L,$$

where t_l is the time to stow the luggage.. As for seat interference, it has no direct connection with the row number. We simply define the average seat interference time as $t_{S:I}$. So the total expected interference time is

$$T_{\text{total}:I} = \sum_{r=1}^{n}(t_{A:I} + t_{S:I}) = \sum_{r=1}^{n} P(r)t_L + T_{S:I},$$

where $T_{S:I} = \sum_{r=1}^{n} t_{S:I}$ is a constant.

A passenger with more luggage increases the total. To reduce the effect on interference time, we want to put this passenger as far back as possible.

Simulation Results of LDC

Through simulation, we compare outside-in and reverse-pyramid strategies with our LDC strategy. With our LDC strategy, boarding times for all sizes of aircraft can be reduced by 2–3 min. That is because we send passengers with much luggage to the back of the plane, which reduces the number of interference times.

How to Implement LDC?

Before passengers board, they exchange their ticket for a boarding card with their seat number. Our strategy is to assign seat numbers according to the amount of carry-on luggage. For the distribution of number of pieces of luggage, we use 60% have one piece, 30% have two pieces, and 10% have three.

We divide the seats from back to front in these proportions. We assign to passengers a seat in the group according to number of pieces of luggage; if seats in that group are exhausted, we still follow our basic principle: the more luggage a passenger takes, the farther back the seat.

Orderly Deboarding

Deboarding Strategies

Most airlines conduct deboarding without any organization. As a result, passengers in the front rows can easily get off first, stalling those behind, much like an inverse back-to-front procedure. This process is still faster than boarding. However, if we could adopt a strategy like outside-in, that is, let aisle passengers all get their luggage and get off the plane, then the middle passengers, and finally window passengers, we could fully use the aisle space without interference, leading to higher efficiency.

We put forward the deboarding strategies reversed from boarding strategies: random, front-to-back, inside-out, and V (the strategy derived from the reverse-pyramid boarding strategy).

Deboarding Simulation Model

We develop a simulation model to compare deboarding strategies. Differing from the boarding process, deboarding has its own characteristics, as follows:

- All passengers start in different positions ("their own seat") and go to the same destination ("outside").

- There is no seat interference, since in most cases passengers in the same row will leave from aisle seat to window seat.

- In the boarding simulation model, passengers enter the plane one by one, forming a queue. During deboarding, the passengers are a crowd and everyone tries to get out of the plane first.

Rush to One Goal: Object Position

During deboarding, passengers occupy the aisle. We cannot move the passengers according to a certain order, as in the boarding process, but have to

consider the conflict that one position is wanted by several passengers. Therefore, we define the concept of *object position*, the position that a passenger wants to get into in the next time step. Our simulation program allows passengers to move forward by one cell in one time step; it can find out passengers' object positions before moving them, determine which passengers want to move to the same object position, determine which passengers cannot move because of obstacles, and then confirm which passengers can move forward and which must stay still. If an object position is wanted by several passengers, we randomly choose one to move and the others have to wait.

Applicability

Our deboarding strategies are to divide passengers into several groups, and then let the groups deboard in order. We define a *PAD (Passengers Allowed to Deboard) set*, a set of passengers allowed to deboard together.

Simulation Results and Analysis for Small Planes

We simulate each proposed deboarding strategy 100 times. Inside-out took 9.9 min, V 10.25, random 12.6, and front-to-back 14.0.

Compared with random and front-to-back, inside-out is better because it makes full use of the whole aisle, while the other two strategies only partly use the aisle. The main reason that we think the V-strategy is no better is that it needs to have more groups and it doesn't make full use of the aisle at the beginning and end of deboarding.

Is there any better strategy? Can inside-out be improved? During deboarding, passengers in the plane can still get their luggage as long as the aisle near their seats is empty. But during boarding, passengers who haven't boarded can do nothing but wait. Considering this, we find that there is no need to let the next group of passengers wait to deboard until the previous group is completely off the plane. We modify our model by changing it to when proportion α of the previous group still remains on board, we allow the next group to start to deboard—our *advanced inside-out strategy*. We find that $\alpha = 15\%$ to 20% yields best results, a deboarding time of about 9.4 min instead of 9.9. There is no need to get an exact optimal value of α, since it will be almost impossible for the flight crew to implement an optimal strategy exactly.

Deboarding with Luggage Distribution Control

If the airline is using our LDC boarding strategy, we already know the distribution of luggage. In this case, our simulation program does not need to judge if a passenger has to get luggage and how long it takes. We simulate the inside-out strategy with different values of α under the luggage distribution given by our LDC boarding strategy. Again, $\alpha = 15\%$ to 20% gives best results. The deboarding time too is reduced by 2–3 min; our LDC strategy can reduce

not only boarding time but also deboarding time, because we put the passengers who need less time to get their luggage in the front of the plane. (The optimal value of α is not sensitive to the distribution of luggage.)

Results for Midsize and Large Planes

When we apply the advanced inside-out strategy in midsize and large planes:

- The optimal value of α increases to 20–30%. The reason for this is possibly the increased number of rows in the deck.

Testing of Simulation Models

Are our simulation results reliable? We apply probability theory.

We ran each simulation model 100 times. The times are independent trials from the same distribution. According to the Central Limit Theorem, the sample mean has approximately a normal distribution. As a result, we can make an interval estimate [Rozanov 1969]:

$$T = \overline{X} \pm \frac{s}{\sqrt{n}}\, t_{\alpha/2, n-1},$$

where s is the sample standard deviation and $n = 100$. We choose 95% confidence. We find for each boarding strategy an interval of ± 1 min, meaning that our simulation results are reliably consistent.

Sensitivity Analyses

In reality, the boarding and deboarding times are influenced by various random events. Will these factors influence our simulation results?

- Occupancy level below 100%, that is, there will be empty seats. To show how occupancy affects our simulation result, we resimulate the strategies under occupancies from 20% to 90%. Result: If occupancy is more than 90%, there are no distinguishable changes in results with variation in time step size. If it is below 90%, the boarding time will be quite short and therefore affect boarding strategies very little.

- Passengers (especially those flying for the first time) may get into the wrong aisle in a midsize or large plane, which has more than one aisle. So we test strategies under a wrong-aisle possibility of 5%. Result: The boarding time increases by an average of 3 min. That is a long time! Proper guidance from the cabin crew is essential on midsize and large planes.

- Our boarding strategies can be implemented on all kinds of aircraft, because the outside-in strategy divides passengers by columns, so small variability in seat numbers won't affect our boarding strategy much.

Further Discussion

Passing

Our simulation models assume that passengers do not try to pass other passengers in the aisle. But in reality, research indicates that on average, one person in 10 does this.

Boarding Stairs

We assume a boarding bridge, but in reality a boarding stairs may be used (e.g., on the Airbus A380). The difference is that the airport must send a bus to take the passengers from the waiting room to the boarding stairs. Airports want to make full use of the bus and take as many passengers as possible. As a result, boarding in groups according to our strategy is hard to implement. But if the number of passengers in the bus equals the number in each group, we can still adopt our boarding strategy. When they are not equal, we adopt the following boarding strategy: Let R be the number of rows in the deck, with $R = pm + q$, where m is the half-capacity of the bus, p and q are integers, and $q < m$. We implement outside-in for pm rows in front; the other passengers are in one group and get on the plane randomly.

Disobedient Deboarders

Some passengers do not follow directions. We introduce an obedience factor β, the proportion of obedient passengers, picked at random. Disobedient passengers get off the plane if they get the chance, regardless of whether it is their turn. When obedient passengers are less than 40%, any strategy is useless.

Strengths and Weaknesses

Strengths

- We develop a simple theoretical model that gives a rough estimate of airplane boarding time, considering the main factors that may cause boarding delay.

- We design a new boarding strategy that assigns seats according to amount of luggage, which could save about 3 min in boarding.

• With 95% confidence, our simulation results fluctuate by only 1 min.

Weaknesses

• We don't consider the weight balance of a plane. Usually, the passenger and luggage distribution on the plane should be as uniform as possible.

• There are differences in seat configuration between our model and some actual planes.

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