# The Exploration of Boarding Speed and Revenue Under Various Boarding Strategies and Aircraft Sizes by Using Agent-Based Modeling

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Author Note

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Abstract

Nowadays, air travel has become more and more popular. According to International Air Transport Association (IATA), 7.2 billion is the number of global air passengers predicted by 2035, nearly doubling 2016's 3.8 billion. Typically, airports will charge airline fees to use their airport, like landing fees, ATC fees, and fee-based amount of time they stay on the tarmac. Therefore, one thing that is always controversial is that the ways for airlines to ask passengers to board the plane might affect their revenue tremendously, even though some airlines are providing some paid services to allow passengers to pay to get on board earlier. So, finding the most optimal way to board the plane is required. This model will demonstrate how will the change in boarding strategies and aircraft sizes affect the boarding speed and revenue of the airline.


*Keywords*: airplane boarding, airline revenue, agent-based modeling, multi-agent modeling.

# The Exploration of Boarding Speed and Revenue Under Various Boarding Strategies and Aircraft Sizes by Using Agent-Based Modeling

According to Nyquist and McFadden (2008), the cost of parking an airplane at the terminal for an airline is around \$30 per hour. Thus, assuming 1500 flights per day, each minute saved in flight turnaround time has the potential to save nearly \$16,000,000 per year (Steffen & Hotchkiss, 2012). Before to 1970, the average speed for passenger boarding an airplane was around 20 passengers per minute. This speed has dropped to around 9 passengers per minute by 1998 (Marelli et al., 1998). A paper show that when travelers have two carry-on bags versus zero, the difference in boarding times is about 60% more when carry-on exist when employing an average boarding strategy (Nyquist & McFadden, 2008). The boarding time will impact the revenue of the airline. In 2007, the entire cost of airline delays in the United States was estimated to be \$29 billion; They break down the cost into three categories: airline costs \$8 billion, passenger costs \$17 billion, and lost demand costs \$4 billion (Ball et al., 2010). This shows that more effective boarding processes could save airlines and passengers a lot of time and money.

Although the boarding process is not the primary reason a flight is being delayed, to be able to accelerate the boarding process could still save a tremendous money for airline and increase airport throughput. Furthermore, lowering the number of time passengers must stand and wait after being informed that boarding is beginning to get to their seat could improve the satisfaction rate (Jaehn & Neumann, 2015).

Each airlines have a different boarding strategy, but most of them are using these methods:

1. Random
2. Front to back
3. Back to front

4. Window to aisle

Most airline also give priority boarding privilege to some passengers like:

1. People need assistant to board
2. Military
3. Airline loyalty member
4. Allow passenger to paid to board early

Creating a model using an agent-based model in order to better examine the boarding speed and revenue under various boarding strategies and aircraft sizes is imminent.

## Agent-Based Modeling

In the natural and social sciences, multi-agent or agent-based modeling has proven to be extremely effective at modeling emergent patterns in complex systems (Wilensky, 2001). Agent-based modeling is far more significant and useful than other modeling methodologies, especially when it comes to natural events; Agent-based models are more useful when the agents are not homogeneous, such as in the stock market for trades and occurrences. Agent-based modeling will be extremely useful in a variety of domains, including biology, epidemiology, business, and social science (Wilensky & Rand, 2015). This will be a good fit for agent base modeling because the phenomenon is homogenous, and agents are required to represent those passengers.

### The Basic Model: Airplane Boarding

This model is highly customizable by user. The user can setup a single-aisle single cabin(Economy) airplane with a minimum of three rows and two seats per row, up to a maximum of one hundred rows and ten seats per row using this model (Figure 1). The model simulates the airplane using patches; the blue patch represents the airplane door, the white patches represent the aisle, the yellow patches represent seats that have not been assigned to anyone, the red patches represent seats that have been assigned to someone but the passenger has not yet taken their seat, and the green patches represent seats that are occupied by passengers (Figure 2). Depending on the size of the plane, there will be a minimum of five and a maximum of one thousand passenger agents (Figure 1). Passengers with priority boarding privileges are also taken into account in this model; the user will be able to control the proportion of a certain group of priority boarding passengers (Figure 1). Priority boarding customers are seated in the following order which follows a common boarding position used by most major airlines in the US: Customers requiring assistance or additional time to board, Active Duty U.S. Military with ID, frequent flyer with loyalty membership, then paid priority boarding. The model can simulate a variety of boarding tactics employed by airlines, including random, front to back, back to front, and window to aisle. The user can choose the percentage of passengers for each group (Figure 1) in front-to-back and back-to-front tactics, and the following group will not begin boarding until the previous group has done so. The user has the ability to define a budget for each passenger, which can then be used to compute the revenue generated from ground operations (this will come from the portion of the plane ticket). A slider is provided to set the revenue for each passenger decided to pay to get priority boarding privilege (Figure 1). To set the expense during the boarding process, four sliders are set up (Figure 1): terminal use fee (charged per passenger), gate use fee (one-time charges), landing/take off/ATC fee (one-time charges), and fixed base operation fee (charged per ticks, include parking, customer services, cleaning, etc.).

While the model is running, seven monitors are provided to observe the model (Figure 1): the maximum number of passengers that can fit on this plane, passengers waiting at the gate, passengers boarded enroute to their seat, passengers already seated, total wait time for all passengers at the aisle, average wait time for each passenger at the aisle, and real-time revenue. While the model is running, four plot diagrams are constantly plotting, which can assist the user in better understanding the "story." The following plots are provided: seated passengers over time, enroute passengers over time, passengers who have not boarded over time, and the average wait time for passengers waiting in the aisle over time.

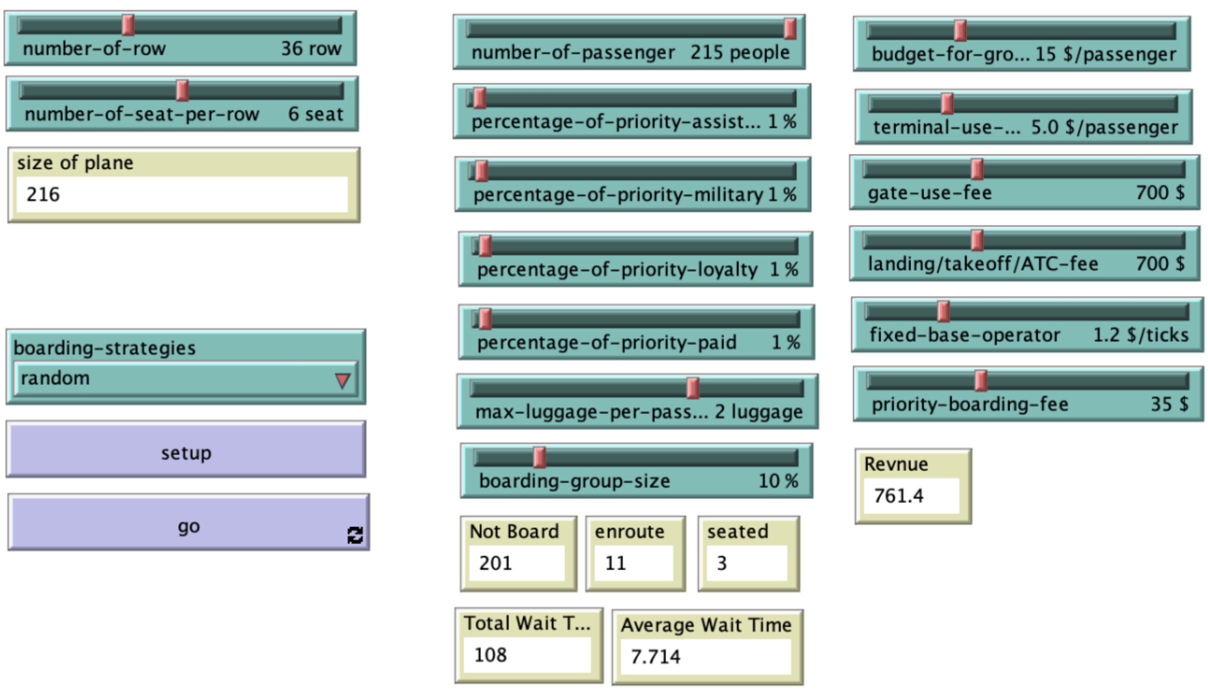


*Figure 1: User setting for the model*

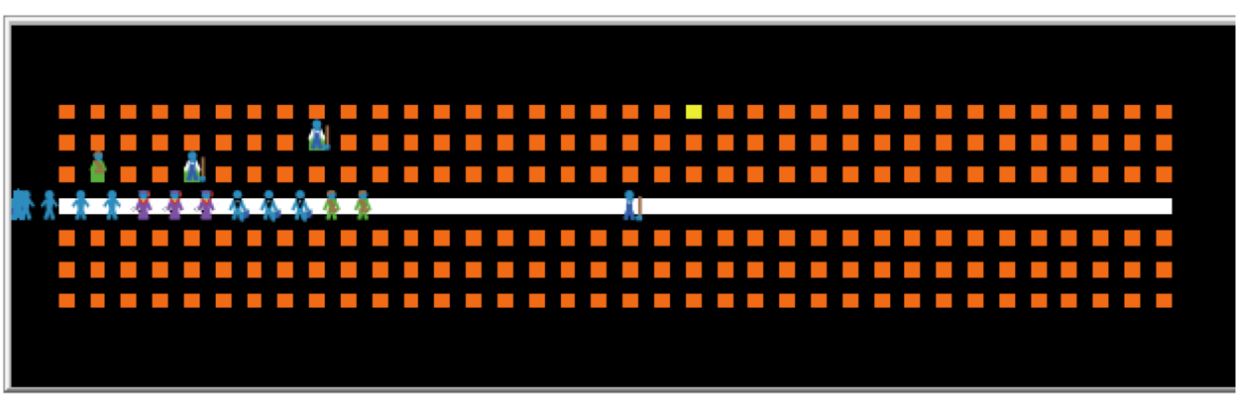

*Figure 2: The airplane for the model*

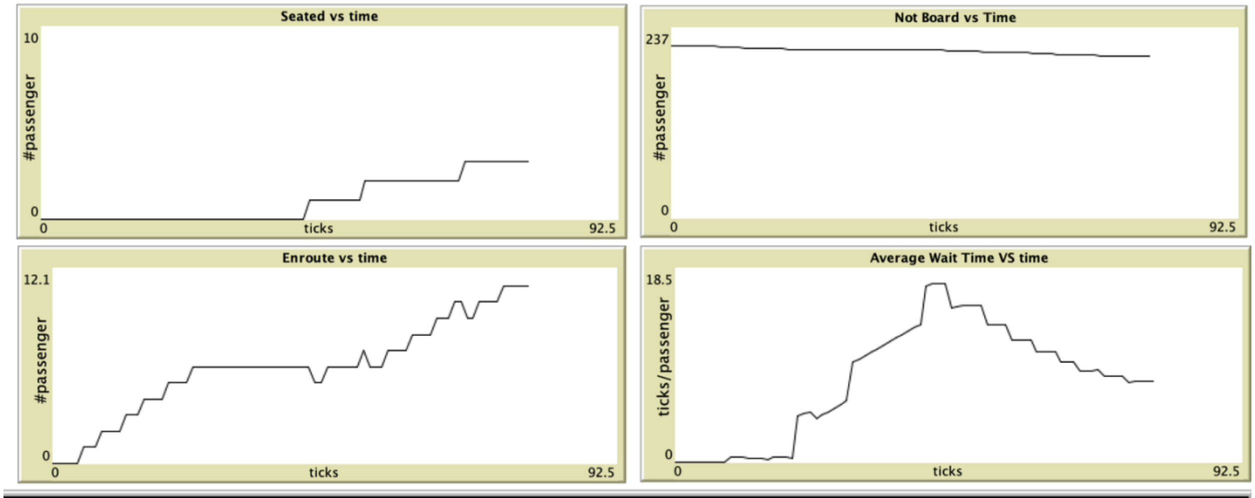


*Figure 3: Plots for the model*

When the user clicks "setup," the model will be reset, and the plane is recreated, with passengers generated and seats assigned at random.

When the user presses the "go" button, each passenger checks to see if it is their turn to board. They will proceed to board the plane when it is their turn. Passengers will move forward until they reach their row or someone in front of them stops. If the passenger has carry-on luggage, they will clog the aisles by handling each piece of luggage for 20 ticks, causing a traffic jam. When passengers enter their seats from the aisle, if someone sitting next to them has already boarded and blocked the row, passengers must wait 10 ticks for each passenger to move out and back in, further congesting the aisle.

## LevelSpace Extended Model

The LevelSpace extended model enables the user to run all four boarding strategies at the same time. However, it only allows the user to specify the number of rows, the number of seats per row, the number of passengers, and the boarding group size for "front to back" and "back to front" boarding strategies (Figure 4). A switch gives the user the ability to reveal or hide the model view at any time, which is useful given that hiding the model view can significantly boost its running speed (Figure 4). In addition to this, there is a total of 16 monitors that have been set up to record the final ticks, final total wait time, final average wait time, and final income for each of the four different tactics (Figure 4). If the user is given the ending variable, they will be able to quickly analyze the results of four distinct boarding techniques based on the size of the airplane and the number of passengers. Four plot diagrams are also provided to graph all four strategies for seated passengers, enroute passengers, passengers waiting at the gate, and average wait time (Figure 4).

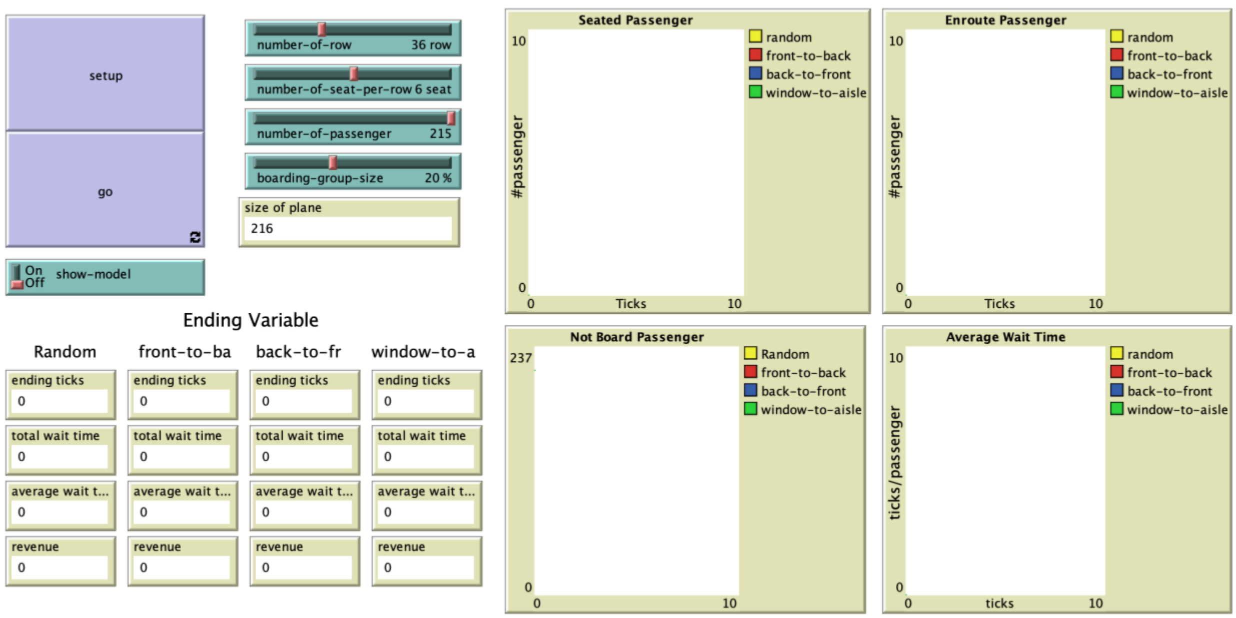


*Figure 4: LevelSpace extended model layout*

## Analysis and Discussion

### Basic configuration model

To better evaluate from the mode, the model is configured to the largest single aisle airplane currently in use, the Airbus A321, which can carry a maximum of 216 passengers onboard with 36 rows and 6 seats per row. Setting the passenger to fill the entire cabin and disabling all priority boarding passengers is required to better observe which boarding strategies are the most efficient. Carry-on luggage is limited to the amount allowed by most airlines within the United States, with a maximum of two pieces. Each boarding group for front to back and back to front strategies is set to 15% of passengers, which is also the most common configuration in the US. The revenue model is likewise based on the average fee charged by the majority of US airports.

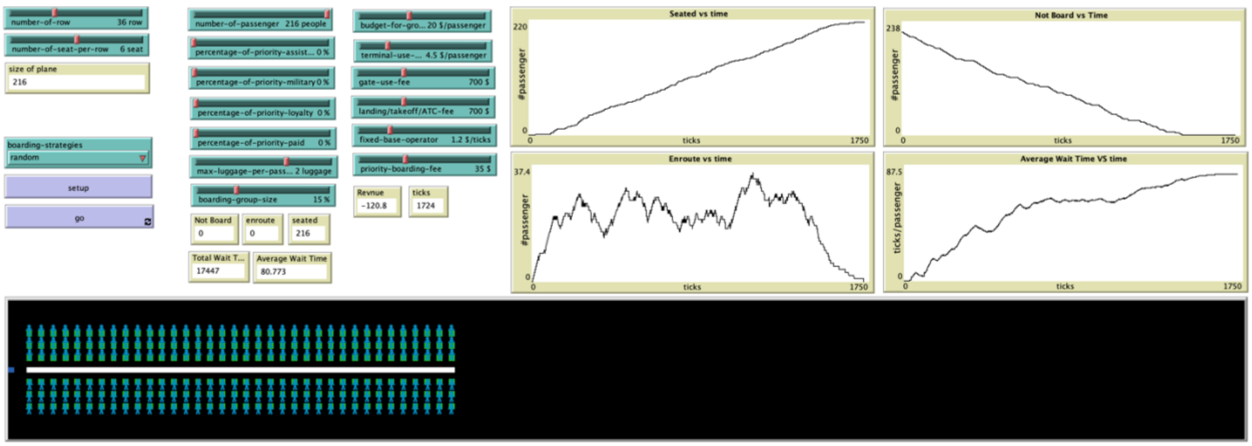


*Figure 5a: 216 passengers boarding a 216-seat airplane with random order*

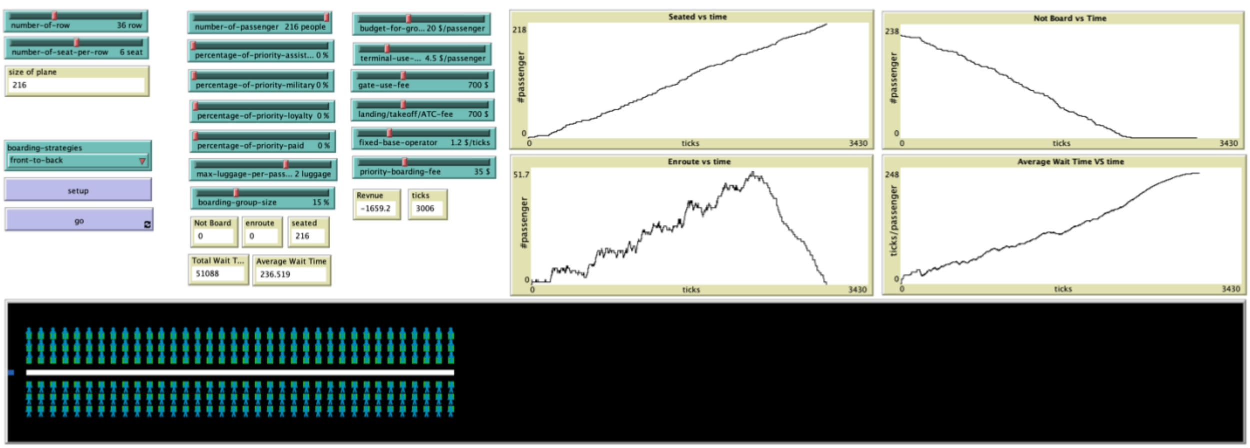


*Figure 5b: 216 passengers boarding a 216-seat airplane with front to back order*

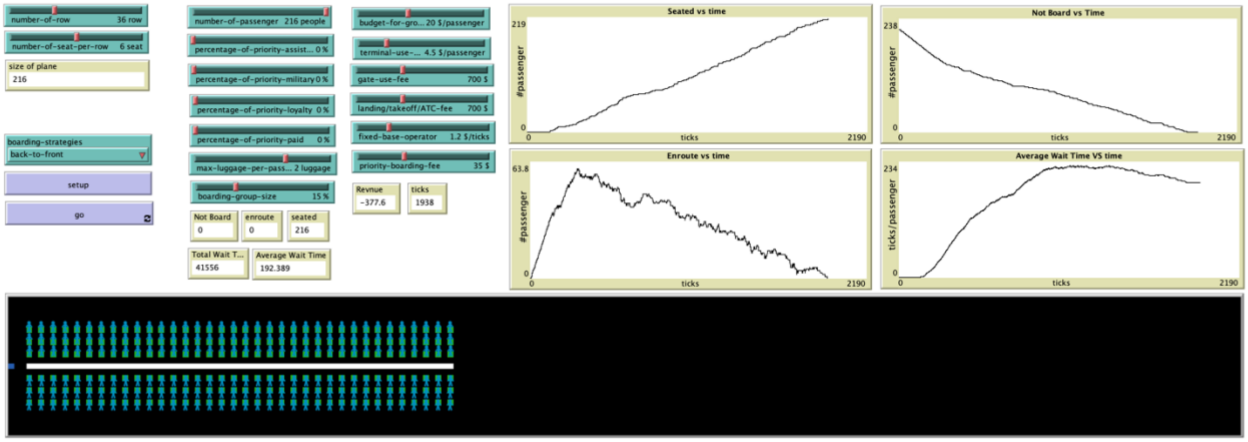


*Figure 5c: 216 passengers boarding a 216-seat airplane with back to front strategy*

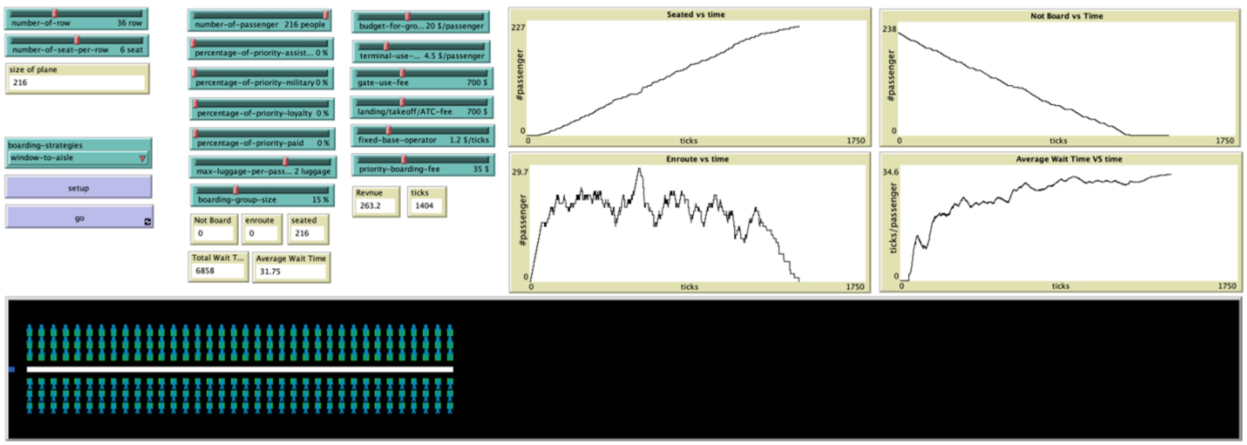


*Figure 5d: 216 passengers boarding a 216-seat airplane with window to aisle strategy*

After running the model, it is not hard to find that window to aisle strategy (Figure 5d) use the least time to board all passengers (1404 ticks), lowest average wait time (31.75 ticks) and highest revenue ($263). Although there are some fluctuations in the average wait time vs time plot, it appears that it is steady with a specific amount. The not board vs time plot shows a steady fall, indicating that there isn't much traffic at the gate.

The second most efficient method of boarding an airplane is random boarding (Figure 5a). It takes 1724 ticks to board all passengers, with an average wait time of 80.773 ticks per passenger and revenue of $-120.8. The average wait time vs time plot is increasing, indicating that passengers who board later have a longer wait time than those who board earlier. And there is some flat trend at the not board vs time plot, which seems that there are some jams that is block the gate.

Following that is the back to front strategy, and it takes 1938 ticks to load all of the passengers onto the airplane (Figure 5c). The average wait time for each passenger is 192.38 ticks, and the revenue is negative by $377.6. Passengers who board when more than half of the other passengers have already done so have the longest wait time, as seen by a plot of the average wait time vs the passage of time, which shows an upward trend followed by a slight downward trend.

The method of boarding the airplane from the front to the back is the method that is the least efficient (Figure 5b). The amount of time required is significantly longer than the method described above; it takes a total of 3006 ticks for all of the passengers to be seated in the aircraft, with an average wait time of 236.52 ticks per passenger and a revenue loss of $1659.2 for the airline. The average amount of time that passengers must wait is steadily growing longer, and the passenger who is seated in the very last row of the aircraft and is the last to board has the greatest wait time.

**Basic configuration with priority boarding model**

The most setting will stay the same as the configuration described in the basic configuration model; however, priority boarding passengers will be added to the total number of passengers. The number of passengers eligible for priority boarding is calculated based on the average number of priority boarding passengers found on flights throughout the United States. The percentage of passengers who require assistance is one percent, the percentage of passengers who are active duty military is one percent, the percentage of passengers who are loyal frequent flyer members is one percent, and the percentage of passengers who paid for priority boarding is three percent.

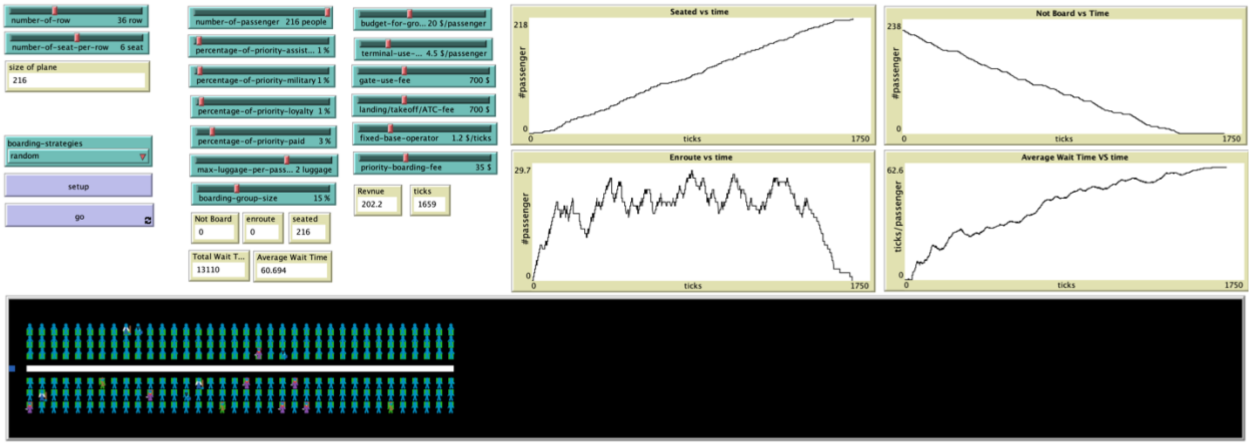


*Figure 6a: 216 passengers boarding a 216-seat airplane with priority boarding in a random order*

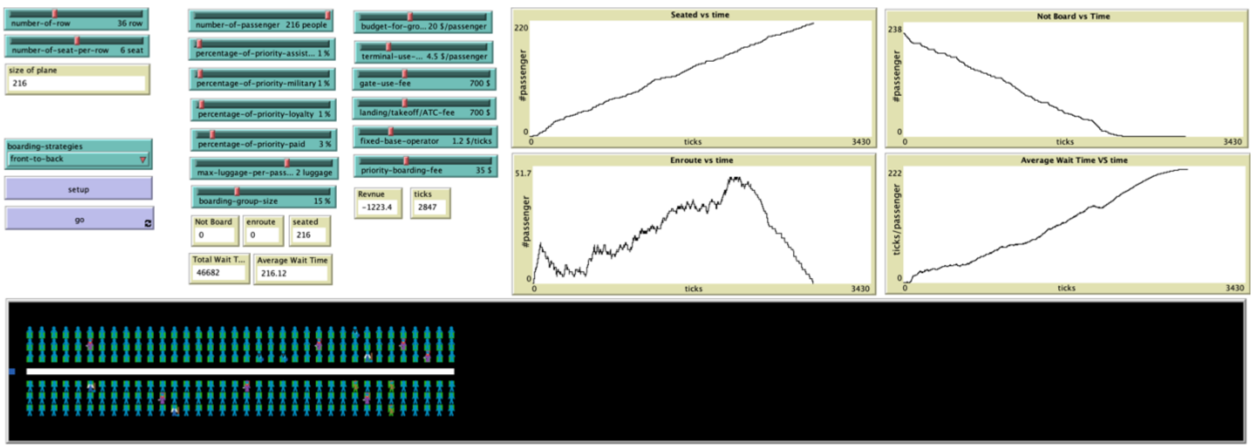


*Figure 6b: 216 passengers boarding a 216-seat airplane with priority boarding in a front to back*

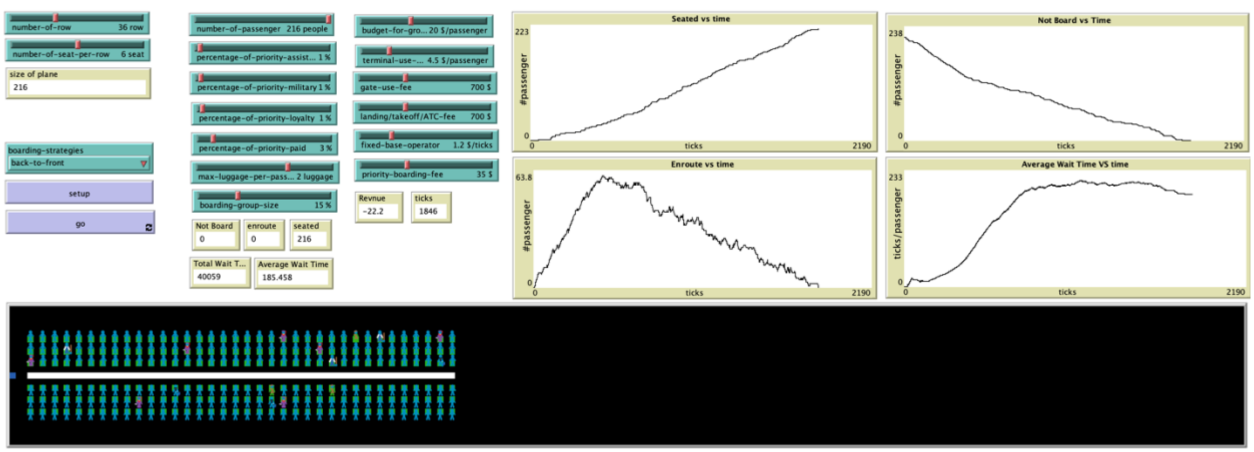


*Figure 6c: 216 passengers boarding a 216-seat airplane with priority boarding in a back to front order*

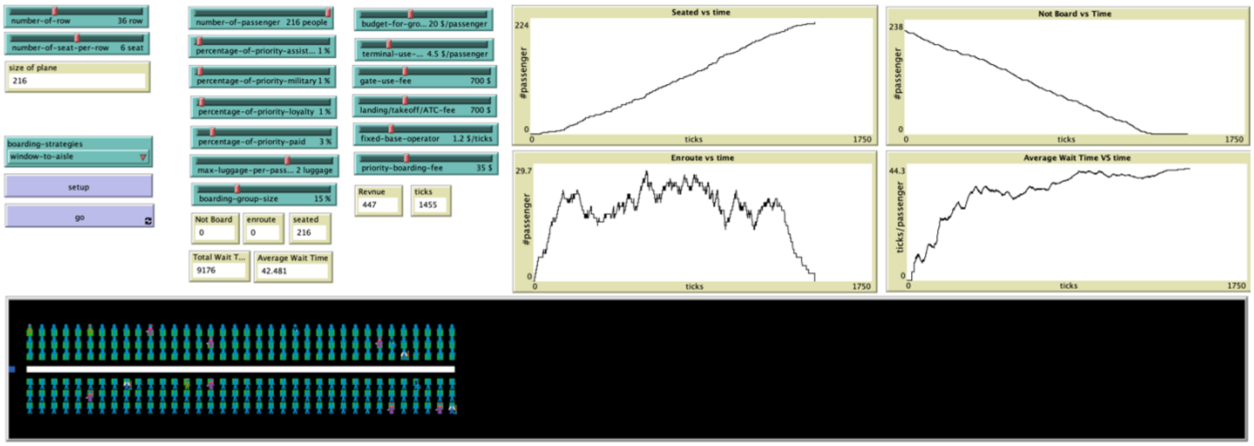


*Figure 6d: 216 passengers boarding a 216-seat airplane with priority boarding in a window to aisle order*

When the results of the basic configuration with the priority boarding model (Figure 6a, 6b, 6c, 6d) are compared with the results of the basic configuration model (Figure 5a, 5b, 5c, 5d), there does not appear to be a significant increase or decrease in the overall usage of ticks, the average wait time, or the revenue. It's possible that this is due to the fact that there are only 6% of passengers eligible for priority boarding, and the maximum number of people that a single traveler has to get through is 2. Therefore, it should not have a significant impact on the priority passengers who are traveling on an Airbus A321 flight.

**Huge airplane configuration model**

What would happen if the passenger was flying on a huge plane with only one aisle available to them? Even though this airplane does not now exist, it will be fascinating to observe the outcomes that are associated with aircraft of this type. The majority of the parameters remain the same as they were for the basic configuration model, with the exception that the airplane is now configured to contain 1000 passengers, 100 rows, and 10 seats in each row (Figure 6). Priority boarding passengers are not included.

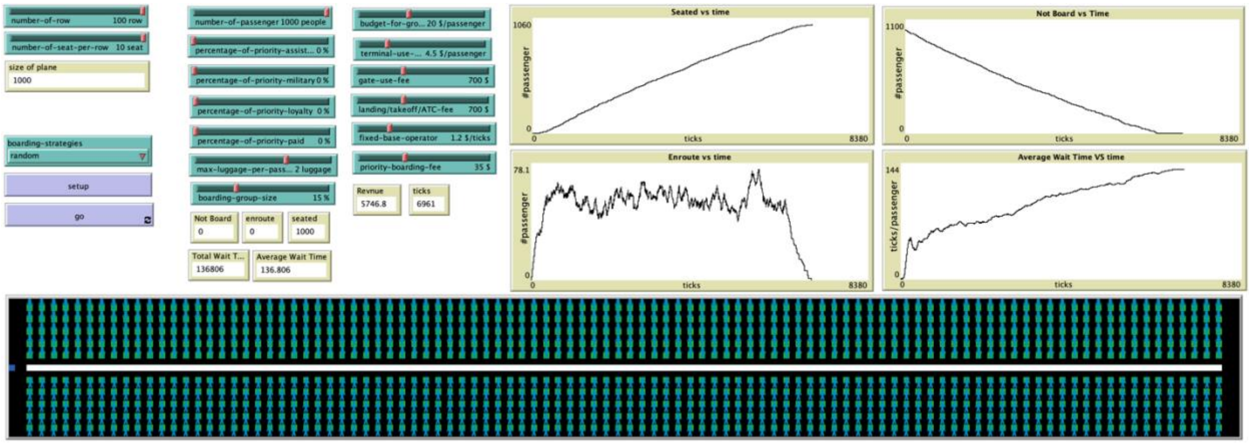


*Figure 7a: 1000 passengers boarding a 1000-seat airplane with random order*

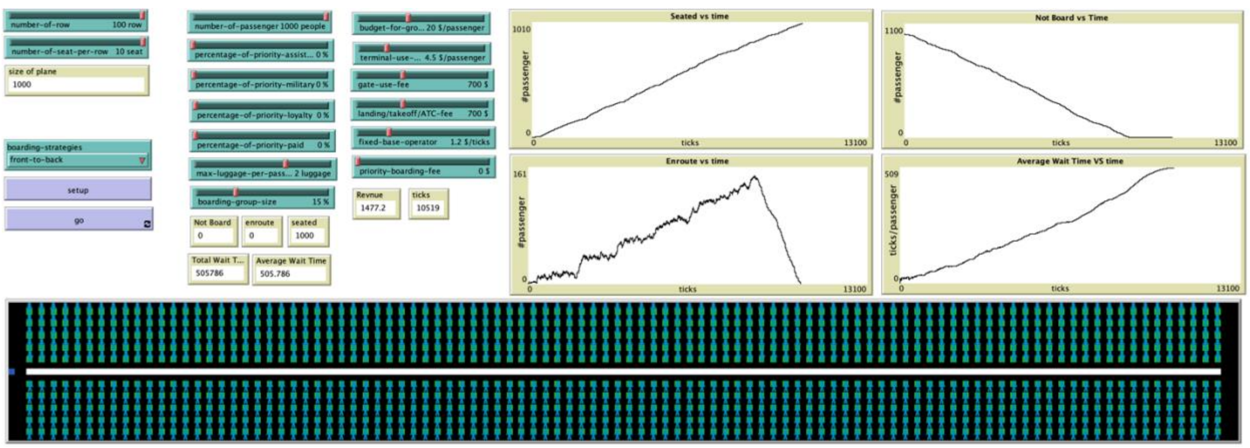


*Figure 7b: 1000 passengers boarding a 1000-seat airplane with front to back order*

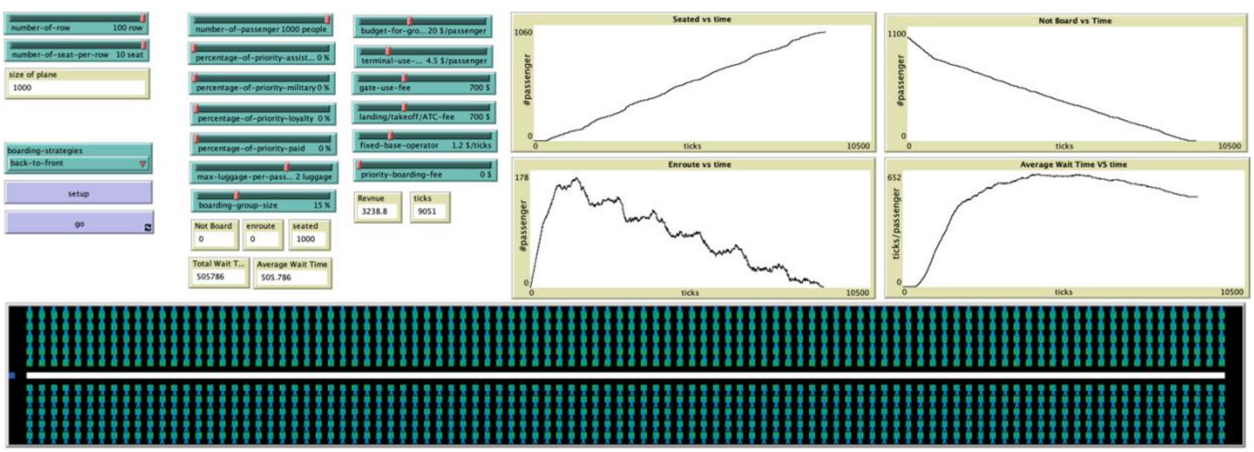


*Figure 7c: 1000 passengers boarding a 1000-seat airplane with back to front order*

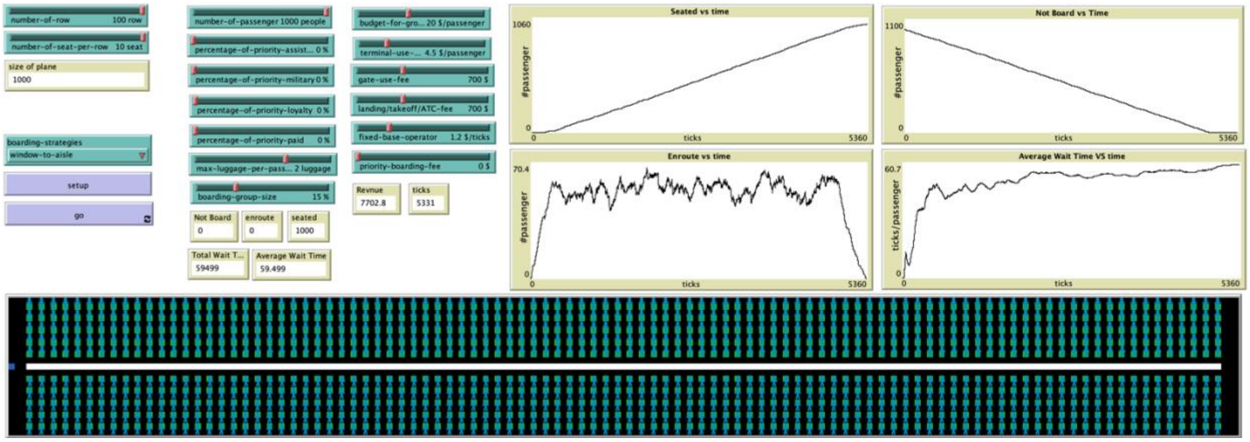

*Figure 7d: 1000 passengers boarding a 1000-seat airplane with window to aisle order*

The fluctuation of the graph appears to be the same when comparing the result (Figure 7a, 7b, 7c, 7d) with the result from the basic configuration model (Figure 5a, 5b, 5c, 5d). However, the average wait time increases tremendously, and the number is significantly higher than the basic configuration model (Figure 7a has a reading of 136 ticks/passenger, whereas Figure 5a has a reading of 80 ticks/passenger), even though revenue has increase. Basic on the findings of this model, it has been determined that designing a huge aircraft that has only one door to board or only has one aisle is not a correct course of action.

The window-to-aisle method is still the most time-effective way to board an airplane (Figure 7d). This method requires 5331 ticks, has an average wait time of 59.49 ticks per passenger, and generates $7702.8 in revenue. Next, we have the random boarding techniques (Figure 7a), which involve using 6961 ticks and having an average wait time of 136.8 ticks for each passenger. This results in a revenue of $5746.8. Figure 7c shows that boarding an airplane from the front to the back is the third efficient way to do so. It takes 9051 ticks to board all of the passengers, the average wait time is 505.76 ticks per passenger, and the revenue is $3238. The method of boarding passengers from the front to the back remains the method that is the least effective (Figure 7b). It takes 10519 ticks to board all of the passengers, with an average wait time of 505.76 ticks per passenger, and it generates a revenue of $1477.2.

## Conclusion

According to the result and the findings of the analysis, it would appear that window to aisles boarding tactics is the most efficient way to board the aircraft while also costing the airline the least amount of money. After that comes the strategy of random boarding, followed by the strategy of boarding from the back to the front. The most inefficient method for boarding an airplane is known as the front-to-back strategy. Not only does it take significantly more time than the window-to-aisle or random boarding methods, but it also costs the airline the most money. Even though airlines have a lot of things to take into consideration when deciding on what boarding strategy to use, having this model and the finding of the model might help airlines in the selection of which boarding approach they wished to use. The model might also be used by airplane manufacturers to decide the configuration when they decided to develop a new aircraft. The model's demonstration, as well as the model itself, provide an experimentally testable prediction of changes in boarding tactics and aircraft sizes that effect the airline's boarding speed and revenue.

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