Modeling Airplane Boarding Procedures

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Summary

We describe two models that simulate the process of passengers boarding an an aircraft and taking their seats. Using these models, we simulate common boarding procedures on popular aircraft to analyze efficiency. The second model is more ambitious and tries to model the situation more accurately, but even the first one addresses the major problems involved in boarding an airplane.

From running the simulations and analyzing the data, we find that the fastest and most consistent procedures are outside-in and reverse-pyramid. Both allow those closest to the windows to be seated first and proceed inward (though reverse-pyramid is slightly more complex). Reverse-pyramid is slightly faster.

Introduction

It would seem that the quickest way load passengers onto a plane would be simply to line all the passengers up in order of seat assignment, starting with the back-row window seats and working up to the front-row aisle seats, and march them onto the plane in that order. However, this is far from "simple"; the logistics would be extremely difficult to manage, not to mention that customers would dislike being forcibly lined up.

The response of airlines has been to try to control the randomness in passenger boarding order by seating passengers in groups, thereby localizing the

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disorder to a particular part of the plane. The traditional approach is back-to-front boarding, where a certain number of rows are seated, starting from the back and working forward. Other procedures include:

- **Outside-in:** Also called WilMA (for Window, Middle, Aisle), passengers with window seats are seated first, followed by those with middle seats, and finally those with aisle seats.

- **Rotating-zone:** Similar to back-to-front, except that after a set of rows in the back of the plane are seated, a set of rows in the front are seated. Back rows and front rows are alternated until the plane is full.

- **Reverse-pyramid:** Reverse pyramid resembles a mix of outside-in and back-to-front, giving preference to seats as far back and to the outside as possible. First seated would be the back half of window seats, then the back middle seats and the front window seats, then the back aisle seats and the front middle seats, then finally the front aisle seats.

- **Random:** Some airlines purposefully do not try to control the order of passengers on the plane. Random seating can be done with or without some seats assigned. Often the plane is still boarded in stages, with the passengers lumped into groups by check-in time or by another method.

Much research has been done to determine what procedure is fastest. While some studies have been analytic in nature [Bachmat et al. 2006a, 2006b; Van den Briel et al. 2003], most have adopted the approach of simulating the phenomenon [Ferrari and Nagel 2004; Bazargan et al. 2006; Van den Briel n.d.]. One problem with available simulations is that they focus on at most one plane size and type. In particular, in many models, a small plane with one aisle and three seats on each side of the aisle is taken to be representative of all aircraft. In reality, most planes that carry more than a small number of passengers have two aisles, and some have two floors as well.

We describe a model that aims to address these problems. We simulate aircraft boarding for any size plane (number of passengers), any layout (number of aisles, number of seats in each row), and most importantly, any order for seating passengers. We use the model to estimate the relative efficiency of various boarding procedures.

Motivating the Model

The process is slowed when boarding passengers have to interact, events we call *interferences*. *Aisle interference* occurs when a passenger cannot continue down the aisle to the seat because the aisle is blocked. *Seat interference* occurs when a passenger can only reach the seat by going past already occupied seats. Seat interferences increase the time it takes to sit down and may also lead to prolonged aisle interference if the people currently sitting down must get into the aisle to let a person in.

Assumptions

- **The plane is full.** While this is not always true, if a plane is far below capacity, any boarding method will probably work well.

- **All passengers are in the economy class and there are no special-needs passengers.** First-class passengers pay a premium price and expect to be seated first. We model only the seating of economy passengers. Likewise, we do not take into account pre-boarding by passengers with special needs such as the disabled, the elderly, and those traveling with small children.

- **There are no late passengers.** All passengers in a particular boarding group get in line to board as soon as they are called.

- **All pieces of carry-on luggage are the same and there is always enough room for them.** Passengers enter the plane with a randomly assigned number of bags (within a reasonable range such as 0–3). If there are already passengers seated in a particular row, it may take longer for an arriving passenger to stow bags, but the passenger can eventually do so.

- **No one can pass a passenger in the aisle.** This is the principal cause of aisle interference. In reality, a passenger might be able to squeeze past another, but we do not allow this. This is a reasonable assumption because in general passing a person in the narrow aisle of an airplane is a difficult and slow task anyway.

- **There is only one entrance.** Some airlines allow boarding from two entrances, but the majority of airlines have only a single entrance. Moreover, planes that allow multiple entrances tend to be small, where the boarding is already not as difficult as in large planes.

- **All seats are assigned.** This assumption primarily affects the random boarding procedure, for which we assume that the order of passengers entering the plane is completely random but each passenger has a unique seat that they are headed for when they enter. In unassigned random seating, there is the added problem that the passengers likely do not have a specific seat in mind when they get on the plane. When they enter, they head to either a seat that they consider "desirable" or to a seat that is easy to get to. We do not model this choice process.

- **Every passenger sits in their assigned seat.** Any seat-switching happens after take-off and so does not affect the boarding time.

- **Deboarding is always the same.** This is probably the most significant assumption that we make. We assume that the passenger unloading process will be the same no matter what the boarding process was, or the reverse of what the boarding process was, an assumption that seems to match the way airlines currently operate.

Estimating Parameters

There are few data for the speed at which passengers board planes, the time that it takes to stow luggage, and so on (though Bazargan et al. [2006] have some estimates). Thus, we had to estimate these quantities ourselves; consequently, the boarding times from in our model probably do not correspond directly to actual times. Our model strives to compare boarding procedures, which can be done by taking a standard set of "reasonable" values. We later discuss what happens to the model when parameter values are varied.

Modeling Airplane Boarding Procedures

We built two separate simulation models, which we will refer to as the Array Model (or AM) and the Graph Model (or GM), both implemented in Python. In general, the AM is more simplistic, while the GM tries to simulate the situation more accurately.

In the Array Model, the plane is represented internally by a two-dimensional array. Some columns of the array are aisles, and the rest are seats. The seats are either occupied are unoccupied, as are aisle cells. In this model, a person in the aisle completely blocks all the people behind. The AM can simulate different boarding procedures as well as different plane sizes and types, but with only one type of plane geometry at a time.

The Graph Model represents the plane internally by a graph, where the nodes and edges are weighted to represent the delay associated with crossing that node or traversing that edge. While more complicated, the GM is more flexible, allowing passengers to pass one another in the aisle (subject to a corresponding time delay, of course), and allowing for different plane geometries in different sections of the plane. This gives the possibility of modeling first-class seating as well, where the seating structure is different from economy seating. Also, in larger planes there is a second level of seating, which might have a different configuration from the primary level.

In the following two sections, we give the details of the two models and the relevant parameters in use. Then we give results for the tests that we did using the AM and the GM.

The Array Model

The array model is built based on the motivation of the Game of Life, devised by mathematician John Horton Conway. We treat the layout of seats and aisles as a matrix of four different values: occupied and unoccupied seats, occupied and unoccupied locations on aisles. The only objects that interact with this matrix are passengers. By moving up and down, right and left, inside the matrix, passenger change cell values in the matrix. Of course, passengers cannot move freely; they must follow certain rules that depend on the current layout of the matrix.

Parameters

The AM is based on several parameters. To make the model more accurate to the real world situation, we assign most parameters a normal probability distribution so that they vary slightly from run to run.

- **Interval boarding time**: This is the time that the airline staff checks a passenger's boarding pass. Default mean 4 s, standard deviation 1 s.
- **Time sensitivity**: This is the interval of time for which our model will update itself. The default value is 0.25 s.
- **Luggage stowing time**: This value depends strongly on the number of passengers there already (which also means that their luggage is already there). The more passengers, the longer it takes for a new passenger to stow luggage. By default, mean time and its standard deviation are 4 s and 1 s for an empty row, 8 s and 2 s for a row with one passenger, and 14 s 3 s for a row with more than one passenger. (In all the airplanes that we examined, no seat has more than two seats between it and an aisle, so we need to consider at most two passengers already seated.)
- **Seating time**: Similar to the luggage stowing time parameter, this value depends greatly on the number of passengers already there. By default, we set the mean time and its standard deviation to 3 s and 1 s for an empty row, 7 s and 2 s for a row with one passenger, and 17 s and 3 s for a row with more than one passengers.

The behavior of the model as it handles seat and aisle interference can be seen best by examining a screen shot of the AM simulating a plane using the back-to-front procedure (**Figure 1**).

The Graph Model

The graph model builds the airplane seating from a graph of nodes, each connected bidirectionally to applicable adjacent nodes in one of the four cardinal directions. Each node contains an occupant. Aisles have connections in all directions and seats have connections horizontally.

Passengers are tracked as they pass through the plane. Each is randomly assigned with uniform probability zero, one, or two carry-on bags that must be stowed before the passenger is seated. It is assumed that the passenger takes the aisle closest to the assigned seat in every case, crossing no more seats than is absolutely necessary.

Figure 1. Screenshot for AM model.

Storage bins are considered shared among several rows, usually two or three. The time required to load one additional bag into an overhead bin is proportional to the square root of the number of bags currently there. Thus, time to load bags is on the order of the 3/2 power of the number of bags.

Because of the structural flexibility present in the model, it can emulate planes with inconsistent geometries, such as the Boeing 767-400 with 2-2-2 in the front and 2-3-2 in the back. We can also, although with more difficulty, implement planes with two floors, such as the Airbus 380.

The graph model can use a smaller sample size because of the recomputation of random data. Every time a node's delay is computed, it is re-randomized; thus, a single run incorporates a broadly normalized set of random data. For this reason, we consider 200 runs per configuration to be sufficient to represent accurately the performance of a configuration.

Parameters

- **Aisle-aisle movement delay:** How long it takes for a person to move one node through an aisle. Default: 2 s.

- **Aisle-seat movement delay:** How long it takes to move from an aisle to a seat. Default: 3 s.

- **Seat-aisle movement delay:** How long it takes to move from a seat to an aisle. Default: 3.5 s.

- **Seat-seat movement delay:** How long it takes to move from one seat to another. Default: 7 s.

Strengths

One strength includes accurate simulation of shared luggage bins: A passenger loading a bag into a bin two rows ahead may influence the loading time of a piece of luggage elsewhere. In addition, luggage bins are shared for both sides of an aisle, which accurately models people's tendency to put luggage on either side of the aisle.

Another is that aisle spaces are allocated for people moving across already taken seats, simulating the requirement of everyone clearing the occupied seats for the newcomer to move in. This accentuates the effectiveness of modifications to the strategies, such as the even-odd variation or the staggered variation.

A third strength is that if there is an aisle, an empty seat, a filled seat, and the target seat, in that order, and a passenger moves into the empty seat on the way to the target seat, the passenger can get to the target seat only when the aisle is clear, according to the rationale that all swapping must be done through an aisle.

Weaknesses

One weakness of the model is that it does not simulate people traveling very far to get to an empty luggage bin. Rather, luggage bins are assumed to have unlimited capacity, and people do not prefer those with smaller delays.

Further, in our model, when a passenger enter the aisle to make room for someone who needs access to a inner seat, the passenger does not move toward the front of the plane; if the cell toward the back cannot be taken, then there is extra delay. This is somewhat inaccurate.

Using the Model

Plane Configurations

To analyze how the model reacts to different types of planes, we developed several plane configurations based on actual popular plane configurations.

Small Planes:

- **S1:** 3–3 (three seats, an aisle, and three more seats), 23 rows, 138 seats. (Based on the Airbus 320)
- **S2:** 2–3–2, 25 rows, 175 seats. (Based on the Boeing 767-200)

Midsize Planes:

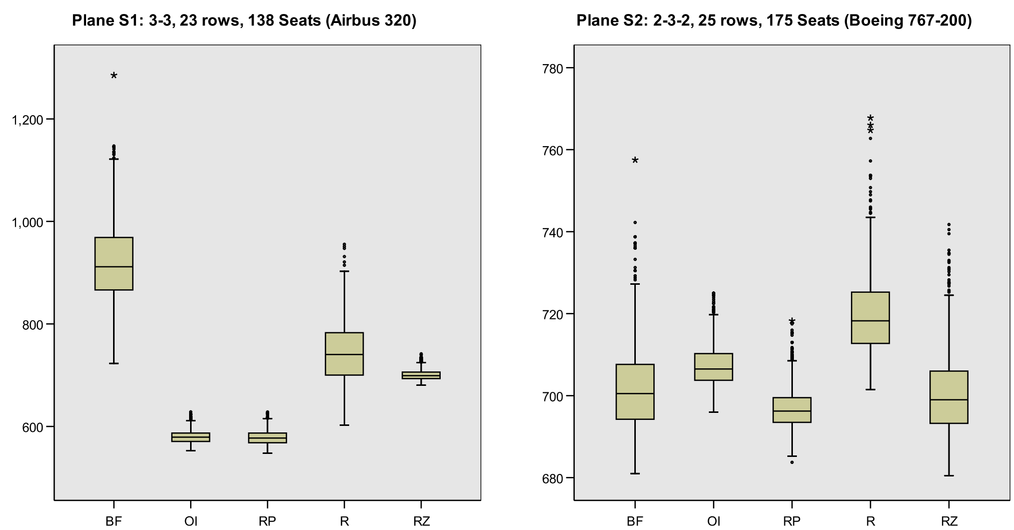
- **M1:** 2–3–2, 35 rows, 245 seats. (Based on the Boeing 767-400)
- **M2:** 2–4–2, 40 rows, 320 seats. (Based on the Airbus A300-600)

Large Planes:

- **L1:** 3–4–3, 40 rows, 400 seats. (Based on the Boeing 747)
- **L2:** 3–4–3, 40 rows on bottom level. 2–4–2, 30 rows on top level. 640 seats total.
  (Based on the Airbus 380)

Array Model Tests

For each plane configuration, we ran the simulation for the following boarding styles: back-to-front (BF), outside-in (OI), reverse-pyramid (RP), random (R), and rotating-zone (RZ). Data were gathered for 1,000 runs of each procedure. Shown in **Figure 2** are a boxplot and the mean and standard deviation for two of each plane size and each boarding procedure.



Plane S1:

Procedure	Mean	SD
BF	919	77
OI	580	12
RP	578	14
R	743	58
RZ	701	10

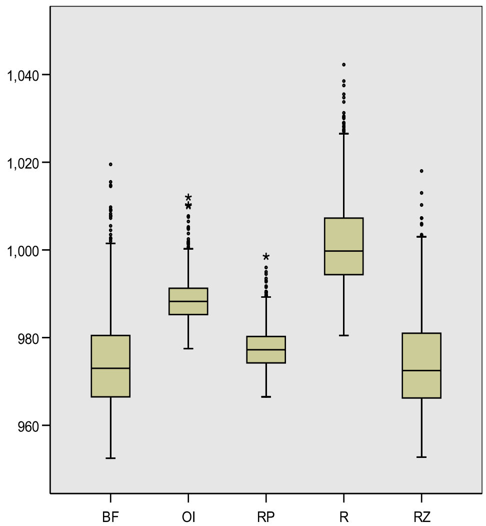
Plane S2:

Procedure	Mean	SD
BF	702	10
OI	707	5
RP	697	5
R	720	10
RZ	701	10

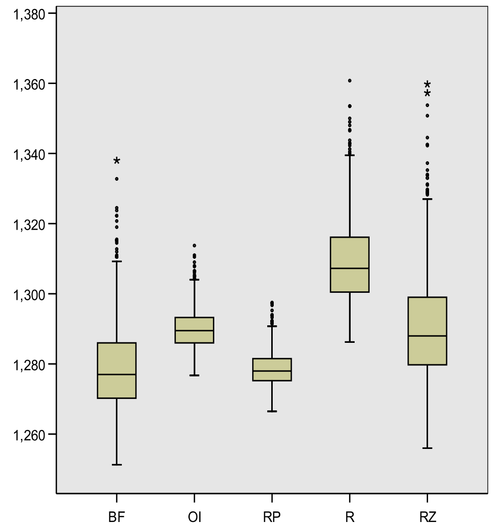
Figure 2. Results based on the array model: Small planes.

Except for Plane S1, where it performed horribly, back-to-front boarding actually performed quite well. This suggests that the conventional wisdom of the airline carriers is well-founded. Random boarding did not perform particularly well on any configuration, contrary to the opinions of airlines that are beginning to adopt it. The only procedures that consistently performed the

Plane M1: 2-3-2, 35 rows, 245 seats (Boeing 767-400)



Plane M2: 2-4-2, 40 rows, 320 seats (Airbus A300-600)



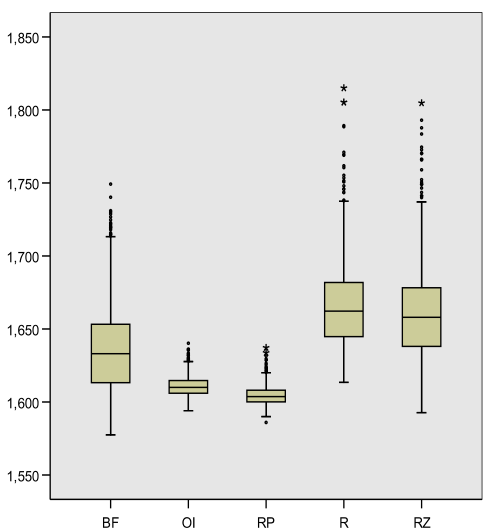
Plane M1:

Procedure	Mean	SD
BF	974	10
OI	989	5
RP	978	5
R	1001	10
RZ	974	10

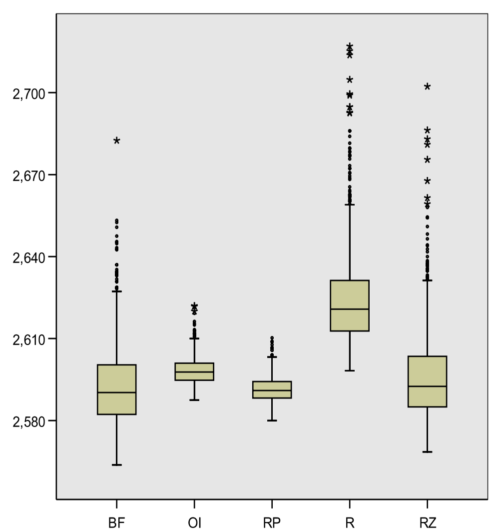
Plane M2:

Procedure	Mean	SD
BF	1279	12
OI	1290	5
RP	1279	5
R	1309	12
RZ	1290	16

Plane L1: 3-4-3, 40 rows, 400 seats (Boeing 747)



Plane L2: 3-4-3, 40, 2-4-2, 30, 640 seats (Airbus 380)



Plane L1:

Procedure	Mean	SD
BF	1636	30
OI	1611	7
RP	1605	6
R	1666	29
RZ	1661	33

Plane L2:

Procedure	Mean	SD
BF	2593	15
OI	2598	5
RP	2592	5
R	2624	17
RZ	2596	17

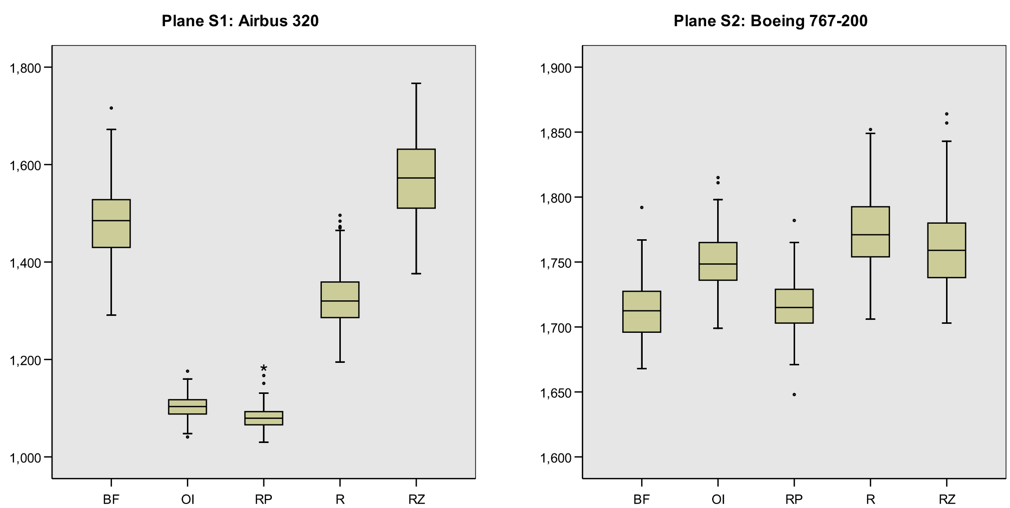
Figure 2 (continued). Results based on the array model: Midsize and large planes.

fastest were outside-in and reverse-pyramid, with reverse-pyramid having a slight advantage.

However, the most interesting aspect of the data is not the mean times, but rather the standard deviations. Outside-in and reverse-pyramid consistently had standard deviations almost half that of the other procedures. This is very important, because besides wanting to make boarding as fast as possible, airlines need to keep on schedule, so they do not just need the fastest but the most consistently fast. With this in mind, outside-in and reverse-pyramid seem clear winners according to the AM.

Graph Model Tests

As with the AM, we ran the five boarding strategies on each of the six plane configurations (**Figure 3**). Since the GM includes more randomization internally, we ran each simulation only 200 times, which still gives a 95% confidence interval about the mean with a radius of less than five time units, which is enough precision for our purposes.



Plane S1:

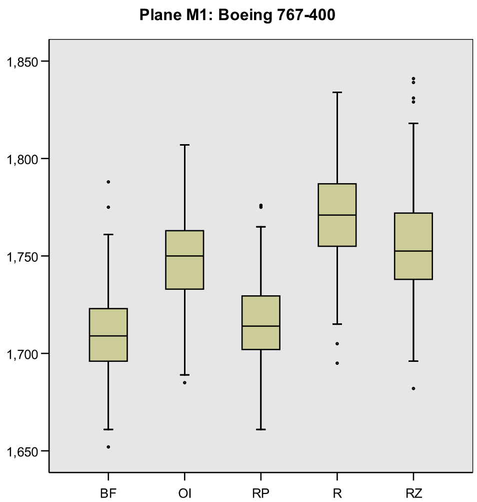
Procedure	Mean	SD
BF	1479	74
OI	1103	22
RP	1081	22
R	1326	58
RZ	1575	80

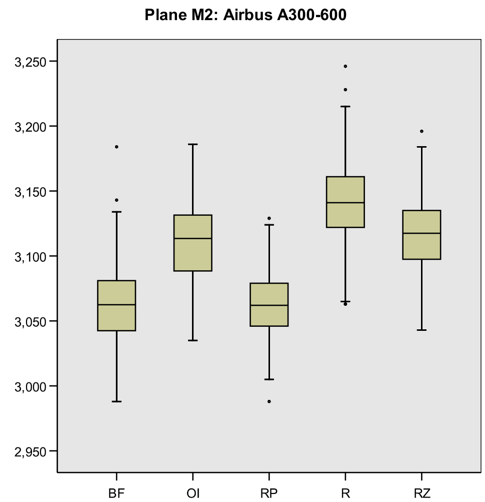
Plane S2:

Procedure	Mean	SD
BF	1712	21
OI	1749	21
RP	1715	20
R	1773	29
RZ	1760	28

Figure 3. Results based on the graph model: Small planes.

The data generated by the Graph Model are not easily interpretable. As in the Array Model, back-to-front does quite well; outside-in does not do quite as well as before. However, reverse-pyramid is still the best boarding strategy.



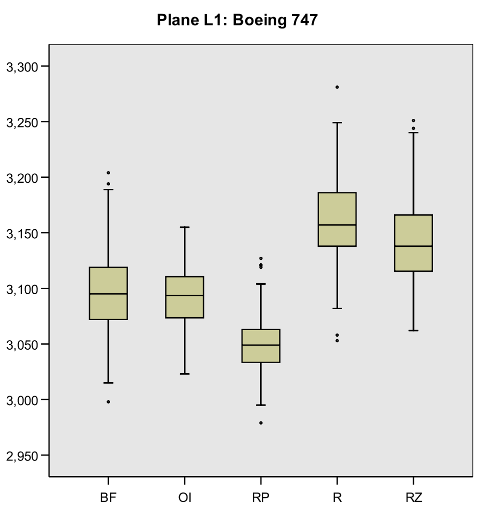


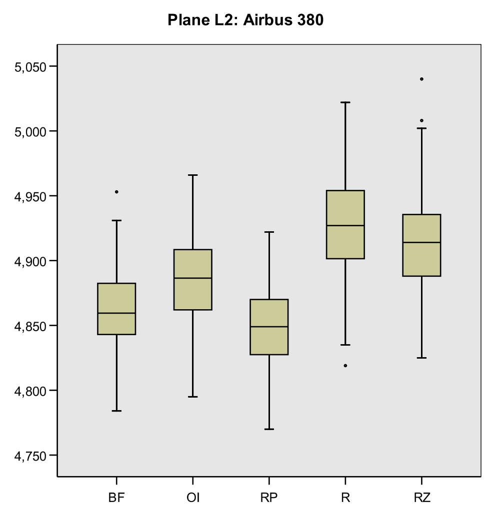
Plane M1:

Procedure	Mean	SD
BF	1710	21
OI	1749	22
RP	1716	19
R	1771	25
RZ	1756	27

Plane M2:

Procedure	Mean	SD
BF	3063	31
OI	3112	29
RP	3062	24
R	3142	33
RZ	3117	27





Plane L1:

Procedure	Mean	SD
BF	3098	38
OI	3093	27
RP	3050	25
R	3161	37
RZ	3141	3

Plane L2:

Procedure	Mean	SD
BF	4862	30
OI	4885	31
RP	4849	31
R	4927	39
RZ	4913	37

Figure 3 (continued). Results based on the graph model: Midsize and large planes.

according to this model. The only plane for which it performed worse than another model was the M1 plane, where it was beaten out by back-to-front by less than 7 time units. The standard deviations for reverse-pyramid are in general less than those of the other strategies, though by not nearly as much as in the Array Model.

One very perplexing aspect of the Graph Model data is the actual numerical values returned. Even more so than the Array Model, the Graph Model has not been tuned to actual time, so the time units in the results cannot really be taken as seconds. Still, planes S1, S2, and M1 all have simulation values in the range of 1,000 to 1,800 despite different plane sizes, yet the values for M2 and L1 jump dramatically up to the range of 3,000 to 3,300. We had expected a more gradual growth as plane size increased.

New Boarding Strategies

One benefit of the flexibility of the Graph Model is that we can devise our own boarding strategies and see how they compare with common ones. We tried taking an existing strategy and modifying it so that for a given group, the passengers in even-numbered rows board, followed by those in odd rows. We also considered the "staggered" modification, which is similar to the even-odd modification, except that even-numbered rows are boarded on one side of an aisle and odd-numbered on the other side. These modifications are to an existing strategy, so the original groupings still remain. For instance, in OI.EO (outside-in, modified by even-odd), the even-numbered window seats are boarded, then the odd numbered window seats, then the even middle seats, and so on.

The performance of these alternative strategies generally shaves a few time units off of the simulation time, but the relative results are the same. Shown in **Figure 4** is a graph comparing the 15 boarding procedures on the M2 plane.

Evaluating the Model

Array Model Sensitivity

To test the sensitivity of the Array Model, we ran the simulation 100 times each on the M2 configuration for a value higher and a value lower than the default on each of interval boarding time, luggage stowage time, and seating time. The changes alter the boarding time, but we were primarily concerned with whether the qualitative assessment of the different procedures changes as well.

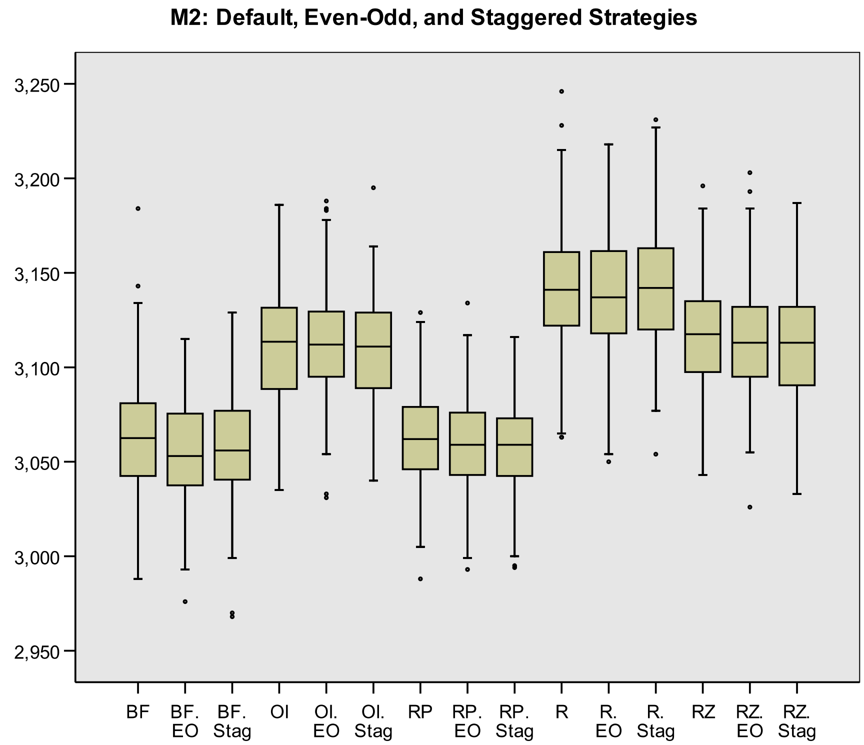


Figure 4. Comparison of modified and original strategies.

Boarding Time

We ran the simulation with a parameter values of (2,0.5) (that is, a mean of 2 and a standard deviation of 0.5), and a value of (7,3), and compared them to the default value of (4,1). The relationship between the outside-in, reverse-pyramid, and random procedures remains about the same; back-to-front and rotating-zone become comparatively faster as the boarding time increases (meaning that passengers are entering the plane at a slower rate). However, we must keep in mind that in the example where the mean boarding time is 7 (one passenger boards every 7 s), the total time to load the plane is over 2,000 s (more than 30 min). The difference in means is less than 1 min, which is not significant. What this means is that as the boarding time increases, the gains of one procedure over another become relatively less.

Stowage Time

For luggage stowage time, we ran the model with parameter values (2,0.5), (5, 1), (10,2)—meaning (2,0.5) for an empty row, (5,1) for a row with one person already seated, and (10,2) for a row in which two people are already seated—and the values (8,2), (14, 3), (20, 4), in addition to the default values (4,1), (8,2), (14,3).

The model is not very sensitive to changes in luggage stowage time. The times returned by the simulation rose slightly as stowage time increased, but not by much, especially compared to how the simulation times changed with boarding time.

Seating Time

The default seating time is (3,1), (7,2), (17,3) and the others parameter values run were (2,0.5), (4,1), (8,2) and (6,2), (12,3), (25,5). As with stowage time, the Array Model is not very sensitive to changes in seating time.

Graph Model Sensitivity

Sensitivity testing for the Graph Model involved choosing six parameters and running the simulation on each plane for each parameter low, high, and normal. More specifically, all but one parameter were normal, and that parameter would be set either low or high. Low was defined to be 50% of normal and high was 175%. The parameters that we chose were:

- Seat-to-seat movement delay per node
- Aisle-to-seat movement delay per node
- Seat-to-aisle movement delay per node
- Aisle-to-aisle movement delay per node
- Luggage bin loading delay per bag
- Delay between successive passengers boarding the aircraft

We ran 25 tests for each configuration, a configuration being a setting of the six variables, a plane, and a loading system. Since the analysis for the Array Model showed that there is little variation, we tested only the original version of each boarding system. Although we found some outliers in the sensitivity analysis, we believe that the results are adequately representative to draw our conclusions, due to the degree of randomness internal to the model.

The primary source of variation in the Graph Model is the delay between passengers boarding the aircraft. Total boarding time is almost directly proportional to the time between individual passengers, suggesting that the main bottlenecks occur outside, rather than inside, the plane. When we decreased boarding time to have a mean of 3.5 s instead of 7 s, the average boarding time was reduced by nearly half. This is the same situation as in the Array Model, where the largest variation was found by modifying the passenger boarding rate.

Other sensitivities were far less noticeable. The aisle-to-aisle transfer time has the next-largest impact on the result, but the variation of the boarding times is well within 15% for a 50% change in the variable. After aisle-to-aisle transfer time comes luggage loading time, whose variation is closer to 10%. Others quickly drop off to below 8%.

Strengths and Weaknesses

Array Model

The strength of the Array Model is mostly in its conceptual simplicity. It represents a fairly simple view of an aircraft and its passengers. It is also easy to modify to accommodate different plane configurations and boarding strategies.

The main weakness is likewise its conceptual simplicity. There is a lot more that can be done to model the aircraft boarding process more accurately. For instance, instead of having the parameters be decided according to a normal distribution at the beginning of each run, a more accurate version might have each individual have their own randomly chosen parameter values. Also, a more accurate model might be able to get rid of some of the assumptions that we made, such as allowing passengers to pass in the aisle in certain situations, allowing for late passengers, and modeling first and business class passengers.

Graph Model

The purpose of the Graph Model was to address the major weaknesses of the Array Model. The Graph Model is even more flexible in allowing different plan geometries, handles passenger interactions more intelligently, and incorporates randomness at the individual level. However, it is not without its problems. It still treats some aspect of passenger behavior and luggage storage in a naive fashion. More importantly, it is even less tuned to actual times than the Array Model, so it would take a large amount of effort to use the model to generate precise time estimates for the boarding procedures.

Conclusions

Despite these problems, we still feel that both our models capture the essence of the plane boarding process. From the Array Model data, we can make a fairly confident conclusion that the best boarding strategies are reverse-pyramid and outside-in, due to their fast times and low amount of variation. However, from results on the Graph Model, we had to slightly revise our conclusions regarding the outside-in strategy, which did not perform particularly well. The reverse-pyramid strategy still performed best in the Graph Model, so it remains our primary recommendation.

Reverse-pyramid is a bit complicated to implement, so outside-in might still be a good strategy. We must also remember that the traditional back-to-front boarding performed well too, so it might not be worthwhile for an airline to switch away from it. Further, a small speed increase can be gained by implementing an even-odd or staggered variation. For an airline trying to squeeze every last bit of efficiency out of their boarding procedures, a variation of the reverse-pyramid is the best bet.

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