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SIMULATION & MODELING

GROUP 3

Fly the Fastest Exit

Enhancing Efficiency with an Agent-Based Model for Aircraft Disembarkation

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Summary

The purpose of our analysis was to simulate and evaluate various disembarkation strategies in commercial aircraft using an agent-based modeling approach. We explored different strategies, including random, Steffen, WILMA, reverse pyramid, front to back, and introduced three new strategies. Our results consistently showed that the random strategy performed remarkably well, surpassing structured strategies in terms of disembarkation time. We also found that demographic group composition had minimal impact, while proper luggage placement significantly influenced efficiency. These findings suggest that implementing a random disembarkation strategy, optimizing luggage placement, and seating family groups together can greatly improve turn-around time and maximize profitability for airline companies.

Introduction

Air travel serves as a vital mode of transportation for millions of individuals worldwide, and the efficiency of passenger flow during boarding and disembarkation plays a crucial role in ensuring smooth operations for airlines. Effective de-boarding methods are particularly significant, as they directly impact turnaround time, on-time departures, and ultimately, airline profitability. Extensive literature demonstrates that aircraft boarding time significantly influences overall efficiency. However, with the evolving landscape of aircraft types and passenger demands, determining the most efficient de-boarding method has become a pressing challenge for airlines.

The period between an aircraft's arrival at the gate and its subsequent takeoff, known as the *Aircraft Turn Time*, encompasses multiple components, including de-boarding, cargo and baggage off-loading, refueling, cargo and baggage on-boarding, aircraft check-up, and passenger boarding. Optimizing the de-boarding process can lead to substantial improvements in airline efficiency and operational performance.

This research aims to address the fundamental question: "How can passenger flow be optimized during the de-boarding process to reduce delays and improve profitability?" To answer this question comprehensively, we conducted a thorough review of existing literature on aircraft de-boarding methods and passenger flow. We subsequently designed and implemented experiments utilizing Agent-Based Model (ABM) simulations and real-world observations to evaluate the effectiveness of various de-boarding strategies for different aircraft types. By employing computer simulations, we created controlled scenarios that enabled the isolation of specific variables and their effects on the de-boarding process.

Given the limited space within the aircraft cabin, passengers often encounter challenges when navigating towards their destination while simultaneously collecting their luggage and making their way to the exits. Our primary objective is to develop a natural and problem-solving approach to address these issues, considering the diverse behaviors exhibited by each passenger. Notably, the human factor significantly influences passenger flow, as individuals strive to reach their destinations promptly, yet their approaches may differ. For instance, anxious travelers may prioritize accessing the aisle ahead of others, while more relaxed passengers might require additional time or willingly yield their position to accommodate others.

The outcomes of this study are expected to provide practical implications for airlines to optimize their operations, reduce costs, and enhance the overall passenger experience. By conducting a comprehensive analysis of the most effective de-boarding methods for various aircraft types and their impact on passenger flow and boarding time, this research contributes to the existing literature and aids in addressing the ongoing challenge of improving efficiency and profitability in the aviation industry.

Background

Efficient aircraft deboarding procedures are essential to minimize turnaround time, optimize operations, and improve airline profitability. This chapter explores the current state of boarding procedures, focusing on the research and development of effective deboarding methods. The literature on aircraft boarding has been a subject of study since the 1980s, with the primary goal of finding the most efficient way to assign passengers to specific boarding groups and reduce overall boarding time.

Airlines strive to maximize profits by minimizing turnaround time, which is calculated as the duration between an aircraft's arrival and departure time. Turnaround time comprises several factors, including disembarkation, baggage unloading, refueling, aircraft maintenance, cargo and baggage loading, and passenger boarding (Soolaki et al., 2012). Among these factors, passenger boarding has received considerable attention in research efforts to improve efficiency.

While significant progress has been made in studying boarding processes, the topic of deplaning has received comparatively less attention. However, recent studies have focused on strategies to reduce deplaning time. Simulation models have been widely used since the 1980s to investigate boarding methods due to their cost-effectiveness, convenience, flexibility, and low risk.

One notable study by Iyigunlu, Fookes, and Yarlagadda (ABM of aircraft boarding methods) provides a global overview of the performances of six different boarding techniques on two popular aircraft models, the Boeing 777 and Airbus A380. Their work is valuable not only for determining the best boarding strategies for these aircraft but also for the development of an Agent-Based Model (ABM) simulation and the consideration of various passenger attributes such as gold membership, children, groups, and business class.

An important aspect worth mentioning is the distinction between seat interference and aisle interference, as highlighted by Briel et al. in "The Aircraft Boarding Problem" (2003). Seat interference occurs when passengers occupying middle or aisle seats board before those in window seats of the same row, requiring the window seat passenger to vacate their seat temporarily. Aisle interference refers to the waiting time a passenger experiences when a fellow passenger in front of them stows or retrieves their luggage before proceeding to their seat.

During the deboarding process, passengers play a crucial role, and empirical observations suggest discrepancies between current practices and optimal strategies. While many studies have focused on the boarding process, this research aims to model and understand the impact of the deboarding process on overall passenger flow.

Efficient deplaning is a key factor in turning an aircraft quickly, leading to on-time arrivals and departures, the ability to recover from irregular operations, reduced costs, and improved customer satisfaction. Current deplaning practices often lack structure, with airlines deplaning an average of 15-17 passengers per minute regardless of the aircraft size. Given that passengers deplane faster than they board, structuring the deplaning process presents an opportunity for hidden improvements.

As mentioned earlier, airlines use Turn Time as a measure of operational efficiency, defined as the time between setting the aircraft brakes and releasing them (Mas Sílvia, Juan Pérez, Angel Alejandro, Arias, Pol, Fonseca Casas, Pau, 2013). The average Turn Time ranges from 30 to 60 minutes, and reducing delays during the deboarding phase is crucial for airlines to optimize profitability (Landeghem & Beuselinck, 2002).

The current literature on deboarding reveals several approaches. Zhao et al. (2007) focused on backward boarding strategies but did not optimize the deplaning process, which is the central focus of our work. Li et al. (2007) conducted passenger distribution analysis, reversing their simulation to simulate deplaning. However, their model's parameters and assumptions were not validated with real-world data. Yuan et al. (2007) explored structured deplaning using a dedicated simulation model, but their approach involved reversing boarding strategies instead of developing an optimized deplaning process.

In summary, the existing literature on deboarding has primarily focused on reverse-boarding strategies or hypothetical models with unvalidated parameters and assumptions. In contrast, our research takes a distinct approach by developing a dedicated deplaning agent-based model that accurately reflects the actual process and incorporates real-world data. Our goal is to optimize deboarding strategies and address the inefficiencies in current practices.

To achieve our research objectives, we will leverage the knowledge and insights gained from the existing literature and theoretical frameworks surrounding aircraft deboarding. Our

research aims to bridge the gap between theory and practice by developing practical, data-driven solutions that address the challenges faced by airlines in managing the deboarding process effectively.
By focusing on real-world data and practical solutions, our research aims to provide valuable insights and recommendations that can enhance the efficiency of deboarding procedures and contribute to the profitability and success of airlines.

Model

As a system made up of many components that interact with each other and the environment, aircraft deboarding can be referred to as a complex system (J. Newman, 2011).
There are two primary approaches to modeling complex systems: macroscopic methods and microscopic methods. Macroscopic methods involve using systems of differential equations to describe the system at a higher level and establish connections between variables. Despite their differing approaches, all these methods share a limitation: they require a comprehensive understanding of the system's dynamics. This can be challenging for complex systems, as their emergent behaviors are not fully understood.
In contrast, microscopic methods take a bottom-up approach and enable the exploration of emergent behaviors by accurately representing the individual components of the system and their interactions. Agent-based modeling serves as an example of a microscopic method.

In order to study the complex system of aircraft deboarding, we have chosen to employ an agent-based modeling (ABM) approach. ABM is a bottom-up modeling technique that simulates the actions and interactions of autonomous agents within a system, allowing for the exploration of emergent behaviors and global phenomena (Macal and North, 2010).

ABM offers several advantages for modeling complex systems and complex adaptive systems, such as the dynamics involved in the deboarding process. Agents in an ABM are self-contained, modular, and identifiable individuals with the ability to make independent decisions (Kluegl and Bazzan, 2012). In the context of our disembarkation simulation, the agents represent the passengers, each with their own characteristics, preferences, and behaviors.

The simulated environment within the ABM represents the cabin, containing elements and information that influence the decision-making and behavior of the agents.

The last element to define is the specification of the agent interactions. In our model, the aircraft cabin is conceptualized as a grid consisting of cells. A critical distinction is made between seat cells and aisle cells to reflect the physical constraints of the cabin. Seat cells allow only one passenger per step, ensuring restricted movement, while aisle cells allow for up to two passengers to stand simultaneously, considering the width of the aisle.

Agent interactions, both among themselves and with the environment, are explicitly considered in the ABM to capture accurate emergent behaviors. The specification of these interactions is crucial to understanding the dynamics of the deboarding process. By modeling the deboarding process at the microscopic level, we can account for the heterogeneity of the passenger population and obtain insights that are difficult to derive from macroscopic information alone (E. Bonabeau, 2002).

One of the advantages of ABM is its ability to analyze both micro- and macroscopic levels of the system while relying on microscopic information. This is particularly valuable in the context of boarding and deboarding simulations, where the characteristics and behaviors of individual passengers vary widely, and obtaining macroscopic information on the effects of deboarding strategies can be challenging. ABM allows us to observe and analyze the system from multiple perspectives, providing a comprehensive understanding of the deboarding dynamics.

However, it is important to acknowledge potential disadvantages of using ABM. Determining the appropriate level of detail to include in the model can be challenging, as simplifications and assumptions are inherent in any modeling process. A balance must be struck between incorporating necessary elements and avoiding excessive complexity. Additionally, validating ABMs can be difficult since recreating the modeled system experimentally may not always be feasible.

Data and Parametrization

To maintain a strong connection with reality while conducting our study, we opted to simulate the data entirely. However, we aimed to ensure that our simulation model closely resembled real-world disembarkation processes. In this paragraph, we will outline the structure of the two aircraft, the distribution of passengers, and other elements that significantly influence our model. It is worth noting that we strived to employ reality-validated values for many parameters, emphasizing their accuracy. For parameters lacking concrete validation, we implemented a model calibration process to ensure the appropriateness of the assigned values. Through this approach, we aimed to strike a balance between maintaining a realistic simulation and achieving a reliable representation of the disembarkation process.

Aircrafts

For our analysis, we selected the Boeing 737 and Boeing 777 as the aircraft models to represent the widely utilized aircraft for international transportation. These aircraft were chosen due to their high passenger capacities, which can contribute to complex and time-consuming deboarding processes. The Boeing 737, known for its widespread use, especially in Europe through airlines like Ryanair, has a capacity ranging from 162 to 189 passengers. On the other hand, the Boeing 777 can accommodate up to 396 passengers.

The cabin layout of these aircraft may vary depending on the specific version of the aircraft and on the airline flexibility based on their specific requirements and passengers needs. However, for our analysis, we considered reasonable to implement the following configurations:

Boeing 737 (simple configuration)
Single-class layout
186 passengers in a 3-3 seat configuration.
Single aisle
31 rows

Boeing 777 (complex configuration)
First class: 8 seats in 1-2-1 seats.
Business class: 48 seats arranged in a 2-4-2 seat configuration
Economy class: 200 seats in 3-4-3 seats

Passengers

Passenger distribution within an aircraft can be categorized based on various factors, including physical characteristics such as age, gender, and mobility, as well as psychological factors like familiarity with airplane and deboarding processes. In our model, we focused on grouping passengers into children, elderly individuals (aged 60 and above), and family groups, in addition to the general category of "normal" passengers.

Determining the distribution of passengers among these groups is a complex task without a universal solution. It depends on several factors, including airline policies, flight type (domestic or international), and flight duration. To establish a reasonable distribution, we referred to research conducted by J. Milne and A. Kelly in their work on boarding methods, which suggests that children typically make up around 10% of passengers, while adults comprise approximately 70%. Similarly, the percentage of elderly individuals is around 10%. For family groups, exact figures are challenging to ascertain due to varying definitions, but studies by Iyigunlu et al. (2014) indicate that family groups generally account for approximately 20% of all passengers.

In order to capture the heterogeneity among passengers and its influence on the disembarkation time, we considered that the category group of a passenger directly impacts passengers' maximum achievable speed during the deboarding process. As explained in the next paragraph, in our model, a "normal" passenger is capable of reaching a maximum speed of 92 m/s while walking in the aisle. However, elderly passengers and children have reduced maximum speeds compared to the "normal" passengers. By incorporating these variations in maximum speed, we can accurately simulate a slower disembarkation process for elderly, child passengers and groups, reflecting the real-world scenario.

Model parameters

In our aircraft disembarkation ABM, we implemented several key parameters to simulate and analyze different strategies for efficient passenger flow during the disembarkation process.

Upon activation, each agent in our model follows a set of rules for movement. The first step is to navigate towards the nearest empty space, primarily by heading towards the closest aisle. Once in the aisle, the agent proceeds towards the nearest exit in the aircraft. By incorporating these directional guidelines, we aimed to replicate the realistic behavior of passengers seeking the most convenient and efficient path to exit the aircraft.

The speed was determined based on factors such as passenger type, which included distinctions such as age and physical ability. Additionally, we adjusted the speed dynamically by considering the overall flow of passengers within the aircraft. As more individuals disembarked, the average speed of the remaining passengers increased, reflecting the observed phenomenon of accelerated movement during the process $maxspeed \cdot e^{-\frac{n^{\circ}agents}{max\ agents}}$.

Determining the appropriate level of detail for the model can be challenging due to the inherent simplifications and assumptions in the modeling process. Achieving a balance between incorporating necessary elements and avoiding excessive complexity is crucial. In order to ensure realism and prevent unrealistic acceleration in the narrow aisle space, a maximum speed limit of 0.92 m/s was imposed for passengers, as suggested by the Simulation of Aircraft Disembarking and Emergency Evacuation study (2014). This constraint helped strike a balance between efficient movement and the limitations of human locomotion in a crowded environment. Additionally, to account for the additional time required by children and elderly passengers to exit the aircraft, the maximum reachable speed in the model was adjusted accordingly. However, it is important to note that the specific reduction in speed for these groups was determined through calibration due to the lack of available references in existing literature.

An essential consideration in aircraft disembarkation is the impact of hand luggage on the speed of passengers. Although incorporating the exact interactions between passengers and their luggage within our model was challenging due to limitations in agent movement, we addressed this by considering luggage as a negative factor affecting speed. To determine a reasonable percentage of passengers carrying luggage, we conducted model calibration, considering a range between 80% and 95%. Subsequently, we employed a normal distribution (mean 10s and standard deviation of 5s) to assign the delay to each agent due to its luggage.
While our model captures several crucial aspects of the disembarkation process, it is important to acknowledge its limitations. The complexity of interactions between passengers and their luggage, including instances where passengers must navigate in opposing directions to retrieve their belongings, was not fully accounted for due to the constraints of our model structure. Nonetheless, by incorporating the luggage factor as a negative impact on speed, we successfully introduced a realistic element to our analysis.

Model calibration

To ensure a strong connection with reality, the simulation model used in this research closely resembled real-world disembarkation processes. The structure of the aircraft, passenger distribution, and other influential elements were implemented based on realistic values, as described previously. Since concrete validation was not available, a model calibration process was conducted to ensure the appropriateness of the assigned values. According to the "Aircraft Boarding and Deboarding Time Model" by S. AhmadBeigi, A. Cohn, and Y. Guan, the average deboarding time for a Boeing 737 with 189 seats was determined to be 11 minutes and 23 seconds. Therefore, we calibrated our parameters through multiple tests to achieve a similar result for the random strategy that was thus used as a baseline.
Specifically, we calibrated the percentage of passengers with hand luggage and the reduction in speed due to the demographic group the single passenger belongs to.

The simulated random strategy yielded valuable insights for model calibration by providing a range of plausible parameter values. Among the various combinations tested, we identified seven parameter value sets that resulted in a random disembarkation time of approximately 11 minutes (equivalent to 605-620 steps in our model). To ensure consistency and fairness in the subsequent simulations, we randomly selected one of these parameter value sets and applied it to all the tested strategies in the following simulation process. This approach allowed us to establish a consistent baseline and effectively calibrate the model for further analysis and comparison of the strategies.

Strategies

In our ABM setting, we tested various disembarkation strategies to evaluate their effectiveness:

- **random strategy**: it mimics the current unstructured deboarding process commonly adopted by airline companies. This strategy allows passengers to exit the aircraft in a random order, as spots become available. We chose this strategy as a baseline for parameter calibration, as it is straightforward to implement and provides a reference point for comparison.
- **Steffen strategy**: passengers seated in odd-numbered rows exit the plane first, followed by passengers in even-numbered rows once the aisle is clear.
- **WILMA**: it involves passengers seated in aisle seats exiting first, followed by those in center seats, and finally, passengers in window seats.
- **Front to back** (F2B) strategy: passengers are instructed to stand up and start moving towards the exit when the row in front of them becomes unoccupied.
- **Back to front** (B2F) strategy: same as F2B but reversed, starting from the back of the plane
- **Reversed Pyramid:** the disembarkation process follows the procedure shown in figure 2c.

These strategies were originally designed for structured boarding processes but can also be adapted for efficient disembarkation.

In addition to these already existing strategies, we devised three new strategies exclusively for disembarkation purposes: The first one is the "**blocks**" strategy, introduced during the COVID-19 pandemic for maintaining physical distancing. However, there is a lack of concrete studies assessing its effectiveness and its impact on disembarkation time.
We also developed an adjusted version of the Steffen strategy, as well as an adjusted version of WILMA. In the **adjusted Steffen strategy**, the exit order follows a modified pattern, as depicted in Figure 2e. Similarly, the **adjusted WILMA strategy** is applicable only to larger aircraft like the Boeing 777, where central rows are deboarded first, followed by a traditional WILMA procedure, as shown in Figure 2f.

Results

We conducted simulations of the disembarkation strategies outlined above in our scenario, repeating the experiment a thousand times to obtain reliable results. Figure 3 presents the outcomes of these simulations. Specifically, we will now discuss the results obtained for the smaller aircraft, the Boeing 737, which has a basic and simplistic configuration.

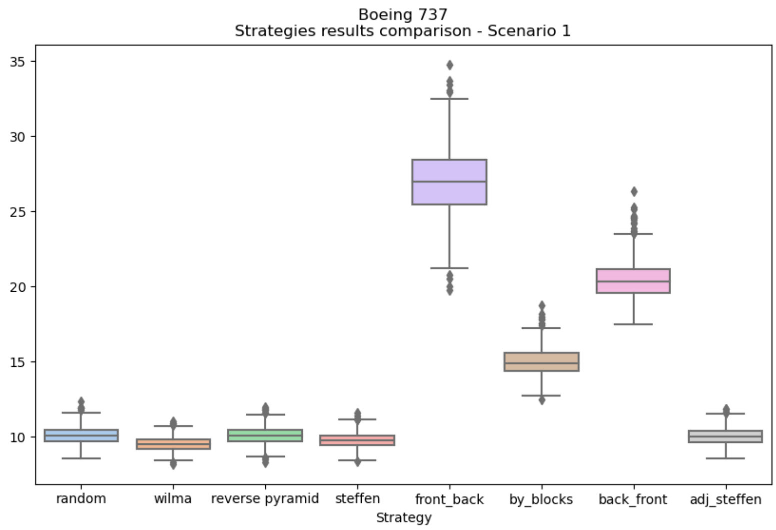


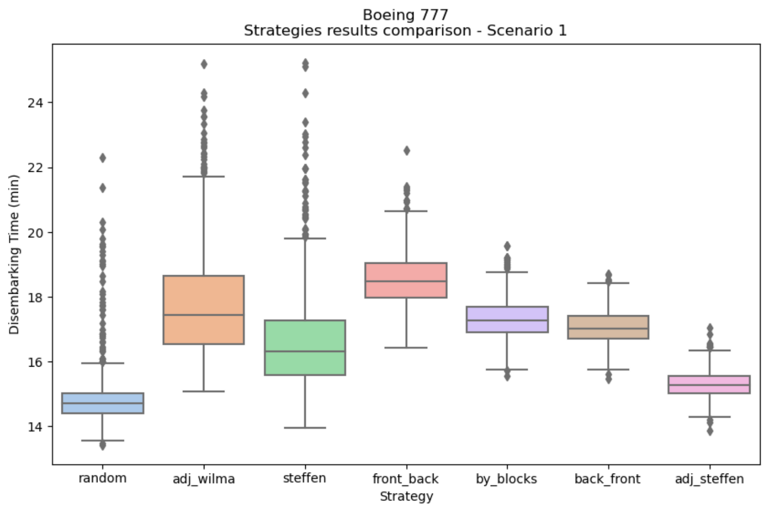
Figure 3: results Boeing 737

One noteworthy observation is that the random strategy achieved a total disembarkation time of 10 minutes, as expected based on our model calibration. Surprisingly, the random strategy performed relatively well compared to other more complex strategies. However, strategies such as front to back, back to front, and blocks exhibited poor performance in terms of disembarkation time. This may be attributed to several factors, including the lack of coordination and organization in the passenger flow, resulting in congestion and slower progress.

Among the strategies tested, WILMA and adjusted Steffen strategies demonstrated better performance on the Boeing 737. Despite achieving an improvement of approximately 5% compared to the random strategy, the absolute reduction in disembarkation time amounted to less than 1 minute. This modest improvement can be attributed to the specific characteristics of the aircraft and the nature of the strategies implemented. Potential explanations for the better performance of these strategies on the smaller and simplistic aircraft could be related to factors such as the shorter distance to the exit, the simpler seating arrangement, and the ease of maneuvering in the cabin.

Furthermore, when analyzing the distribution of results across the different strategies in Figure 4a (appendix), we observed that all distributions exhibited a Gaussian shape. However, the strategies with poorer performance (blocks, back to front) also exhibited greater variability in the results. This variability can be attributed to various factors, including the inherent stochasticity in passenger behavior and the potential sensitivity of these strategies to minor disruptions or delays during the disembarkation process.

Now, let's shift our focus to the results obtained from the Boeing 777, which features a more complex configuration with three distinct classes, two corridors, and a larger number of passengers to deboard. In our simulation scenario, the passengers seated in first class are set to exit the aircraft first, followed by those in business class, regardless of the disembarkation technique employed.



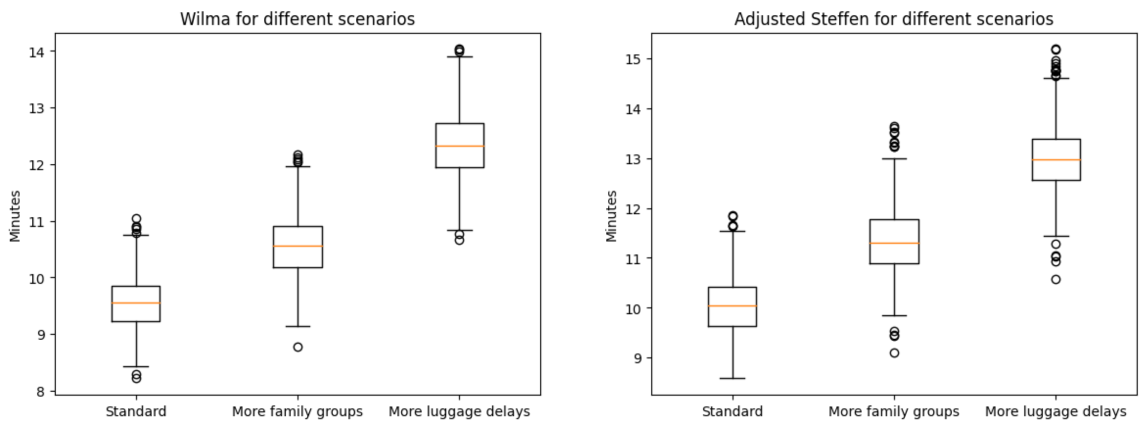
Interestingly, the random strategy emerges as the most effective strategy for the Boeing 777, exhibiting a median disembarkation time of 14.8 minutes. Only the adjusted Steffen strategy achieves comparable results. In contrast, all other strategies lag behind in terms of performance compared to both the random strategy and the unstructured deboarding approach.

This outcome can be attributed to the crowded nature of the aircraft's configuration. While structured deboarding techniques aim to reduce seat interferences and optimize passenger flow towards the exit, the delay caused by passengers having to wait their turn within the predefined scheme offsets any potential advantages. For instance, in the adjusted WILMA strategy, where passengers in the central column deboard first, those seated in the side columns are unable to proceed until the central column passengers have exited. In contrast, employing a random strategy allows passengers to optimize the available space by immediately occupying any vacant spot, leading to a more efficient disembarkation process despite increased interference along the aisle.

These findings highlight the complex trade-offs involved in determining the most effective disembarkation strategy for aircraft configurations with multiple classes and corridors. The results demonstrate that a structured approach may not always yield significant improvements over unstructured deboarding, especially when considering the waiting time and constraints imposed by the seating arrangement.

More scenarios

Lastly, we explored different scenarios on the smaller aircraft by modifying specific parameter values and observing the corresponding effects on disembarkation performance. Specifically, we focused on the two best performing strategies identified for the Boeing 737 (WILMA and adjusted Steffen) and examined their responses to variations in the percentage of family groups and the delay associated with retrieving luggage.



Remarkably, both strategies exhibited similar trends across the different scenarios. Increasing the percentage of family groups in the aircraft to 25% of the total passengers resulted in an approximate additional minute and a half of disembarkation time. This suggests that the presence of family groups, with potentially slower movement and coordination, contributes to a noticeable delay in the overall process.

However, the most impactful result was observed when modifying the luggage delay parameter. Previously, we had considered an average delay of 10 seconds per passenger with a low standard deviation. In the modified scenario, we increased the average delay to 15 seconds and introduced a broader variance. Under these conditions, both strategies performed poorly, indicating that luggage placement plays a significant role in the speed of aircraft deboarding. The increased delay associated with retrieving luggage evidently hampers the efficiency of the disembarkation process.

One possible explanation for this outcome is that when passengers encounter delays in accessing their luggage, it prolongs their time spent in the aisle, causing congestion and hindering the progression of other passengers. Additionally, the broader variance in luggage delay introduces unpredictability and inconsistency in the timing of individual passenger movements, further impeding the overall efficiency of the disembarkation process.

These findings emphasize the importance of considering factors beyond passenger characteristics and seating arrangements when optimizing disembarkation strategies. Luggage-related delays can have a substantial impact on the overall performance of strategies, underscoring the need for efficient luggage handling procedures and well-designed cabin layouts that facilitate prompt access to personal belongings upon disembarking.

Conclusions

In conclusion, our project implemented an agent-based modeling (ABM) approach to simulate and analyze the disembarkation process in commercial aircraft. While ABM provides a valuable tool for capturing dynamic and emergent behaviors among agents, it also has its limitations. One challenge we faced was determining the appropriate level of detail to incorporate into the model. Additionally, for parameters that could not be directly validated in reality, we relied on calibration to ensure the assigned values were reasonable.

The results of our simulations indicated that the random strategy consistently performed well in both the Boeing 737 and Boeing 777 aircraft. This finding was particularly evident in the simulation of the Boeing 777, where the random strategy outperformed all other structured strategies. Although the random strategy was not the absolute best performer in the Boeing 737, it was a close contender. It is important to note that even with more structured strategies, the improvements in performance were minimal. Moreover it is worth noting that the time invested in explaining and implementing such strategies to the crew may not yield significant benefits!

One significant observation from our analysis was that the demographic composition of the passenger groups had minimal impact on disembarkation delays. However, we found that luggage placement played a crucial role in the efficiency of the process. Therefore, we recommend that airlines employing the random strategy take measures to seat family groups together to minimize congestion in the aisle. Additionally, implementing structured luggage placement during the boarding process can significantly reduce delays during disembarkation.

Even if there are notable differences between the boarding and disembarkation processes in terms of aisle and seat interferences, a proper and optimized luggage placement emerged as a key factor linking the two processes and offering potential for substantial decreases in turn-around time, a significant challenge faced by airline companies.

While our project simplified the complex reality of airline operations, it is important to acknowledge that airline companies are multifaceted businesses with numerous other factors to consider. Nonetheless, if our initial goal was to suggest a more sophisticated disembarkation technique to reduce turn-around time and increase profitability, our findings suggest that by adopting a random disembarkation strategy, airline companies are already maximizing their profits by optimizing the flow of passengers out of the aircraft.

In future research, it would be valuable to explore additional factors and strategies that could further enhance the efficiency of the disembarkation process, taking into account the specific operational constraints and objectives of airline companies.

Appendix

Figure 1: aircraft design

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BOEING 737

Economy Class

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              BOEING 777

              First Class

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     |  X      X  X        X  |

            Business Class

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    |  X  X   X  X  X  X   X  X  |
    |  X  X   X  X  X  X   X  X  |
    |  X  X   X  X  X  X   X  X  |
    |  X  X   X  X  X  X   X  X  |

             Economy Class

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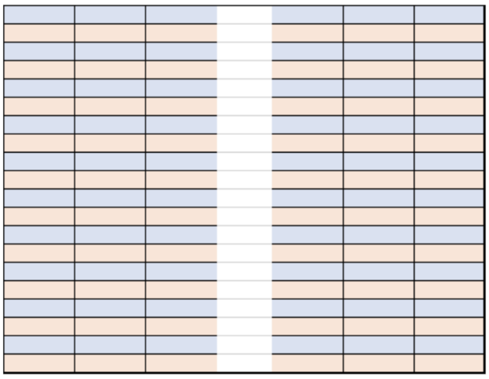
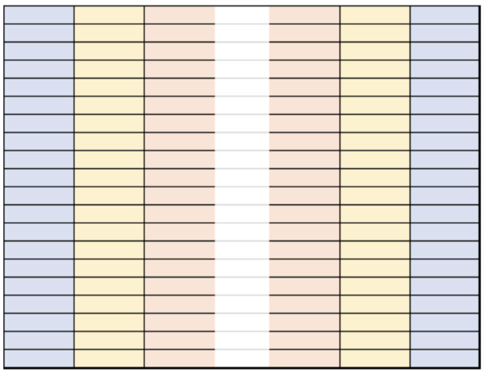
Figure 2: disembarkation strategies

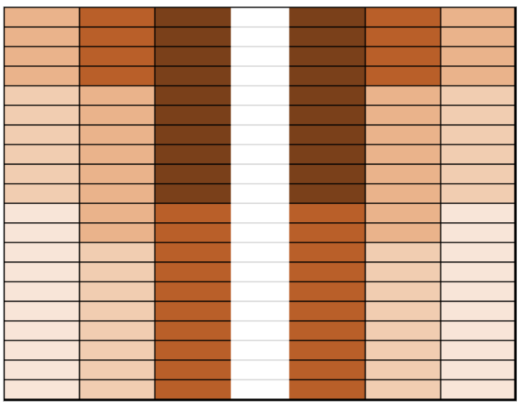
(a) Steffen



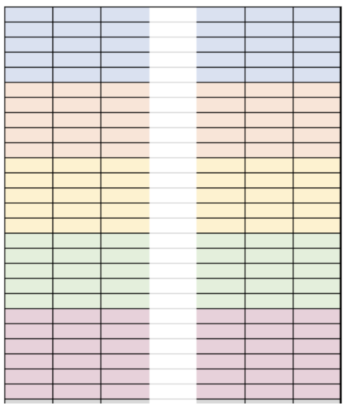
(b) WILMA



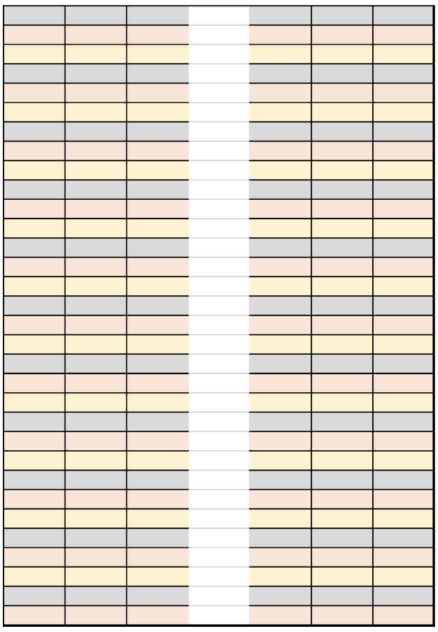
(c) Reverse Pyramid



(d) Blocks



(e) Adjusted Steffen



(f) Adjusted WILMA

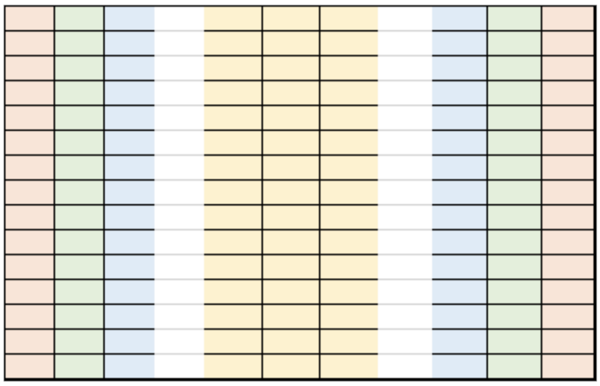
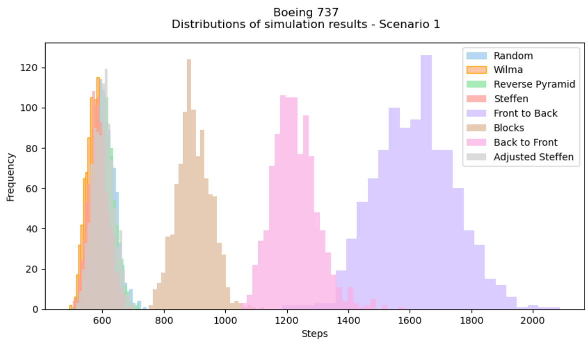
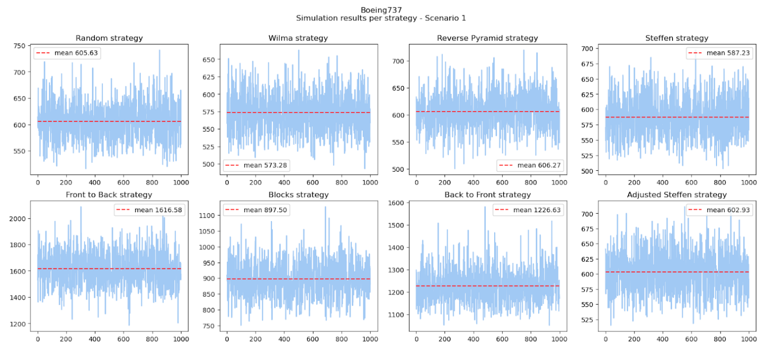


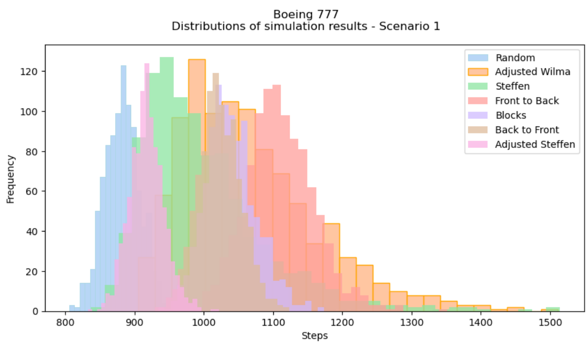
Figure 4: Distribution of the results

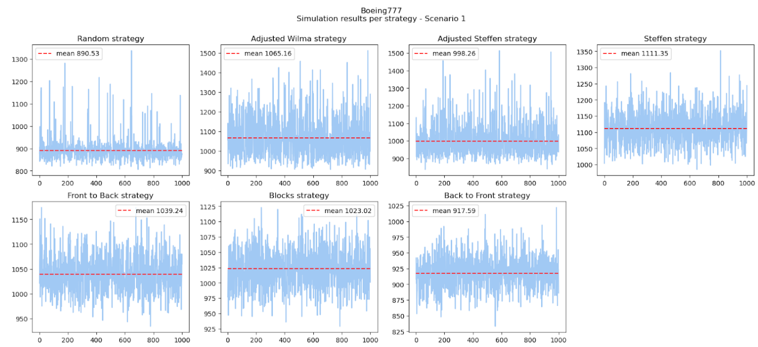
(a) Boeing 737





(b) Boeing 777





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