

Fall 2009

A Comparison of Algorithms That Estimate the Effectiveness of Commercial Airline Boarding Strategies

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A COMPARISON OF ALGORITHMS THAT ESTIMATE THE EFFECTIVENESS OF COMMERCIAL AIRLINE BOARDING STRATEGIES

by

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A Thesis Submitted to the
Department of Human Factors & Systems
in Partial Fulfillment of the Requirements for the Degree of
Master of Science in Human Factors and Systems

Embry Riddle Aeronautical University
Daytona Beach, FL
Fall 2009

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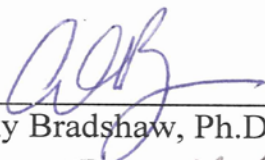
Dalila Giraldo

This thesis was prepared under the direction of the candidate's thesis committee chair, Jonathan French, Ph.D., Department of Human Factors & Systems, and has been approved by members of the thesis committee. It was submitted to the Department of Human Factors & Systems and has been accepted in partial fulfillment of the requirements for the degree of Master of Science in Human Factors & Systems.

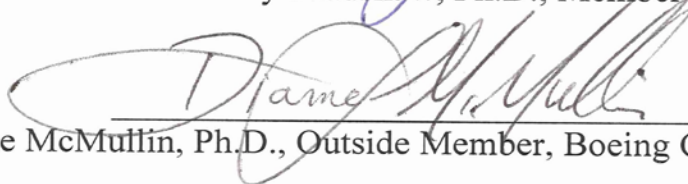
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Abstract

The number of passengers carried by commercial aircraft has increased dramatically over the past 50 years, closely in-step with advances in aircraft design. This makes unloading and loading an aircraft, called turn-around time, critical to the success of the airport, the aircraft and the airlines. A number of mathematical algorithms have been developed over the years that purport to determine the most efficient boarding strategy for passengers by decreasing turn time. This thesis evaluated the boarding strategies most often used by the airlines and algorithms used to predict boarding efficiency. The models used were obtained from the literature and from personal communication with the authors. The strategy and the model associated with the greatest predicted reduction in turn-around time, and the amount of time to deplane and enplane commercial airliners was determined. The Kruskal-Wallis one way analysis of variance test was used to determine that the Random boarding strategy had the greatest boarding rate and the rotating zone strategy had the slowest. It was also determined that one of the models, the Ferarri and Nagel sensitivity analysis algorithm, was consistently predictive of the empirical observations of boarding strategies.

Table of Contents

List of Tables	5
List of Figures	6
Introduction.....	7
Background	7
Thesis Structure.....	7
Airport Capacity	8
Airplane Turn Time.....	11
Boarding Strategies	13
Modeling Approach.....	16
Specific Hypotheses	27
Research Objectives and Methods	28
Empirical Data Collection.....	28
Validity.....	31
Apparatus	33
Validation of Results.....	34
Modeling and Simulation Data Collection.....	35
Statistical Methods	35
Results.....	36
Discussion.....	42
Conclusion	49
Recommendations.....	51
Acknowledgements.....	56
References.....	59

List of Tables

Table 1. An itemization of the steps involved in turn time and the estimated time for each.

Table 2. Summary of boarding processes used by major US airlines.

Table 3. The models selected for comparison in the study.

Table 4 Details on empirical data collection

Table 5. The average number of passengers, seconds to board used in the calculation of passengers per minute for Figure 3

Table 6. The average seconds and the average number of passengers in each of the boarding sequences examined.

List of Figures

Figure 1. Increase in passenger volume worldwide and predicted in the future

Figure 2. Time allocation of activities during boarding

Figure 3. Passengers Per Minute based on observed lobby data by boarding strategy. Error bars are based on standard deviations.

Figure 4. Comparisons of the model predictions with the Lobby (empirical data) Error bars are based on standard deviations.

Figure 5. Comparisons of the model predictions with the Lobby (empirical data) Error bars are based on standard deviations.

Figure 6. Comparisons of the model predictions with the Lobby (empirical data) Error bars are based on standard deviations.

Figure 7. Comparisons of the model predictions with the Lobby (empirical data) Error bars are based on standard deviations.

Figure 8. An overall comparison of boarding strategy predictions.

Figure 9. Comparisons of the Passenger Per Minute during individual stages in the boarding process; those boarding early, the general boarding and those who boarded late. Error bars are based on standard deviations.

Introduction

Background

The overall goal of this project was to evaluate published computer based algorithms for their ability to predict real world boarding times. First several boarding strategies currently used by airlines to board passengers were observed to determine the criteria with which to compare the predictive models. As airports struggle to accommodate larger aircraft and greater numbers of aircraft, the most efficient turn-around time is critical to the economic well being of the airport, the aircraft and the airline. The strategy and the model associated with the greatest predicted reduction in turn-around time and the amount of time to deplane and enplane commercial airliners was determined. The advantages and disadvantages of the modeling approach are discussed as well as alternative ideas for improving turn-around time for large high volume aircraft in the future.

Thesis Structure

First, the serious challenges that airports and airlines face in the immediate future from the steady increase in aircraft transportation is described. Then current boarding strategies in use by airlines and other short term solutions to reducing turn time are discussed. Next, the mathematical algorithms designed to identify the most efficient boarding strategy are detailed. Finally, the approach taken to observe boarding strategies in operation at large airports in the United States and to empirically identify the most efficient boarding strategy and the mathematical model that predicted it will be explained.

Airport Capacity

Air travel has become an important part of the travel plans for governments, industry and ordinary citizens. Long lines, frequent delays and less than optimal security processes create the perception of an unreliable, unsafe and uncomfortable experience. Recently, some news media have suggested that the current fall in the world economy has set in motion a reduction in customer service and amenities that large international air carriers used to offer. Although there has been a drop in air travel for the short term, tickets prices have been kept at inflation adjusted dollars, perhaps by sacrificing these services and amenities. From observations, it can be seen that meal services, luggage accommodations, pillows and blankets, young and attractive flight attendants and other commodities are not the norm of today's flights. Jones (2006) compares flying airplanes today with riding a Greyhound bus in 1970. He goes as far as claiming that the airline customer service is literally gone and that the steady decline in the past decade has gotten worse since 9/11. Alamdari and Fagan (2005) explain how low cost airlines are setting a new standard for the flying public with lower fares. For this business model, the lack of services is expected. Still, traditional airlines are struggling to distinguish themselves and stay solvent by offering previously standard services to attract customers without having to exponentially increase their ticket prices. According to Torrance (2006) they have been forced to look at creative ways to save on their expenses in order to remain competitive.

An area recognized as a big expense to every airline is turn time, the time that an aircraft is not spent flying during the flight business day. One of the reasons why turn time is so costly is the increasing charges from airports and the lost revenues airlines accrue when their aircraft is not flying (Van Den Briel et al., 2005). By streamlining this

process airlines could not only save money but also create a better experience for their customers by making the boarding process less hectic and more efficient (Pan, 2004).

Airports are struggling to handle the increase in passenger volume that has risen steadily over the last 40 years (Goetz, 2006) and this increase is projected to continue for the foreseeable future. Figure 1 shows that air traffic in 2006 has risen to the current level of four billion Revenue Passenger Kilometers (RPK) and this figure is expected to double within 15 years (Airbus, 2009). Aircraft turn time compounds this problem by increasing the time that aircraft are on the ground. Passengers before 1970 could board the aircraft at a rate of about 20 passengers per minute (PPM) but this rate has been steadily decreasing and is currently at about nine PPM (Marelli, Mattocks and Merry, 1998). The authors attribute this dramatic reduction in PPM to an increase in passenger luggage and carry-ons and an increase in passenger carrying capacity of current aircraft. It was unusual to see aircraft in the 1970's that could seat more than 300 passengers and now this is becoming common place. As more people turn to air travel to accommodate their travel plans, the volume of air traffic will swell airport capacity far in excess of their design. Norman Mineta, the former Secretary of Transportation, explained that the FAA forecasted in 2004 that there was going to be 1 billion passengers in the air by 2015 and airports needed to accommodate for this growth (Mineta, 2004.)

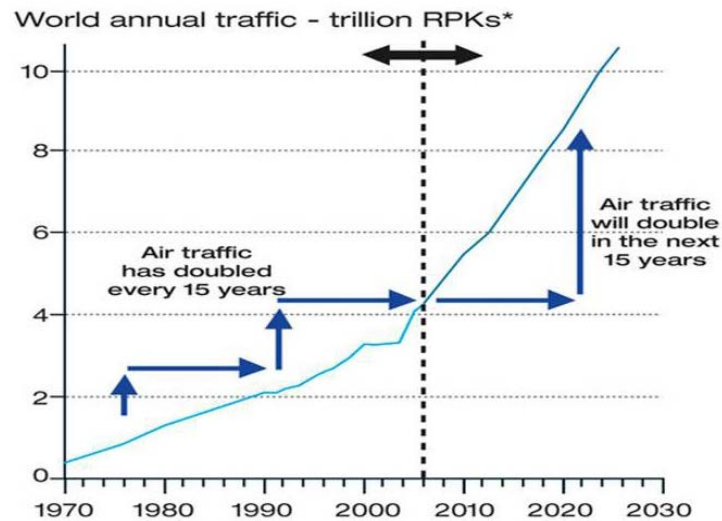


Figure 1: Increase in passenger volume worldwide in the past and predicted in the future. Source ICAO, Airbus

The U.S. Department of Transportation released a study in 2004 that examined population trends, economic and societal shifts, and the changing dynamics of the airline industry. The report entitled "Airport Capacity Study" found that as air traffic levels continue to grow over time, additional demands placed upon the national airspace system will strain the system's airport capacity. The report also found 23 airports in some of America's most vibrant and growing cities will need additional capacity over the next two decades, particularly in the South and Southwest where retiring baby boomers are expected to move and where the industrial base is projected to grow rapidly (Mineta, 2004). In the next 10 years it is expected that 18 airports and eight metropolitan areas will have capacity issues to address including Las Vegas, Birmingham, Houston, San

Antonio, and Chicago's Midway. For this reason, for the past 5 years, the department of transportation has commissioned seven new runway projects, allowing for more than 840,000 additional takeoffs or landings annually with an estimated cost of \$5 billion (Mineta, 2004).

Major redesigns of commercial airports have led to higher costs to carriers associated with such improvements. For Airline companies, the more their aircraft are flying the more revenue they can make. The airlines have considerable billions of dollars invested in their aircraft and the more time those aircraft are flying, carrying passengers, the greater the likelihood of a profit. The most obvious way to accommodate both airport and aircraft owner is to reduce the amount of time that aircraft spend on the ground. Larger aircraft with a greater passenger carrying capacity may lead to a short term solution for the problem. However, airline companies are currently focused on improving aircraft turn time and moving aircraft in a timely manner.

Airplane Turn Time

Airplane turn time is the time required to unload an airplane after its arrival at the gate and to prepare it for departure again (Marelli et al., 1998). Reducing aircraft turn time is where airlines have an opportunity to improve the efficient utilization of their aircraft and their bottom line. According to Funk (2003), turn time is estimated to cost \$22.38 per minute spent by an aircraft at the airport gate in the United States. This can accumulate very quickly; as Andre Miller (2005), chief executive of the Center for Asia Pacific Aviation, stated -these charges could potentially add up to tens of millions of dollars annually for a large fleet. An itemized analysis of the steps involved in turn time,

Table 1 shows that the activities that comprise turn time can be divided in three groups. Each component has a time attached, and reducing these times could potentially reduce the airport fee associated with it. Below is an estimated turn time for each component.

Table 1

An itemization of the steps involved in turn time and the estimated time for each relative lengths of time for turn-around time operations.

→ Passenger Transfer (Enplane/Deplane)	25 minutes/ +-15 minutes
→ Cabin Cleaning	12 minutes
→ Luggage Transfer-Forward Hold (Unload/load)	15 minutes / +-22 minutes
→ Luggage Transfer-Aft Hold (Unload/Load)	12 minutes/ +- 18 minutes

Note: Adapted from Marelli, S., G. Mattocks, R. Merry (1998)

When analyzing the steps involved in Table 1, it is evident that at least three main areas could be improved or modified to reduce these times: airport architecture, aircraft design and airline efficiency. Further, it can be seen from the table that passenger transfer is one of the most time consuming areas of turn time. This transfer of passengers is often referred to as boarding strategies. Finding the most efficient boarding strategy offers a potentially lucrative improvement in airline efficiency. Figure 1 displays the time line for each of the events described in Table 1. It is important to note that these

events could happen simultaneously. This has led to a proliferation in the variety of boarding strategies used to enplane passengers.

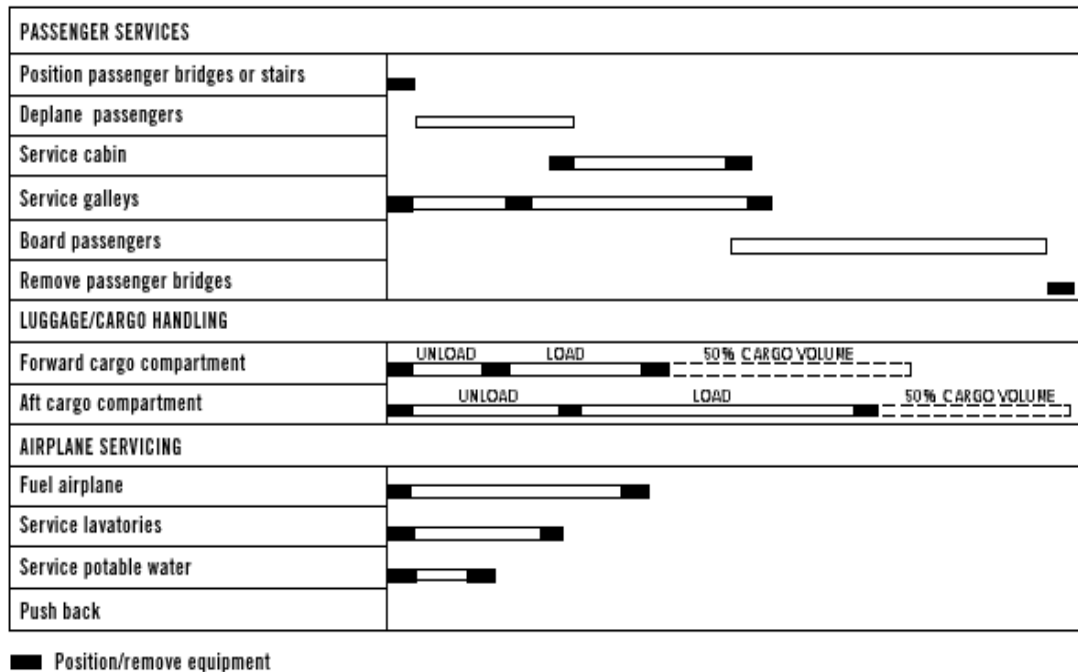


Figure 2 Time allocation of activities during aircraft turnaround. (Marelli et al, 1998).

Boarding Strategies

Boarding strategies have traditionally been created to improve passenger transfer time, hence airline efficiency. Airlines have adopted different boarding strategies throughout their years of operation and many areas of research have tried to answer the fundamental question of which strategy works best. A number of very clever and innovative strategies have been employed. Some of these strategies were formulated by authors that come from a diverse background including physicists, social sciences and mathematicians. The most popular strategies utilized today are summarized in Table 2.

A diagrammatic view of some of the more popular boarding strategies is provided in Appendix 1.

Table 2.
Summary of boarding processes used by major US airlines

Major US airlines	Boarding method
American Airlines	Block; Traditional block method
	By groups, starting at the rear of the aircraft and moving forward, about 1/5 of the rows at a time
Continental Airlines	Back to Front; Traditional by-row method
	By rows, starting at the rear of the aircraft and moving forward, about 1/4 of aircraft at a time
Delta Airlines	Rotating Zones; Non-traditional method
	By zones, starting with the back few rows, followed by the middle and then front sections, then back to a rear section
Northwest Airlines	Random; boarding method
	Passengers line up and take their assigned seat in no particular order
Southwest Airlines	Random; Open seating method
	Passengers are assigned a group and boarding number based on check-in times. After group is called, passengers take a position next to the column representing their number and proceed onto the aircraft. Passengers choose their own seats once onboard
United Airlines	Non-traditional method
	WilMA—Window seats first, followed by middle, then aisles
US Airways (America West)	Reverse Pyramid; Non-traditional method

Major US airlines	Boarding method
	window seats first, followed by middle, then aisle and loading diagonally

Note: Adapted from Lewis and Lieber (2005), Yu (2006), Reed and Yu (2006) and Mitchell (2008).

Pan (2004) advises that the use of an appropriate boarding strategy can offer the passenger satisfaction, safety and punctuality. Van Den Briel et al. (2005) define passenger boarding as the bottleneck in the turnaround process. Goldratt and Cox (1986) agree that in order to improve the [boarding] process the efforts must be concentrated on reducing the cycle time of the bottleneck. It is easier to reduce the time of cleaning or fueling the aircraft than to reduce passenger boarding time since it requires impacting the behavior of passengers. Considering the high impact of boarding process in the turn time, an in-depth study of each strategy utilized by airlines seems appropriate. This is an area for huge improvement in airplane efficiency but one that is deeply complicated by the human behavior on which it depends.

Boarding Strategies used today include variations of the groups in Table 2 such as: back-to-front, rotating-zones, random boarding with assigned seats, block boarding, reverse pyramid, outside-in and random boarding with unassigned seats (see Appendix 1). The first goal of this project is to evaluate the boarding strategies to determine, based on observations of a large number of passengers, which is the most efficient in terms of passengers per minute.

Van Landeghem and Beuselinck (2002) claim that the boarding process can be divided into three stages with causes of delays associated with each of them. The first

stage is the queuing of the passengers in the gate as the agent calls to announce the start of boarding. Card control is the second stage where the agent checks the boarding pass and passport or identification, if necessary. The last stage is the entrance to the aircraft by means of bridge (also called Jetway) or directly by the stairs (Van Landeghem and Beuselinck, 2002). Some of the airlines have turned to modeling and simulation to identify the most efficient turn time for their operations. This has led to a proliferation of models and data in support of one boarding strategy or the other. Although most airlines consider the three stages above in their efforts to improve turn time but most boarding, a review of the current models show that they don't consider these important steps. As expected, the conclusions of these mathematical models are frequently at odds with one another and airlines are left hoping that their experts have identified the best model, one that will give them a competitive edge in on time arrival or passenger and aircraft efficiency. We turn next to an examination of several models and the predictions before describing the test procedures we employed to validate the model and to identify the one most consistent with real world operations.

Modeling Approach

Modeling and simulation are tools utilized by most systems engineers and represent an established approach in governmental (primarily the military) and industry settings where complex forces such as human behavior are at work. Airlines have experimented with boarding strategy models to improve their aircraft turn time procedures. The developers of models of passenger behavior typically have approached the issue as an interesting application of mathematical probability models to the field of human behavior. Early work established baseline data for models by empirical

observations of passenger movements through the aircraft (Ferrari & Nagel, 2005; Marelli et al., 1998; Van Landeghem & Beuselinck, 2002) although with small sample sizes. Later work used exclusively analytical modeling (Bachmat et al. 2005; Steffen, 2008; Bazargan, 2007; van den Briel et al., 2005).

Previous studies (Parker et al., 2003) have argued that the modeling approach allows human behavior to be studied through the simulated interactions of [modeled] entities and their environment without explicit definition of the interaction conditions. In other words, the modeling approach is an appropriate tool for studying complex systems such as human behavior in a complex environment, even if we don't understand all the complexities of human interactions in the environment. This claim was assessed during the investigation.

The main approach to modeling passenger boarding strategies has made extensive use of discrete event simulations. In discrete event simulation models (DES) theoretical ideas of people in queues are carefully defined while allowing for elements of random behavior. Activity is modeled in a linear series of time-steps, with a known start and end-point to each task (Carson, 2005). DES allows passenger interactions to be visualized as moving dots or other entities as they traverse through the system. The whole DES process can be thought of as a flow chart of the procedure under investigation. In this task based environment, each passenger occupies a defined task and the movements are clearly described programmatically (Ferrari & Nagel, 2005). In an innovative study in this field (Steffen, 2008) made use of statistical mechanics (Monte Carlo simulations) to model the boarding process. Statistical mechanics models are more commonly used by physicists to describe the motion of particles when under the influence of a force and its application to

the domain of aircraft boarding is a new concept. However, it must be noted that any simulation cannot completely capture the actual freedom of choice available to human beings (Kirchner et al., 2003). This is the perspective of the current paper, that “all human behavior computer models are wrong, some are just more useful than others” (French, 2008). All models are simplifications of reality so there are always trade-offs with the level of detail included in the model. If too little detail is included in the model, there is a greater risk of missing relevant interactions. If too much detail is included in the model, it may become overly complicated and actually preclude the development of understanding. The models were selected for this study on the basis of the availability of their predictions. The authors of each of the models were contacted directly and if they were willing to supply the results from their model on a selected problem, they were included in the analysis. The models chosen are shown in Table 3. A complete description of these models is provided in Appendix 2.

Table 3.

The models selected for comparison in the study.

Author	Model
Ferrari and Nagel (2005)	Computer Simulation Sensitivity Analysis
Jason Steffen (2008)	Markov Chain Monte Carlo optimization algorithm
Menkes Van den Briel et al.	Binary integer programming (nonlinear assignment model)

(2005)	
Empirical Data	Lobby Observations

Note: Many more model authors were contacted than are shown here. These were the only ones who were able to supply us data given the conditions of the model for evaluation. A brief description of these models follows.

Ferrari and Nagel (2005) used computer simulation sensitivity analysis to simulate the boarding process inside the aircraft. More specifically, they utilized a microscopic cell-based simulation, which means that every single individual is represented in a grid as an occupied cell that moves according to specified rules reproducing passenger's behavior. All conditions having an influence on the simulation result were integrated into models and formulated mathematically.

Their aircraft model defines the dimensions of the airplane as well as the interior layout, e.g. the spacing between seats. For their considerations they used our specifications where possible. Their model used as an airplane consisting of 123 seats that are distributed over 23 rows. Walking speeds of passengers and restrictions - such as one in which passengers cannot pass other passengers in the aisle - were included in the passenger model. The seating model contained movement decisions while seating - e.g. the fact that passengers occupying a middle seat have to get up for people with window seats. Last but not least with the bin occupancy model, carry-on luggage was taken into account. To every passenger, certain pieces of luggage were assigned in compliance with a predefined distribution (e.g. 60% of passengers were carrying only one piece). In the simulation it took longer for a traveler to store more pieces of luggage.

This sensitivity study is known as the “average worst case” boarding time model (Ferrari and Nagel, 2005). Calculations determined that those boarding strategies which yielded good performance figures also yielded good “average worst case” boarding times and vice versa. It is important to note that with regard to the sensitivity of the “best” strategies to varying aircraft dimensions, Ferrari and Nagel (2005) further determined that non-traditional strategies were more robust than traditional strategies. In addition, they advocate that “all efficient strategies have a tendency to separate neighbors from each other” This means that the way efficient nontraditional boarding strategies are defined through both simulated and continuous equation modeling is to require passengers traveling together to board the aircraft at different times. Passengers could still sit next to one another with reserved seating capabilities; however, the problem of not being able to board together poses questions with regard to families traveling with young children or special needs partners.

Jason H. Steffen (Steffen, 2008) utilized a Markov Chain Monte Carlo optimization algorithm to find the passenger ordering that minimizes the time required to board an airplane. Steffen’s started with an initial passenger count that would fill the airplane and recorded this boarding time. Then, starting with that initial order, he exchanged the positions of two random passengers and loaded the airplane again. In order to create another new passenger order, the first two were either accepted or rejected depending on the boarding time they yield. If the airplane boarded as fast or faster than the previous iteration, then the new passenger order was accepted, the positions of two additional random passengers were swapped, and the process repeated. If the current configuration loaded more slowly than the previous one, then the change was rejected,

and the previous configuration was set up having the process was repeated starting at that point. Steffen ran about 10,000 iterations because he argued that adding additional steps would not significantly change the results.

Steffen created an aircraft and passenger model he calls the Optimal Loading Order model. Assumptions to the model include an aircraft with 120 seat passenger aircraft with six passengers per row in 20 rows. Since the focus was on the general boarding procedures used in this study, there was no first-class cabin, no priority seating, and each flight was completely full (Steffen, 2008). The passengers were each assigned a seat and the number of time steps that they need to load their luggage, a random number between 0 and 100 unless otherwise stated. Steffen explains in detail human nature assumptions in his 2008 paper,

Steffen's model (2008) did not accommodate for the effects of boarding aisle versus window seats. His also didn't take into consideration the clustering of passengers into companions or families, or other effects of human nature. According to him "while adding these features might improve the accuracy of the results, they are not likely to be the primary issue and consequently should not be of fundamental concern when finding the general strategy for a passenger boarding scheme" (personal communiqué). "Moreover", he continued, "many of their effects can be accounted for once the optimal-boarding method that is based upon the stated assumptions is identified."

To test the robustness of the optimal boarding scheme Steffen conducted two experiments. The first experiment was to change the distribution from which passenger's loading times were selected. The second was to make random changes to the passenger ordering including swapping the locations of several random pairs of passengers and

shifting the entire line by some random number (moving people at the end of the line to the front). Steffen's model assumes that a passenger loading his luggage consumes the bulk of the time that it takes for them to be seated.

Steffens (2008) concludes that boarding in groups where passengers whose seats are separated by a particular number of rows, by boarding from the windows to the aisle, or by allowing passengers to board in random order one can reduce the time to board by better than half of the worst case and by a significant amount over conventional back-to-front blocks which, while better than the worst-case performed worse than all other block-loading schemes. His discoveries also pointed out that a look at the optimal boarding method shows why loading from the back of the plane to the front does not provide any benefit. If the back two rows of passengers were to board the airplane first, they would occupy roughly 12 rows of the aisle. All but the first few would be putting their luggage away while the others waited their turn—the passengers load their luggage serially.

The optimal boarding strategy uses this aisle space more efficiently because each member of the first group of passengers who enter the airplane can put their luggage away—they load their luggage in parallel. In this manner the aisle is not used as a passive extension of the waiting area, but rather as a place for passengers to actively situate themselves. Ideally, the passengers inside the aircraft should either be seated or be loading their luggage with none waiting. One issue that arises from this is whether or not it is practical to implement the optimal boarding scheme whereby each passenger enters the airplane in a particular order. Such a scenario may well be possible since Southwest Airlines has recently implemented a similar policy, at least to some extent. Given that,

however, there will always be some fraction of passengers who are out of order; there will always be families or other groups who board together regardless of their assignments.

Another approach distinguished in the literature in an analytical studies approach. The one chosen by Van den Briel et al. (2003) is a mathematical approach, treating the aircraft boarding problem as integer-programing model. Anothe one, by Bachmat et al. (2005) tried to solve the problem using Einstein's theory of relativity. This particular approach was not included in this data collection due to its complexity.

Van Den Briel et al. (2005) selected a Binary integer programming (nonlinear assignment) model to estimate boarding times for different strategies. As described by Iusem 2001, linear and nonlinear programming is an area of applied mathematics that tries to answer how to “find numerical values for a given set of variables so that they are feasible i.e., they satisfy certain constraints, typically given by equalities or inequalities and also a certain criterion, called objective function, which depends on such variables, is optimized, that is it attains its minimum value among all the combination of feasible variable” (Iusem 2001, p.8868). In addition, if the unknown variables are integers, the problem is named an integer programming problem. The objective of the Van Den Briel et al. (2005) model was the minimization of the boarding time. That was achieved by way of minimization of passenger interferences. Van Den Briel et al. (2005) defined two types of interferences:

- Seat interferences, which happen when a passenger is already in the aisle seat or in the middle seat and another one has to occupy another one closer to the window.

- Aisle interferences: which come about when passengers are storing up their hand-luggage in the overhead bins, and other passengers are jammed in the aisle just behind them.

Therefore, the objective function, that is, the function to minimize, is a very complex expression which considers all the possible interferences and an associated penalty for each of them. The problem is defined as "...a nonlinear assignment model with quadratic and cubic terms in the objective function." (Van Den Briel et al. , 2005, p.193)). They described their model as a Non-linear assignment model with quadratic and cubic terms. Van Den Briel et al. (2005) collected data by videotaping actual aircraft boarding procedures with two cameras, one inside the jet-bridge, and one inside the aircraft. The data collected from the videos included time between passengers, walking speed, interference time and time to store luggage in overhead bins (Den Briel et al. , 2005).

Den Briel et al. (2005) used simulation to validate the results obtained from the mathematical model. They built a simulation model using Promodel 2001. They analyzed eight strategies, four of which were variants of back-to-front and the remaining four were those which minimized the interferences according to the analytical model. For each of these strategies 100 experiments were run. Den Briel et al. (2005) described that time savings came from the reduction of seat interferences. However, it was assumed that all aisle and seat interferences would be weighted the same in time allotments, thus no interference type was considered to be superior in penalty over another. Upon reflection the research authors stated: It might be the case, however, that aisle interferences should be weighted more heavily than seat interferences, and maybe aisle interferences that

occur within groups should be weighted more heavily than aisle interferences that occur between groups. It is very difficult to estimate these weights and determine how important each interference type is compared to other interference types.

Using the results from the analytical models, Van Den Briel et al. (2005) developed a new boarding pattern called reverse pyramid which was accepted and implemented by America West Airlines in 2003. The reverse-pyramid design is a hybrid strategy that combines aspects of the previously stated efficiency of boarding by seat or seatgroups by Van Landeghem and Beuselinck (2000) and the logical benefits of boarding back-to-front and outside-in. The reverse-pyramid design is essentially a seatgroup strategy (outside-in), but the boarding zones are created to load diagonally so that a boarding group consists of passengers who are actually boarding a few seats in the front of the plane, while other passengers within the same group are boarding in the middle of the aircraft. An alteration to the seat group (outside-in) strategy is the reverse-pyramid, designed by Van den Briel et al. (2005).

The reverse-pyramid logic was developed in an attempt to discover a way to board outside-in and utilize as much of the aircraft as possible. Boarding in groups, whether by row or outside-in, of back-to-front or front-to-back blocks always leaves sections of the aircraft underutilized. Upon reviewing the findings of their simulation model, the back-to-front strategies yielded the greatest number of interferences and thus longest boarding times. The reverse-pyramid strategies and seatgroup strategies (outside-in) yielded the least amount of interferences and thus the more efficient boarding times. Boarding time for the best-case scenarios of four blocks, outside-in, was observed to be 22.9 min and the reverse-pyramid scenarios of five and six blocks was observed to be 23

and 23.1 min, respectively (Van den Briel et al., 2005). The average boarding times of any traditional block and or seat-group strategy tended to increase when the number of boarding zones was either greater than four or less than three. This may be attributed to the notion that fewer boarding groups mandate more passengers per group, causing greater intra-group congestion, while having too many boarding groups becomes complex and difficult to control (i.e. more than the designated group is now actually on the aircraft causing interference among each other), further indicating that an optimal number of boarding zones is four groups when implementing pure outside-in or back-to-front approaches.

According to the data, the reverse-pyramid strategy overcomes the complexity and interference problems resulting from greater than four boarding zones because the zones are more evenly dispersed throughout the aircraft. Simulation results suggest that the reverse-pyramid strategy generates increased passenger dispersion, thereby reducing both intra-group and inter-group interferences. Additionally, study results concluded that a time savings of 39% could be achieved through the use of two ticket agents. This is due to the fact that the bottleneck for the reverse-pyramid strategy appeared at a much lower time between passengers. The reverse-pyramid design allowed for passengers to be seated faster than the traditional back-to-front block strategies once inside the aircraft, therefore allowing for a more expeditious ticket scanning process.

These models are not the only ones but they have been published in peer reviewed literature and their authors were kind enough to offer explanations and collect data to be analyzed here. There were at least 3 other models considered but were not used because either no data was collected or the authors were non-communicative or didn't want their

model compared in this way. Still the models that were used represent a variety of approaches and many other models are simple variations of these. These models are representative of the modeling and simulation approach. The paper considers 2 specific questions with regards to the data analysis. They are detailed in the next section. Descriptive statistics were used to summarize data and non-parametric (distribution free) procedures were used to evaluate the results because assumptions of normal distributions could not be made for most of the models and because the sample size was small in all cases. In all cases, the dependant variable was passengers per minute (PPM) and the two-tailed alpha level was set at $p < 0.05$.

Specific Hypotheses

Empirically quantify the passenger boarding time for the most common airline boarding strategies by physically observing the enplane times at a variety of airports around the United States. This will provide evidence for the most efficient boarding strategy in terms of passengers per minute under the conditions of the study. It is predicted that the semi-random, free-for-all boarding strategy typically used by Southwest Airlines and called Random herein will enplane the greatest numbers of passengers compared to the other strategies. This was based on the literature and on personnel observations from frequent travels of the aircraft boarding process.

- 1.) Compare the three algorithms used in the study with the empirically determined boarding strategies to select the most predictive algorithm. This will suggest which model is the most predictive of actual passengers per minute boarding under the conditions of the study. Given the limitations of the modeling

approach, it is predicted that none of the models will be distinguished in their ability to closely match the observed boarding times. There is currently no rational basis to expect any of them to perform better than the others.

Research Objectives and Methods

This study attempted to determine the best boarding strategy in terms of the greatest passenger per minute rate obtained through actual observations of airline operations at major US airports. Furthermore, data output from published mathematical algorithms purporting to estimate the most efficient boarding rate were compared to determine which is most consistent with real world observations. Data was collected from two sources: Observations (empirically) and model outputs.

Empirical Data Collection

The data was collected by observational field research. Bernard (1994) in “Research Methods in Anthropology” describes two main areas of direct observation research: Reactive and Unobtrusive. Reactive observation is utilized when the subject knows that is being observed and reacts to the observation. Unobtrusive observation is utilized when the subject does not know that is being observed. For this research, passengers were not aware of a study happening, therefore, the method of Unobtrusive Observation was utilized. Bernard (1994) divides Unobtrusive Observation into Behavior Trace Studies and Disguised Field Observation. In Trace Studies researchers gather data on a behavior or outcome after the action or event have been performed. In Disguised Observation researchers “act” as one of the subjects in order to study the behavior. For this study the researchers observed subjects in airport gates from the

perspective of another traveler. As far as the subjects were concerned, the researcher was going to be boarding the plane with them sometime during the boarding process.

Utilizing this kind of observation allowed data gathering without disrupting the boarding process or changing any subjects' behavior. Disguised Observation is often also called Covert Observational Research. There are several advantages to this approach including the fact that the behavior of passengers did not change or were contaminated by the presence of the researcher. Although this type of observation may raise some ethical questions, for the purpose of this research they were not considered to be a threat since the inclusion of an anonymous researcher did not directly affect their safety. An example of an observation that could raise ethical questioning could be for example, a particular group of people being observed and having the researcher observing them without their knowledge in a religious act, or any other private or sacred circumstance. Because the research observations were made in a public setting and the process observed was also of public domain, one that was performed without any discrepancy in race, gender, religion, etc. the researchers don't believe that they infringed any ethical boundaries and it is not believed that any ethical boundaries have been infringed.

The investigators travelled to one of 8 airports for observations in the early morning, some more than once to collect data during the course of a year. Funding for this travel was provided by a university grant for a related purpose but for which the investigators would prefer remain anonymous. The investigators, sometimes 2-3, had a list of aircraft with gate information and arrived at the gate to collect data. Often 8-10 aircraft, each with 50-150 persons boarding, were observed by each investigator in a day. A total of of 1500-2000 people was observed in a day. Days of the week that were used

varied but most were weekdays. This was important for the research because the goal was to observe the greatest variability of travelers and common notion suggests that weekend travelers could differ from travelers during the week, for example, family versus business travelers. Hours at the airport were typically between 9 AM and 5 PM. In the evening, the investigators took a return flight back to the Daytona Beach area. Data was entered into a standard Excel spreadsheet for processing. The table below displays the type of aircraft observed, the airlines, and the airports where data was collected as well as all the data points collected for each observation. An expansion of those items being coded is available in the apparatus section.

Table 4

Details on empirical data collection

<i>Aircraft</i>	<i>Airlines</i>	<i>Airports</i>	<i>Data Coded</i>
737 767 747 A340 MD80 737	Delta Virgin American Alaska Air North West Southwest	Atlanta New York Dallas Seattle Los Angeles Orlando London Heathrow London Gatwick North Carolina San Diego Newark	Location, Destination, Seat Location, Bin Interference, Frequency Bin Interference, Time Seat Interference, Frequency Seat Interference, Aisle Jumping, Passing, Part of Group, Time of boarding (pre-gen-late), Percentile, Gender, Age, Bag Type, Assisted Passenger, Following Distance, aircraft info.

Validity

In terms of validity, the literature considers observational research findings to be strong. Professor Trochim (1997), from Cornell University, states that validity is the best available approximation to the truth of a given proposition, inference, or conclusion and that observational research findings are considered strong in validity because “the researcher is able to collect a depth of information about a particular behavior” (Trochim, 1997.P. 126) However, there are several negative aspects of this type of research that had to be taken into consideration. The literature suggests that the most important aspects that could represent a problem with validity are: reliability and confirmation bias.

- Reliability: Laura Brown (2008), from Cornell University, explains that reliability refers to the extent that observations can be replicated. For the research it was estimated that any future researcher could approach the same airports at similar time of the year and gather similar data.
- Generalizability: or external validity is described by Trochim (1997) as the extent that the study's findings would also be true for other people, in other places, and at other times. It is important to note that there is a possibility that in observational research, findings may only reflect a unique population and therefore cannot be generalized to others. Several steps were taken in order to reduce this bias including:
 1. Conducting observations at different airports around the country in order to minimize regional customs in regards to passengers and carriers.

2. Conducting observations at different times of day.
3. Conducting observations during different times of the week, month and year.
4. Including the largest variability of airlines possible.
5. Including the largest variability of types of aircraft.
6. Conducting large amounts of observation.

These steps aimed to create a higher external validity. It is important to note that the study was only conducted on continental US, so the results may not reflect passengers from other countries with significantly different cultural backgrounds.

- Confirmation bias or “seeing what one wants to see” was recognized as another area of concern in this type of data collection. The aim of the study was to observe a population performing a certain task (boarding an aircraft) for this reason this bias was not of great concern, but several steps were taken in order to minimize its impact. For example, more than one researcher collected and analyzed the data together with a faculty member. Other step taken to reduce this bias was the use of a validated apparatus to collect the data. Although these steps were taken in order to try to control for it, its full impact is actually unknown since it may play a larger role and the exact extent of it is difficult to calculate.

Apparatus

A specific form was created in order to gather the appropriate information at the gate (Appendix 3). This form is the result of several trials and errors utilizing several forms and upgrading them to better accommodate for faster data collection. One of the main challenges in the data collection was that the researchers had limited time to collect a large amount of data, so an efficient form was crucial. The researchers positioned themselves so that they were able to accurately observe the passengers enplaning the aircraft. For each flight, the number of children, adults and seniors were gathered as well as their gender. For each age range the observers also gathered the type of baggage carried to the aircraft. Specifically, they identified bags as either small or large. Bags were marked as small if they could fit under the seat. Large bags were those that obviously could not fit under the seat such as roller bags, large soft bags, or oversized backpacks.

The observers first timed pre-boarding for those aircraft companies that had a pre-boarding policy. This usually included first class passengers, elite club members and parents with small children. Once pre-boarding was complete the observers timed the general boarding of the rest of the passengers. An attempt was made to gather information regarding any late arrivals. Also, the researchers gathered data regarding the efficiency of the flight attendants. Because efficiency is hard to measure, a scale from 1 to 5 was devised and a note section next to it allowed for an explanation of the given rating. Efficiency of attendants was expected to have an effect on the total boarding time, but that analysis was not carried out for this particular research because it is outside the scope of the study.

For each flight the observers also gathered information regarding the type of aircraft, departure and arrival locations and flight number. They also collected data regarding groups. If a group was observed that might affect the boarding time a note was made on the observation sheet. Any situations that affected loading times, such as delays due to mechanical issues were noted. For each aircraft the observers also noted the boarding policy that was used. The amount of flights observed at a location depended on a variety of factors such as delays due to weather, mechanical problems, or other aircraft operational issues.

Airport size and arrival gates of aircraft also had an effect of data gathering. For instance, if the observers were not present at the gate to observe when pre-boarding started, they were not able to gather data from the flight as data had already been missed. This presented a challenge in that the observers had to know beforehand which gates would be appropriate for observation. A stop watch was used to measure the time spent to board each group.

Validation of results

In order to validate our results a convergence with other sources of data--using variation kinds of triangulation and comparisons with the literature were utilized. This triangulation was able to directly compare results from modeling techniques utilized in past research and analyze differences or similarities with other (non-empirical) methods of prediction.

Modeling and Simulation Data Collection

All published authors were given an opportunity to participate in the data validation phase of this research. Each author was asked to run their model at least five times to improve the variability (stochasticity) of the data to make them amenable to statistical comparisons. These five outputs were considered trials for each of the models. Each model was additionally asked to estimate a single aisle aircraft with the following specifications listed.

Assumptions:

All models assumed a single aisle aircraft with 23 rows of economy seats and 3 rows of business class with a total of 150 passengers and with a seat configuration of 3X3, meaning 3 seats in each side of the aisle. All models were also to provide simulation results for 100, 80, and 60 percent loading factor. Simulations also were to run results for four boarding strategies (see Appendix 3): Back to front, Reverse Pyramid, Rotating Zone and Random. Lastly it also assumed that first class passengers will board the aircraft first.

Since most authors returned just one sample for each of the 100%, 80% and 60% load factors, there were just these 3 observations per model. These were compared to the lobby data used in the analysis.

Statistical Methods:

The lobby data were collected during 2007-2008 from airports during weekday flights during the primary business hours of from 0900-1700 EST. It was assumed that

the distribution of the observed data would be approximately bell shaped or Gaussian in nature so parametric comparisons were made from the lobby data. Specifically, a parametric one way analysis of variance was conducted for the lobby observation data when only boarding strategies were compared (Figure 3) and when the boarding sequence was evaluated (Figure 8). For Figure 3 and for all the models, all the data were based on one airframe, the Boeing 737. For Figure 8, the boarding sequences included a Boeing 767 aircraft to increase the observed sample size. Otherwise, since the remaining comparisons were based on mathematical models for which the underlying distributions were not known, particularly for all the models used in the composite comparisons (Figures 4-7) non-parametric or distribution free analyses were utilized. These comparisons utilized the Tukey's test so that all pairs of comparisons could be made. No correction for multiple comparisons were made (such as Bonferroni's) as this was deemed too conservative an estimate given the effect size seen in the figures. Further, since the sample sizes were small in the model comparisons, the Kruskal-Wallis non-parametric test was further justified. This test compares median scores by rank. Post hoc tests used the Dunn's test to compare the individual model data to the Lobby data (control) where the overall group effect was significant. For all comparisons, $p < 0.05$ was used as the alpha level.

RESULTS

The study focused on two main hypotheses. What is the best boarding strategy in terms of passengers per minute (PPM) and which computer algorithm predicts real world boarding results. The first hypotheses required observations of each boarding strategy at actual airports. Since some boarding strategies are used more than others, it was difficult

to get large numbers of lobby data for some. For example, only five observations were obtained for the rarest strategy, Back to Front boarding. In order to keep the numbers of samples consistent between strategies and to thereby improve the power of the statistical comparison, the number of observations for the lowest number of observations (Back to Front boarding n=5 observations ~ 600 passengers) was used as the selection criteria for the others. Hence the 5 observations from Random boarding that were numerically closest to the 5 observations by passenger number with the Back to Front strategy samples were selected for use in the statistical comparisons shown in Figure 3. The data for these observations are shown in Table 5. The total number of passengers involved in the comparison of boarding strategies was 2913 passengers.

Table 5.

The average number of passengers, seconds to board used in the calculation of passengers per minute for Figure 3. See text for details.

<u>Strategy</u>	<u>Average # Passengers</u>	<u>Average # Seconds to board</u>	<u>Average PPM</u>
Random	116.2	588.0	11.9
Reverse Pyramid	110.6	961.0	8.2
Rotating Zone	117.2	1212.0	6.2
Block	118.6	1224.0	6.2
Back-Front	120.0	1368.0	5.7

The one way analysis of variance revealed an significant overall effect ($F_{4, 20} = 0.0128$, $p < 0.0128$) for boarding strategy. Bartlett's test for the homogeneity of variance revealed no significant differences. Tukey's multiple comparisons for the boarding strategy revealed that Random boarding was significantly different from all but Reverse Pyramid boarding as shown in Figure 3.

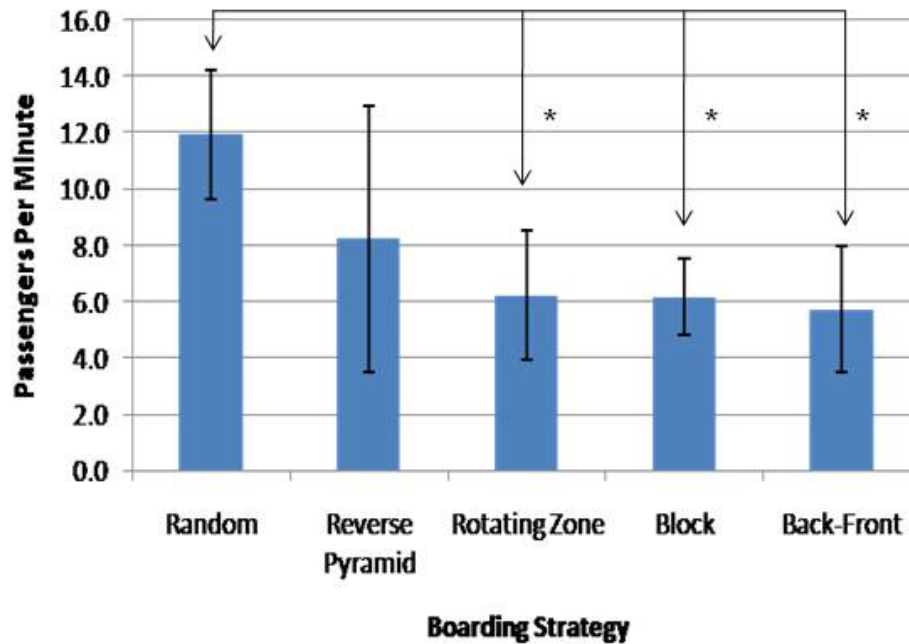


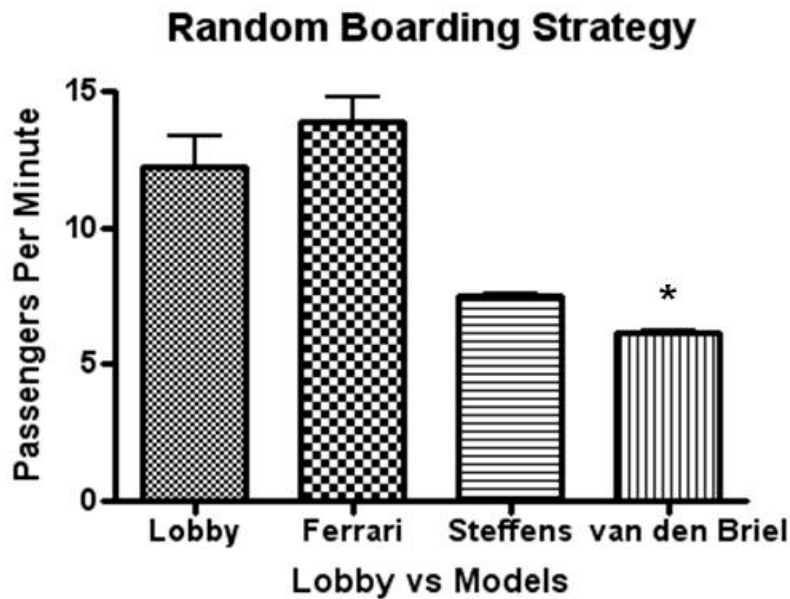
Figure 3. Passengers Per Minute based on observed lobby data by boarding strategy. Error bars are based on standard deviations. * = Comparisons $p < 0.05$

The significant comparisons in Figure 3 are shown by overhead bars. Thus, a bar connects Rotating Zone, Block and Back to Front boarding showing them to be different from Random boarding but not with each other.

The models were compared to the lobby data for each individual boarding strategy to determine if any model might be able to predict the boarding result from the real world observations (lobby data).

A Kruskal-Wallis test was used to compare model predictions of Random boarding observations in Figure 4. There was an overall group effect ($H=13.0$, $p < 0.005$). A Dunn's Multiple Comparison test revealed that the van den Briel model was different

from the Lobby data ($p < 0.05$).



*Figure 4. Comparisons of the model predictions with the Lobby (empirical data). Error bars are based on standard deviations. * = Different from Lobby $p < 0.05$*

An overall model effect was found for the Reverse Pyramid boarding strategy comparisons ($H = 10.9$, $p < 0.012$). Dunn's post hoc analysis revealed this to be the Ferrari model which differed from the Lobby data found for the Reverse Pyramid boarding strategy when the model predictions were compared to the Lobby data ($p < 0.01$). These results are compared in Figure 5. The other models were not different from the Lobby data.

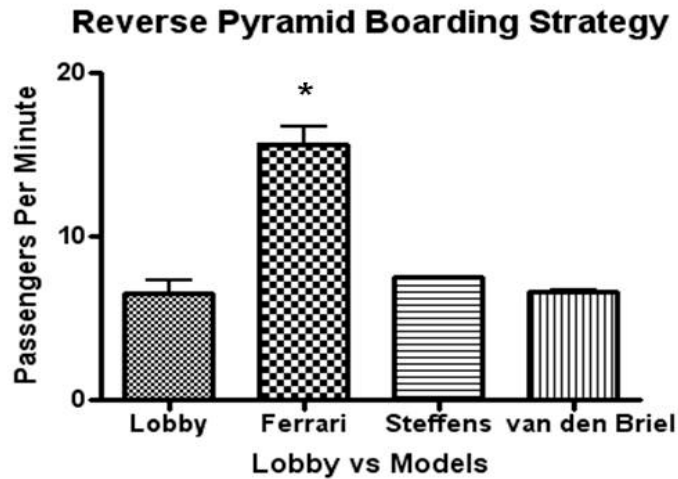


Figure 5. Comparisons of the model predictions with the Lobby (empirical data) Error bars are based on standard deviations. * = Different from Lobby $p < 0.05$

An overall model effect was found for the Rotating Zone boarding strategy when compared to the Lobby data ($H=9.57$, $p < 0.02$). Dunn's post hoc analysis revealed this to be the Ferrari model ($p < 0.01$) as shown in Figure 6.

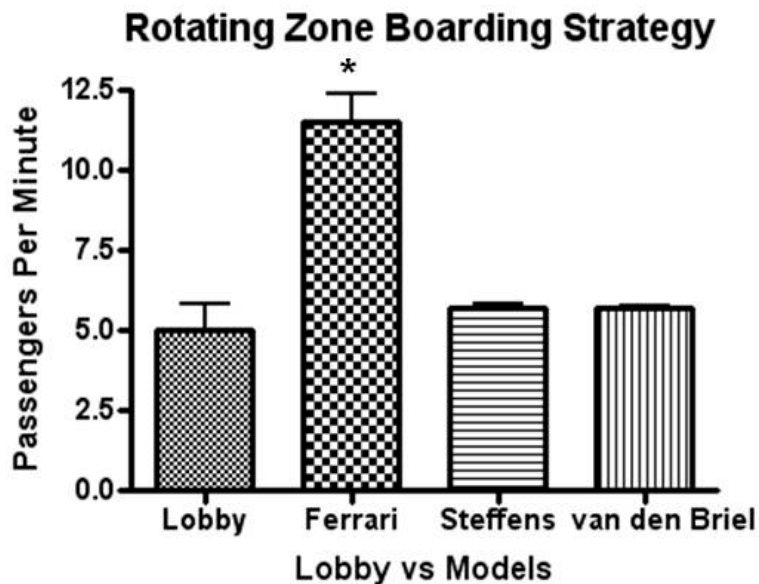


Figure 6. Comparisons of the model predictions with the Lobby (empirical data) Error bars are based on standard deviations. * = Different from Lobby $p < 0.05$

There were no results returned from the Steffens model or the Van Den Biel model for Block boarding so these results are not shown.

Finally, there was an overall model significance effect found for the Back to Front boarding strategy ($H=8.8$, $p<0.03$) but there were no multiple comparison results found with the Dunn's test, as shown in Figure 7.

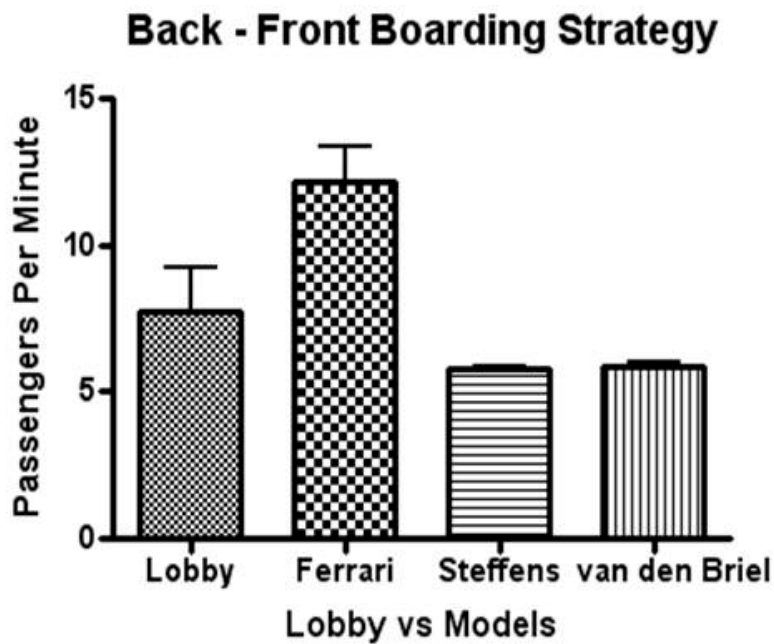


Figure 7. Comparisons of the model predictions with the Lobby (empirical data) Error bars are based on standard deviations.

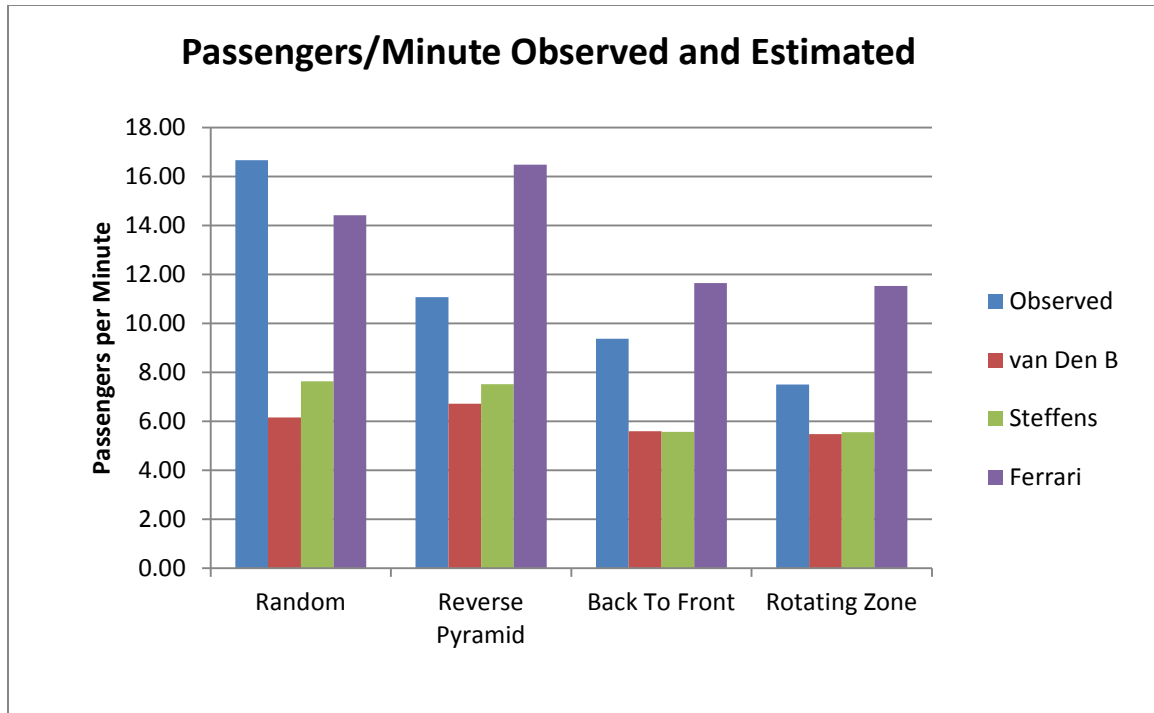


Figure 8. An overall comparison of boarding strategy predictions.

Discussion

As expected, the Random boarding strategy was the most efficient in terms of passengers per minute. A comparison of all the predictions can be observed in Figure 8. Analysis of boarding samples from around the eastern seaboard revealed the Random boarding strategy enplaned more quickly than all but the Reverse Pyramid strategy. These data suggest that Random boarding and the Reverse Pyramid boarding strategies might be able to reduce turn time.

The model comparisons with the lobby data (empirical data) were interesting. For the Random boarding strategy only van den Briels model was different from the Lobby data. This suggests that the other models were within the same distribution as the lobby data for this boarding strategy. On the other hand, Ferrari's model was

significantly different from the Lobby data for the Rotating Zone and Reverse Pyramid boarding strategies. These results argue that perhaps the other models would be more appropriate for these boarding strategies. Although the effect sizes shown in the figures suggest some discussion and that differences might be found if larger sample sizes were used, the results argue that most of the models are predictive of the empirically observed lobby data.

Throughout the research it was noted that late boarders were straggling the boarding process. Although not part of the original research, a closer look at the matter was taken. To understand the importance of this discovery it is important to be aware of how airlines divide boarding groups.

Boarding Groups:

Besides selecting a strategy, airlines separate the travelers into three main groups: Pre-boards, General Board and Late Boards. These differentiations are not present in random seating with unassigned seats, although some low fare airlines provide the option of “upgrades” to board prior to everyone else, with an associated fee. This fee would create a “pre-board” like group.

- Pre-Boarders are travelers that have an elite status within the airline because of miles accumulated or because they have purchased first class seating. Additionally, people with disabilities or that require assistance (including small children) are allowed to pre-board the plane.
- General Boarding represents the main part of boarders. This is the section that will be divided into different groups (by row, column, etc.) and will queue in long

lines in order to board. It has been observed in this research that general boarding is extremely streamlined by airlines; this is the process that they understand the most and are very efficient in minimizing the time associated.

- Late Boarders are the passengers that are either waiting for an assigned seat because they have missed a connection or purchased stand-by tickets. Late boarders also include late arrivals and any other passenger that must be accommodated after the general boarding is completed. Field observations show that this process constitutes for the longest time per passenger and it is one area that significantly affects the total boarding time.

Understanding the gaps between those groups, the transition from one group to the other, and diminishing them as much as possible, is important to streamline the boarding process. Furthermore, another gap can be observed, within the main three groups. These gaps could be attributed to the way that people behave in crowded areas in respect to their personal space. This has been termed Proxemics and is a relatively new area with a potentially large impact on airplane efficiency. Different cultures tolerate different proxemics as do different conditions in which people find themselves. Proxemics will be discussed further in the Recommendation section.

The final result was then based on that breakdown of the boarding sequence. The late boarders are the stand-bys, the passengers who arrive late and represent only a few passengers as can be seen in Table 5

Table 6.

The average seconds and the average number of passengers in each of the boarding sequences examined. These constitute the data in Figure 8.

	PRE_BOARDING		GENERAL BOARDING		LATE BOARDING	
	Seconds	Passengers	Seconds	Passengers	Seconds	Passengers
	214	22	1128	137	365	13
	80	10	569	18	222	9
Total Passengers		194		1237		113

The results of a parametric evaluation of the boarding sequence data are shown in Figure 8. There was an overall sequence effect ($F_{2,3} = 13.88, p < 0.0001$). Subsequent Tukey’s multiple comparison revealed that late boarding was different from both pre-boarding ($p < 0.01$) and general boarding ($p < 0.001$).

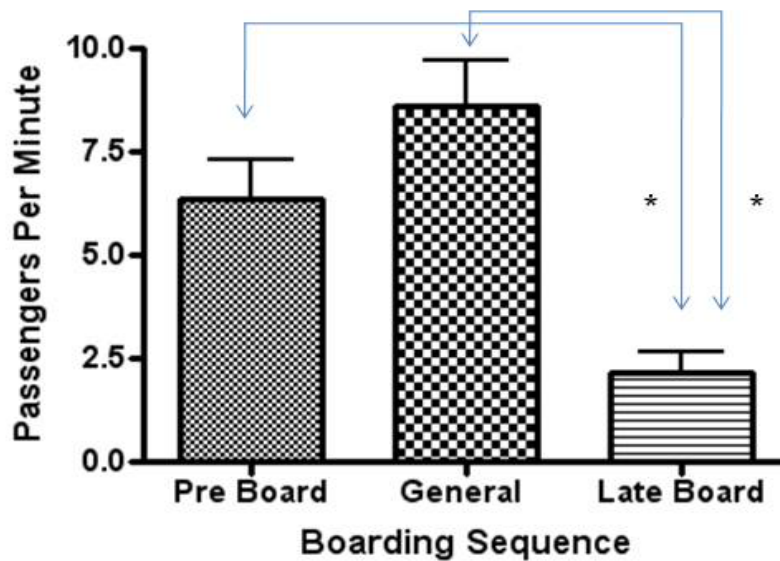


Figure 8. Comparisons of the Passenger Per Minute during individual stages in the boarding process; those boarding early, the general boarding and those who boarded late. Error bars are based on standard deviations. * = $p < 0.05$

The most interesting result is the discovery of the increase in passenger per minute rate for the late boarding individuals (Figure 8). This seems to have a large effect

on the overall time to board. The few people involved who was stand-by or who were late must then find baggage space, get a seat assignment and find their seat on the plane. This late boarding population can account for a large part of the enplaning time. Airlines would be well advised to find ways to speed up this group. Perhaps airlines could begin the stand by boarding earlier or no longer accept passengers who are late or develop means to gate check the bags so that time to board is not taken up by hunting for bin space.

An important part of this research was the learned key strengths and limitations of both empirical data collection and modeling techniques in regards of solving the problems associated with passengers boarding an aircraft. Those findings are described below.

Empirical Data Limitations

One of the biggest limitations of empirical data is the cost associated with collecting it. When research is not sponsored by industries, finding the means to collect empirical data proves to be very difficult. Ideally every research would be backed up by having participants, but this is not the case in many researches because of the monetary limitations. Particularly in this research, to collect empirical data implies air traveling that by itself has a high cost associated with it. The only two models that were able to utilize empirical data were PEDS (1998) and the Van Den Briel et al. (2005) model. PEDS was sponsored by Boeing, and Van Den Briel et al. model was sponsored by West Airlines. All the other models were based heavily on PEDS and Van Den Briel et al. because they were mostly conducted by university researchers (faculty and students)

Their models are still impressive and useful, but they lack a level of validity so important in modeling and simulation that is the comparison to real world outcomes.

Another important limitation of collecting empirical data is the power analysis issue. It is often said that the larger the sample size, the better the results. With more participants and more data the research will be more powerful, but what is the cut-off point? How much data is sufficient? Basing predictions in the right amount of data is a statistical debate that will not be settled easily as it depends on the scope of every research, and also, on the funding capabilities of the researchers.

Empirical Data Strengths

As stated earlier, only two models had empirical data for their validations. As limited as the current predictions might be, without that data, the models would not be able to predict any type of behavior at all, their results would be meaningless. There is not current way to go around collecting empirical data. In the arena of modeling and simulation of human behavior it represents one of the fundamental bases for developing an evocative prediction.

Modeling Limitations

An area important to note as a weakness with any modeling technique is the fact that they are highly dependent the assumptions. This includes, for example, having independent, perfect-knowledge, infallible passengers who always put their luggage directly above themselves, as well as having too perfect scenarios such as planes of equally-sized rows and jet-bridges of constant flow. None of the models incorporated the possibility of having stairs or buses that bring passengers to planes in some airports. None of the

models included passengers being confused about where they sit, or simply wanting to put their bag in the first available bin in the front even if seating in the back.

Additionally, none of the models considered human factors such as the impact on body size, age, and gender. Also, no model considered proxemics or cultural differences of passengers to predict algorithms for airports around the world. This is of particular importance in this industry that connects people from different backgrounds in similar architecture airports and aircrafts. In general, analysis of boarding algorithms that are simulation-based are therefore by nature not exhaustive. There hypothetically could exist some better algorithms that they researchers did not derive or test.

Modeling Strengths

Modeling provides much strength when utilized to study human behavior. For example, the multilayered approach to this particular problem allowed researchers to produce key insights on the process of boarding an aircraft. Furthermore, simulations are in general flexible and can easily be extended to new algorithms and situations with minimal changes. This can be used to address several of the weaknesses listed above in the future. Simulations can also provide the airline industry with a relative ranking of factors affecting boarding speed, not just a ranked list of algorithms they should employ allowing them to make improvements even if they decide not to switch processes. The biggest strength in modeling is considered to be the fact that large changes can be observed and analyzed without incurring hindering expenses. Airlines, for example, can learn more about their customers and their behavior without having to manipulate or stop flights. Aircraft manufacturers can predict the outcomes of architectural changes without

stopping production. Airport authorities can observe the impact of innovative passenger's flows without altering or closing their facilities.

Conclusion

The study of human behavior is an old science. Dedicated scholars and researchers have developed amazing theories over the centuries to understand not only why but also how people behave under certain parameters. It is an understatement to express that with all the advances in science and technology we still fall short when trying to comprehend what should be most familiar to us: our own behavior. As stated by Dr. Liu, professor of Human Factors at Embry Riddle Aeronautical University, soft sciences, those dealing with humans are the most difficult to grasp. Numbers, equations, graphs and computers are exact, tangible, and in many cases, predictable. Humans are anything but exact, tangible, or predictable. Why then spend time utilizing computer models to understand certain human behaviors? Why use modeling techniques to understand how, for example, a few hundred people will board an aircraft? The answer lies in understanding the limitations of our technology. We can embrace the results always keeping in mind where they lack validity. We can formulate answers maintaining a visible line of the shortcomings of those answers.

The temptation with modeling is to create models and then assume that they are the reality rather than just one description of reality. Each of the authors of the models used in this study felt that their model had some better predictive element than another model yet each was somewhat different from the real world data. Using a model prevents the real world data that a sterile mathematical model makes; the people who are depressed, who move slowly because they are intoxicated or who are leaving loved ones

or returning to loved ones. Those who just like to move slowly or fast would also not fare well in a model. Most models attempt to deconstruct reality by looking at a few individuals and trying to predict the great crush of humanity that takes airplanes by amplifying the behavior of a few. This is like trying to study a few trees and bushes to describe the ecosystem of a forest. Models are limited and the better strategy, it seems from the data presented here, is to observe real world behavior as frequently as possible to describe the phenomenon under investigation.

As a researcher in this study I observed over 20,000 different people boarding aircraft, and I can say with confidence that I observed over 20,000 different ways of boarding an aircraft. Where a computer may model 100,000 instances, or even a 1,000,000 it will never account for that old lady in a wheel chair that did not want to board without her bag that was too big to fit into any bin-compartment, or that family that had to wait for the small child to be done in the restroom, or that couple that changed their seats to travel next to each other. No technology so far is able to accommodate for all the possibilities, all the variables that go into a task performed by humans. To reduce our behavior to mathematical equations or filled lines of ones and zeros seems almost an insult, but brave researchers have done it, and their results are impressive.

The researchers listed in this paper formulated answers to a problem in extraordinary ways where most people would not have ventured to explore. They looked at common actions performed by passengers, gave names to them, analyze their effects in the total time a group of people would take to get into an aircraft. Furthermore, they devised creative and improved ways to board, called them clever names and even got

some of them implemented in the real world, by real airlines, and real passengers. That is impressive.

Which model then is closer in predicting “real life” might not be the right way to look at this when “real life” in the end is so hard to predict, as stated by the large variation in our observed data. But every new solution to the problem brought us closer to a general understanding of this complex system. Every new solution brought human modeling techniques to higher levels. Every approach was able to contribute and advance the large pool of science in an area little understood. The exercise of comparing methods and challenging researchers by asking them to take a new look at their models, has allowed us to compile a valuable resource of data and the value will lie only in how it is used in the future to look at possible solutions to eminent problems such as reduced airport capacities, the increasing demand of aircraft, and the success of airlines, airport operators and aircraft manufacturers. A fragile aerospace industry which is easily affected by world events, economic downturns and population trends will need it.

Recommendations

The industry will benefit by further advances and research in several other areas that are still wide open. Cultural differences and proxemics, airport design as well as aircraft architecture are areas that can potentially impact boarding times and because of it might be of interest to further study them.

Cultural differences and proxemics are large areas that have yet to be modeled. It would be of great advantage to better understand how people behave in crowded areas, particularly from different parts of the world. It would also be of benefit to understand

how their differences in personal space, gender differences, and their expectations (or lack of) for service or accommodations will affect how long they take to board. It would be interesting to find out if any of the formulated strategies by the models would have the same effect in Asia, for example, or the Middle East.

The term “proxemics” was coined by researcher Edward Hall during the 1950's and 1960's and has to do with the study of our use of space and how various differences in that use can make us feel more relaxed or anxious. The study of personal space and the behavior associated to it in public and crowded spaces has been the focus of several researchers in the past. According to Mike Sheppard (1996) at the University of New Mexico, proxemics can be divided in two territories:

- **Physical territory**, such as why desks face the front of a classroom rather than towards a center aisle, and
- **Personal territory** that we carry with us, the "bubble" of space that is kept between yourself and the person ahead of you in a line

Sheppard (1996) goes on to explain four areas of personal territory; public, social, personal, and intimate, utilized in the United States.

- **Public space** ranges from 12 to 25 feet and is the distance maintained between the audience and a speaker such as the President.
- **Social space** ranges from 4 to 10 feet and is used for communication among business associates, as well as to separate strangers using public areas such as beaches and bus stops.

- **Personal space** ranges from 2 to 4 feet and is used among friends and family members, and to separate people waiting in lines at teller machines for example.
- Finally, **intimate space** ranges out to one foot and involves a high probability of touching. We reserve it for whispering and embracing.

Personal territories, however, can vary both culturally and ethnically. This point is of particular importance given that airports are hubs for international travelers that carry with them their own interpretation of proxemics. Michael Wuergler (2008) in his thesis titled “Human Factors Characteristics Involved in Commercial Aircraft Enplane and Deplane” explains that Bonvillian and Nowlin (1994) explored how culture affects communication. They found that Americans use more personal space when speaking to each other than Arabs or Africans. This could be a reason as to why, for example, an Asian airline is able to board faster than a Western one, and so on. Cultural and ethnical differences in personal territories are out of the scope of this study but it is clearly an area of interest suggested for further considerations. Wuergler (2008) continued explaining how proxemics have not been appropriately addressed in any of the current models in simulation of human behavior for the boarding process. The lack of consideration in the matter creates significant limitations in the validation of the models and their fidelity. Proxemics may lead to a better understanding of how to encourage passengers to move more quickly. This idea led us to evaluate sequences of gaps in the boarding process which led us to discover the importance of the late boarders in influencing total boarding time, an issue that will be raised in the discussion.

Another area of future research lies in the particular architecture of airports. For example it would be important to find out what can be done to reduce the amount of passengers being late to a flight. Also, what advances can be done in how aircraft are advised to land or taxi in runways could be researched. How transportation from gates could affect the time gap between flights would be another area of interest as well as the effect of the shape of the gates or the jetways. With respect of automatization, such as ticket kiosks, it can be looked at what areas can be further benefit in order create a faster transition from arrival to check in.

Lastly, another area that could be modeled is the direct impact of aircraft architecture. Some areas that are expected to have an effect on boarding time are:

- The size and amount of aisles. For example, would more aisles yield to faster boarders? Would wider aisles reduce the amount of interferences between passengers?
- Shape of bin compartments. For example, would different shape bins compartments benefit or hinder the boarding process? What about removing them? This is an important rate limiting step in aircraft usefulness. Doubtless, some of the individuals who boarded late (Figure 8) had to spend considerable amount of time looking for bin space for their luggage.
- Multiple door or deck aircraft. For example it would be interesting to find out how would boarding an airplane from multiple doors or to multiple decks affect the process. Of all the recommendations, none would have a

greater impact on turn time than the simple solution of opening another door during enplane. Passenger enplane time would be effectively halved or better by this. Critics of this idea have argued that airports don't like having to bring up another ramp and passengers would be walking around the engines and it is hard to keep the order of passengers allowed to walk out to the aircraft on the tarmac. All of these could be solved by a second jetway. In the approaching era of super jumbos, a second jetway seems essential to enplane as well as deplane the passengers. This makes sense for the airport and airliner eager to turn the aircraft quickly. It seems that would be a good motivator for an appropriate solution.

As pointed earlier, airlines need to do something about the late boarders. More than any other human factor, the late boarders slow down the boarding process significantly. Perhaps boarding standbys earlier or being more firm in letting late passengers on board would be a good start. A training video or white paper might be useful to explain the advantages of the Random boarding strategy and what diluting the late boarder effect would do to their revenue. A further study that quantifying these two approaches will be useful for airlines as well.

This project used observed lobby data as one estimate of modeling validity. Since we regarded the real world observations as the control or standard by which to judge a model's predictions, it seems that this would be the preferred strategy in any case, to go out and look at people boarding different aircraft to better estimate boarding times. Modelers should include this kind of data evaluation in their future analysis. It is

recommended that they make it a standard by which the success or failure of models can be compared.

All these are interesting areas that could be researched at in the future and would benefit from modeling techniques since to implement some of those changes will be very costly.

Acknowledgements

It has been only for the generous support of Dr. Jon French that I have been able to participate in this research. Under his tutor I was able to learn during the 5 year BS/MS program more than I did sitting in any other class. The real life component as well as the large amount of responsibility and trust placed upon me by him allowed me to graduate with a larger sense of understanding of human factors and research. His insightful remarks and comments that ranged in topic from life science to poetry have made the ride unforgettable. I hope that all the “gummy brains” that he shared with me during many courses as well as long chats will finally have an effect and I will be able to stand the arduous challenge ahead in my educational path. For the advice, the support, this research opportunity as well the dedication of being an excellent chair, being able to work under extreme situations, from –literally- all over the world, I would like to thank Dr. French deeply.

Dianne McMullin has been my mentor from the moment I met her. From long chats across the desk, to sharing project ideas and allowing me to have an active role in her research, she supported me not only professionally, but also personally as a friend. Being a member of the committee for this thesis did not come easy for her. In the midst

of work, research in England, and many other limitations, she was able to be a more than active participant, and that will beyond be appreciated by me forever. She has become an enormous source of inspiration and she might not know the degree of influence that her role has placed in me. I can only hope to be a fragment of the round individual that she is and I am thankful that I was able to work by her side even if it was a short time.

My very first class in Embry Riddle was taught by Amy Bradshaw: Social Psychology. By far it was one of the most entertaining and insightful classes of the whole program. With her busy and successful career life I am very thankful that she agreed to help me in this project. She was able to provide many insights in the area of social psychology and research in general that made a complete difference by putting the whole project under another perspective, thus bringing it to a higher level. I am proudly one of her first thesis graduates and I can say with confidence that many students will be very fortunate to have her support in the many thesis to come.

I would like thank in the department of Human Factors to Dr. Boquet, who is one of the most extraordinary professor and mentor I had the pleasure of meeting, Dianne Martin, who provides support to everyone in so many levels that the whole place would probably collapse without her, Eric Vaden, Dr. Liu, Dr. Blickensderfer, Dr. Kring, Dr. McBride, Dr Neville and Dr. Doherty. Each person involved in my education had a very personal role and I couldn't have done it without them.

Lastly I would like to thank my family for their support. My dad who listened to each one of my thesis ideas without complaining and received infinite calls from each one of the flights (especially on those delayed ones!) my mom and sisters, as well as my

grandparents and Paris. Jessica Boquet, Stephen Mayo, and Nicole Andrade, the family I chose, who were also crucial in order to complete this report. I love each one of you. Finally, I would like to acknowledge the support of Santiago Giraldo, a friend who stood by me each step of the way and who literally made it possible for me to be an Embry Riddle student. Merci Santi for your all your support, your love, your patience... This thesis is dedicated to you above all.

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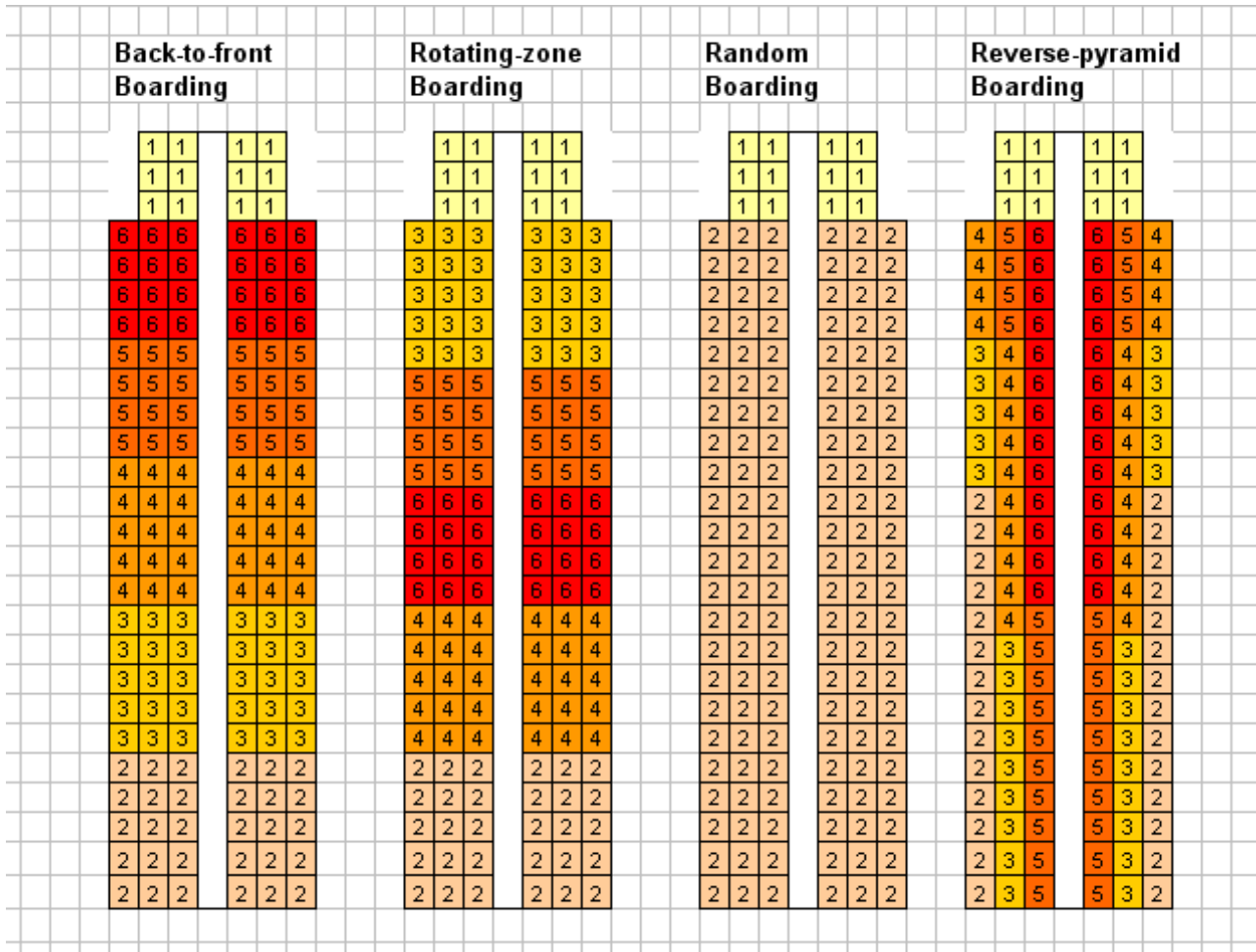
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Appendix 1.

Diagrammatic representations of the boarding strategies used in the study.



Rotating-zone boarding: Boarding groups are contiguous rows, but called in alternating order, with boarding groups in the back called, then those in the front, then those second to the back, etc., until the groups meet in the middle of the plane. Used by AirTran.

Reverse-pyramid boarding: A combination of outside-in and back-to-front, this method is best explained through illustration. Used by US Airways.

Random boarding with unassigned seats: Much like random boarding with assigned seats, except the seats aren't assigned. Used by EasyJet, RyanAir, and Southwest, the most prominent among which is Southwest. Southwest actually uses three boarding groups, assigned based on check-in time, so random boarding with unassigned seating does not necessarily imply a single boarding group.

APPENDIX 2.

Models selected for use in the study.

Major studies	Authors	Journal	Method	Model	Major findings	Data	Validation	Limitations
Arizona State University Study	Van den Briel et al. (2005)	Interfaces	Binary integer programming (nonlinear assignment model)	Interference model	Best strategy: outside-in and reverse-pyramid Average turn time: 22.9 min Optimal number of boarding zones: 4 Two ticket agents: 39% time savings	Videotaping actual aircraft boarding procedures Two cameras, one inside the jet-bridge, and one inside the aircraft. Data collected: time between passengers, walking speed, interference time, time to store luggage in overhead bins.	Simulation (ProModel 2001)	Model makes several assumptions.

<p>Institute for Land and Sea Transport Systems Study</p>	<p>Ferrari and Nagel (2005)</p>	<p>Transportation Research Record</p>	<p>Computer simulation sensitivity analysis</p>	<p>The passenger model Average worst case boarding time model</p>	<p>Best strategy: outside-in or by seat Those boarding strategies that performed the best under optimal conditions also performed the best under the worst conditions</p>	<p>**currently asked for this info</p>	<p>**currently asked for this info</p>	<p>**currently asked for this info</p>
<p>Boeing Corporation Study</p>	<p>Marelli et al. (1998)</p>	<p>AERO Magazine</p>	<p>Discrete event Simulation</p>	<p>PEDS model</p>	<p>Best strategy: outside-in Boarding with 2 doors saved 5 min Boarding</p>	<p>Direct observation of revenue passenger loading Passenger</p>	<p>Observations and tests.</p>	<p>It did not allow observations of all the interactions between passengers or</p>

					with two doors using outside- in saved 17min	loading tests.		with the airplane configurations It only validated simulation predictions of existing airline loading procedures.
Ben-Gurion University	Bachman et al. (2006)		Two dimensional Lorentzian geometry	Space-time geometry and random matrix theory Model	Back-to-front policies are ineffective Random boarding is almost optimal	Not listed	Simulation Model 1000 simulations for several settings	Assumes very thin passengers
Embry Riddle Aeronautical	Bazargan, M. (2006).	European Journal of Operational Research	Linear Programming Approach	Mathematical Model	Best policy for an Airbus-320 aircraft is a hybrid	Used Van den Briel observation results	Simulation Model	Assumes a single aisle aircraft where passengers

University					between Back to Front and WMA			<p>board through a single door.</p> <p>Did not include different boarding zones through different doors;</p> <p>Did not simulate less than a 100% load factor.</p> <p>Did not simulate pre-boarding, Families with kids, Wheel chair Passengers, or Passengers getting into</p>
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								the wrong seat.
Fermilab Center for Particle Astrophysics	Jason Stephen	Journal of Air Transport Management	Markov Chain Monte Carlo optimization algorithm	Optimal Loading Order	Boarding in groups where passengers whose seats are separated by a particular number of rows, by boarding from the windows to the aisle, or by allowing passengers to board in random order one can reduce the time to board by better than half of the worst case and by a	Not listed. As stated by the author: “While the generic features of this model are well understood, a real application of it would require some data so that it can be properly calibrated.”	Conducted experiments that: Change the distribution from which passenger’s loading times are selected Make random changes to the passenger ordering including swapping the locations of several random pairs of passengers	Assumes that a passenger loading his luggage consumes the bulk of the time that it takes for him to be seated

					significant amount over conventional back-to-front blocks which, while better than the worst-case performed worse than all other block-loading schemes.		and shifting the entire line by some random number	
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APPENDIX 3.

Models' Assumptions.

Author	Model	Airplane	Load Factor	Seat Interference	Aisle Interference	Passenger Arrival Times	Limitations	Measurements
<p>Menkes Van den Briel et al. (2005)</p>	<p>Binary integer programming (nonlinear assignment model)</p>	<p>3X3 config 3 rows business 23 rows economy 150 passengers</p>	<p>100, 80, 60, 40, 20.</p>	<p>“Occurs when a passenger, after reaching the row where his seat is and putting his baggage away, sees that there is another passenger already seated, blocking his progress.”</p>	<p>“Occurs when a passenger walks towards the row where his seat is and is stopped by another one, who is standing in the aisle, putting his baggage away in the upper compartments.”</p>	<p>Measure of how fast the gate agent is able to let passengers through, with 1 being very high (fast throughput rate) and 15 being very low. We used an exponential distribution and 1 means that the inter-arrival time of passengers is exponentially</p>	<p>inexistence of different speeds of dislocation from the passengers in the line to find their own seats, the inexistence of different level of difficulty to keep each volume of hand luggage, the</p>	<p>Time in seconds</p>

						distributed with a mean of 1 second. 7 seconds with 1 gate agent and 5 seconds with 2 gate agents	inexistence of intervals on the line of passengers boarding the plane	
Ferrari and Nagel (2005)	Computer simulation sensitivity analysis	3X3 config 3 rows business 23 rows economy 150 passengers	100, 80, 60, 40, 20.	“A passenger seated in an aisle seat is in the way if another passenger has to get into the window seat. In this case the sitting passenger has to get up, leave the row and sit down again after the passenger	“As passengers enter, the overhead bin fills up and it takes longer to find free room for luggage. They may even have to move to another row to store their luggage, but this will not be included	Early and/or late passengers: If passengers are divided into boarding groups, it will often occur that some arrive late or early. The number of these passengers will increase with the number of	Does not simulate passengers travelling together.	Simulation Timesteps, might be able to provide me total time (willask)

				near to the window has installed.”	into the simulation.”	boarding groups. At the ticket reader system, the boarding staff has the possibility to reject passengers that enqueue in a earlier boarding group. For travelers that are arriving late, access is always granted.		
Bachman et al. (2006)	Two dimensiona l Lorentzian geometry	132 pax Width Value **will ask more info	n/a	Considered as a Delay factor	Considered as a Delay factor	Boarding Groups Congestion Parameter (k)	Lacks Empirical data	Units with respect of random (each strategy is X units above or below

		on this.						random)
Bazargan, Massoud (2006).	Linear Programming Approach	3X3 config 737-700 150 passengers	100%	Between and within seat interference M & A Seat Interference 5-20 sec Aisle Seat Interference 2-8 sec Middle Seat Interference 2-10 sec.	Between aisle interference 2-4 sec Within aisle interference Baggage Time 4-20 sec	Boarding Groups Inter-arrival time Arrival Rate (pax/min) 6 thru 20	80% of pax carry luggage. Pax enter aircraft in a single line	Time in seconds
Jason Stephen	Markov Chain Monte Carlo optimization algorithm	3X3 config 3 rows business 23 rows economy 150	100, 80, 60, 40, 20.	Considered as a constant	Considered as a constant	** will ask **		Time in seconds

		passengers						
Empirical Data	Lobby Observations	737 aircraft	100-70	Observed	Observed	Observed	Not exact LF values	Time in seconds

Appendix 4

Lobby form used in this research.

Lobby Information

Form # 1

Date:			
Completed By:			
Time:	AM	PM	Evening

Flight#		Aircraft		Model		Airline	
Jetway Type	Obstructed	Unobstructed	Location:			Destination:	
Strategy:	1.Back-to-front 2.Outside-in 3.Rotating-cone 4.Reverse-pyramid 5.Block 6.Open Seating 7.Other: _____						

Number of Passengers	Male Child	Female Child	Male Adult	Female Adult	Assisted Infant	Assisted Elderly	Group (3 or more)	Small Bag (under seat)	Large Bag (overhead)
Pre-Board First									
Business									
Pre-Board Coach									
General Boarding									
Late Boarding									

Indicate Time	Start	End
Pre Boarding		
General Boarding		
Late Boarding		

Attendants on duty:	At Scanner:	At Counter:	Other:
Communication Method	1. Radio 2. Phone 3.Other: _____		
Boarding Announcements			
Manage Efficiency 1(inefficient)-5(great)	Reasoning:		

