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Summary Sheet

Aboard! Boarding and Disembarking a Plane

Summary

With the ever-increasing number of airline passengers, it is now more and more important to reduce flight layover times. According to a professional study, boarding time accounts for one-third of flight transition, so improving boarding efficiency can effectively reduce flight transit time.

This article mainly focuses on the duration of passengers getting on and off the plane in air transportation. In our model, we suggest that there are several main factors that can affect the total time to get on and off the plane. They are the passenger boarding sequence, the number of passengers and the weight of luggage, and the interference of passengers getting on and off the plane in their original sequence.

In the first model, we discussed the case of narrow-body aircraft. Combining macro and microscopic perspectives, we established a time model using methods such as fluid mechanics, social force models, and linear programming. After that we eventually got an arithmetic expression for total boarding time.

In the second model, we optimized the model for other types of aircraft. We first defined the unit used to measure the cost of giving up seats, and then we listed the various situations of giving up seats and obtained multiple relationships between them. Then, we use the established model to simulate cellular automata. After 1000 simulations, we get the average time for each case. After comparison, we got a relatively optimal solution. For "narrow body" aircraft, we derive one of the shortest times as RP. The second is OI. BF came third and random boarding strategy came fourth. The strategy that takes the longest is FB.

In the third model, we have extended the above two models so that they can be well adapted to flying wings passenger aircraft and two entrance and two aisle aircraft. The conclusions reached are similar to those for narrow-body airliners. After that, we consider the impact of capacity constraints on model decisions under the impact of the epidemic. And obtained the relevant sensitivity analysis model.

Key Words: Boarding and disembarking time, fluid dynamics, social force, cellular automaton, pedestrian flow, integer programming

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1. Introduction

1.1 Background

In air transportation, the length of flight turnaround time is related to airline revenue. One of the effective ways to reduce the operating cost of airlines is to fully exploit and utilize the potential of existing aviation resources for it can improve the operational efficiency and service capabilities of passenger aircraft.

Planes waiting for ground handling services at the airport is one of the reasons for flight delays. Reducing the turnaround time of airlines is an important part of it. This mainly includes the time of boarding and disembarking, loading, and unloading of goods, catering time, and refueling time. Nyquist and McFadden et al. calculated through a field survey that every minute reduction in flight turnaround time would save about \$30 in costs. Boarding time is the most important component of turnaround time, accounting for 40% to 60% of total travel time in short-haul routes. At the same time, rapid and efficient boarding and disembarking can increase the efficiency of ground handling facilities such as boarding bridges and reduce the load on ground handling. Therefore, airlines must reduce boarding and disembarking times.

The premise of solving the existing boarding problem is to understand the mechanism of boarding interference and its propagation law, and on this basis, to carry out the existing boarding strategy. After that, we need to organize, optimize, and manage the boarding process, and then provide practical and effective solutions.

1.2 Restatement of the Problem

Efficiency is time, while time is money. To improve the efficiency of air transportation, we are asked to create a method of boarding and disembarking that is most efficient in actual practice. Specific issues are as follows:

- Build a mathematical model to calculate the total time of boarding and disembarking.
- Apply the model to a ‘narrow-body’ aircraft and discuss how it is affected by boarding methods and the amount of luggage.
- Refine the model so that it can be adapted for two other types of aircraft.
- Due to the pandemic situation, we need to consider the impact of capacity limitations on the methods of getting on and off planes.

2. Assumptions

We make some general assumptions to simplify our model:

- We only consider the boarding time for economy class passengers.
- During the boarding process, only one line of passengers is allowed to pass through the aisle and they won't arrive late.
- Passengers are not allowed to cut in line or pass passengers in front of them.
- The passenger's acceleration is constant.
- First-class generally has early boarding and a small number of people, so only consider the situation of economy class is considered.

More detailed assumptions will be listed if needed.

3. Notation

SYMBOLS	DEFINITION
ρ	The density of pedestrian flow
(x, y)	The location of the passenger
(χ, γ)	Pedestrian expected speed in direction x and direction y
$\vec{e}_\alpha$	The unit vector of passenger target orientation
m_i	The mass of the passenger and the luggage
$v_i(t)$	The speed of the passenger
$v_i^0(t)$	The ideal speed of the passenger
τ_i	The reactive time parameter of the passenger
d_{min}	Minimum spacing between passengers
l	The step length of the passenger

Table 1: Notation

4. Methodology

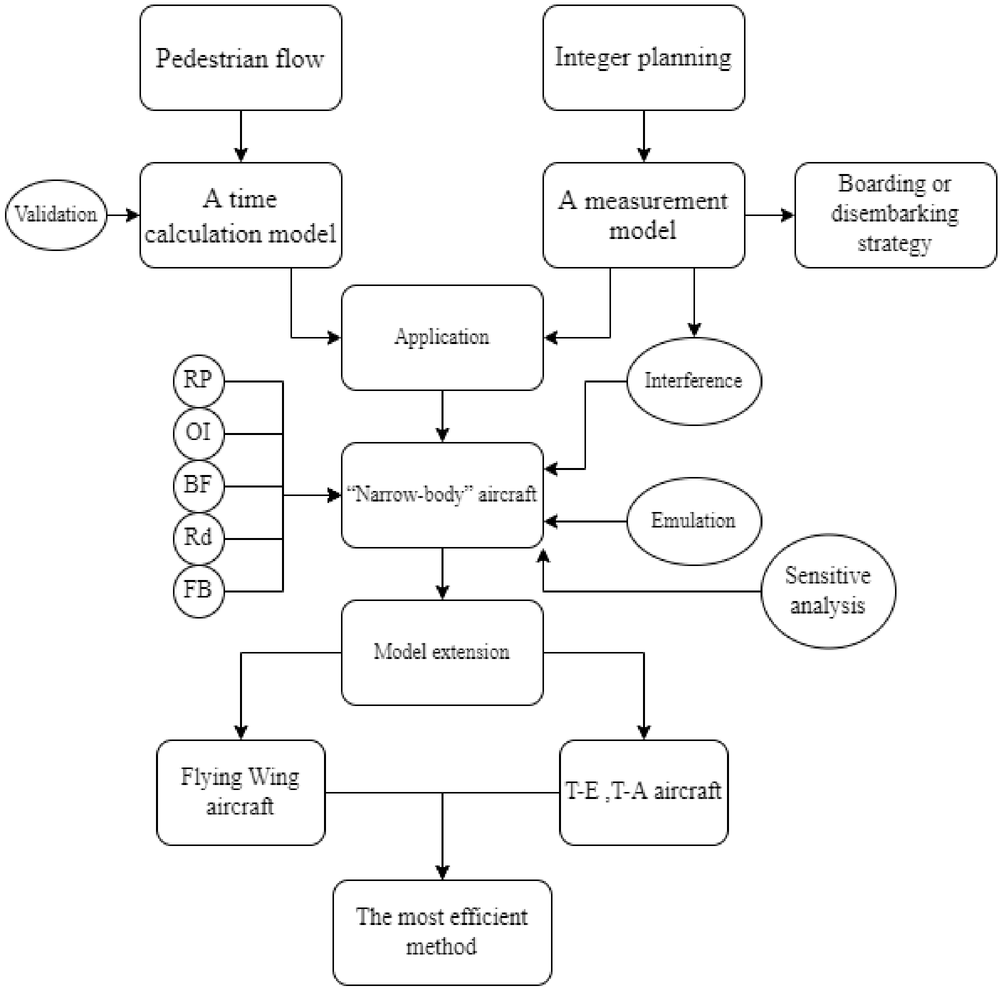

Figure 1 Model overview

In this model, we use the abovementioned method to solve this problem.

5. The Pedestrian flow model

There are many mature and complete pedestrian flow models, such as Hughes: A continuum theory for the flow of pedestrians. But most of them focus on simulating the situation of people moving freely on a two-dimensional plane, and not suitable for slow and crowded situations in the cabin. In our pedestrian flow model, we start from a microscopic perspective, taking into account the various complexities of individuals behaviours at slow speeds.

5.1 The model

From a macro perspective, we can view the pedestrian flow like a fluid. Therefore, the movement of the flow can be regarded as the movement of fluid. At a given time and location (x, y), we can denote the density of pedestrian flow by ρ. Since the pedestrian is moving on a plane during the boarding process, we use (χ, γ) to denote the pedestrian's desired speed in the x and y directions. The pedestrian velocity, flow, and density satisfy the following flow conservation equation:

$$\frac{\partial\rho(t,x,y)}{\partial t}+\frac{\partial\rho(t,x,y)\chi(t,x,y)}{\partial x}+\frac{\partial\rho(t,x,y)\gamma(t,x,y)}{\partial y}=0$$

After some preliminary analysis, it can be seen that the equation obviously cannot reflect the actual situation on a small scale, especially in the more sensitive boarding problem.

Instead, we start at the micro perspective. When studying the change in passenger speed, we equate it as a force exerted on the passenger. This force can be divided into two parts: self-driving force and interaction force.

$$\vec{F}_\alpha(t)=Self_\alpha(t)+Interaction_\alpha(t)$$

where $\vec{F}_\alpha(t)$ stands for the equivalent force on α at time t, $Self_\alpha(t)$ for the self-driving force, and $Interaction_\alpha(t)$ for the interaction force exerted by other objects.

Refering to Social force model for pedestrian dynamics[5], we know:

$$Self_\alpha(t)=m_i\cdot\frac{v_i^0\cdot\vec{e}_\alpha-v_i(t)}{\tau_i}$$

where $\vec{e}_\alpha$ represents the unit vector of the passenger's target heading and v_α^0 represents the target velocity.

We noticed that the directions in Aisle are only entry and exit. Therefore, we might as well define the positive direction as entering. We assume that $\vec{e}_0$ is the positive direction, then $\vec{e}_0=(1,0)$. Then:

$$\frac{\vec{v}_\alpha}{\vec{e}_0}=\frac{\vec{r}}{\vec{e}_0}=\frac{\vec{e}_\alpha}{\vec{e}_0}=\pm1$$

In order to establish a mathematical model of the total boarding and disembarking time of the aircraft, we expand the formula, then we get:

$$\frac{dv_i(t)}{dt}=\frac{v_i^0-v_i(t)}{\tau_i}+\frac{Interaction_i(t)}{m_i}$$

where m_i is the mass of the passenger i, $v_i(t)$ is the speed of the passenger i, and $v_i^0(t)$ is the ideal speed of the passenger i. τ_i is the reactive time parameter of the passenger.

Next, we try to quantify the interaction force. The interaction forces are the influence of other objects on a particular passenger. Since the application scenario of this model is boarding, the external influence is nothing more than the following two: the interaction between people and the blocking effect of the rear wall of the cabin. We stipulate that f and f_W takes $\vec{e}_0$ as the positive direction. Therefore:

$$Interactions_i(t) = \sum_{j \neq i} f(t,i,j) + f_W(t,i)$$

where $f(t,i,j)$ is the interaction force between passenger i and passenger j at the time t, and $f_W(t,i)$ represents the blocking effect of the rear wall of the cabin.

This is most obvious when interference happens, either a passenger stops to store luggage, or someone exchanging seats. The passenger behind him must stop. As a result, the queue of other passengers would stop because the narrow aisle of the plane only allowed one passenger to pass through.

Because in a single-line aisle, a passenger can only contact the previous passenger and the next passenger, so we can get:

$$\forall |i-j| > 1, f(t,i,j) = 0$$

So:

$$Interactions_i(t) = f(t,i,i-1) + f(t,i,i+1) + f_W(t,i)$$

Obviously, the motion state of a passenger is greatly affected by the previous passenger and is less affected by the latter passenger. To distinguish them, we stipulate:

$$\begin{cases} f_\cap(t,i) = f(t,i,i-1) \\ f_\cup(t,i) = f(t,i,i+1) \end{cases}$$

Therefore:

$$Interactions_i(t) = f_\cap(t,i) + f_\cup(t,i) + f_W(t,i)$$

where $f_\cap(t,i)$ represents the force experienced by passenger i as it approaches passenger $i-1$. It is related to the distance and speed difference between the two passengers. We define it as is shown:

$$f_\cap(t,i) = F_\cap(\Delta x_i, \Delta v_i)$$

Where:

$$\begin{cases} \Delta x_i = x_{i-1} - x_i \\ \Delta v_i = v_{i-1} - v_i \end{cases}$$

When $\Delta v_i \geq 0$, the motion state of passenger $i-1$ does not drive passenger i to alter its speed. At this time, passenger $i-1$ has no impact on passenger i. Hence,

$$F_{\cap}\left(\Delta x_i, \Delta v_i\right) = 0 \text{ when } \Delta v_i \geq 0$$

When $\Delta v_i < 0$, passenger i expects that passenger $i-1$ will maintain the speed at this moment. Thus, passenger i will slow down to avoid collision with the passenger $i-1$. In order for passenger i to maintain the maximum speed, the passenger i will make a uniform deceleration movement, so as to reach a relative standstill with passenger $i-1$ at the minimum distance between people. We set it as $d_{\min}$. According to Simulation of Crowd Motion based on Social Force Model[3], we obtain $d_{\min} \approx 0.3\text{m}$.

When $\Delta x_i > d_{\min}$, we get:

$$F_{\cap}\left(\Delta x_i, \Delta v_i\right) = -m_i \frac{\Delta v_i^2}{2\left(\Delta x_i - d_{\min}\right)} \cdot S$$

Meanwhile, it's worth noticing that people often overestimate the danger, which means they are more sensitive to the deceleration of the preceding passenger. We set the sensitivity S, where $S > 1$. The equation can be modified as:

$$F_{\cap}\left(\Delta x_i, \Delta v_i\right) = -m_i \frac{\Delta v_i^2}{2\left(\Delta x_i - d_{\min}\right)} \cdot S$$

But unfortunately, $\lim\limits_{\Delta x_i \to d_{\min}} F_{\cap}\left(\Delta x_i, \Delta v_i\right) = -\infty$, which doesn't conform to common sense. We define the maximum braking capacity of the passenger as $F_{\max}$ to fix this.

When a passenger realizes that he needs to brake suddenly, his minimum braking distance can be approximated as his step length. Then,

$$F_{\max} = -m_i \cdot \frac{\Delta v_i^2}{2l}$$

where l represents the passenger's step length. Therefore, we get:

$$F_{\cap}\left(\Delta x_i, \Delta v_i\right) = \max\left\{-m_i \frac{\Delta v_i^2}{2\left(\Delta x_i - d_{\min}\right)} \cdot S, -m_i \cdot \frac{\Delta v_i^2}{2l}\right\} = -m_i \frac{\Delta v_i^2}{2 \cdot \max\left\{\frac{\Delta x_i - d_{\min}}{S}, l\right\}}$$

In the second situation when $\Delta x_i \le d_{\min}$, we consider that the passenger noticing immediate danger, and stops as soon as possible. That means:

$$F_{\cap}\left(\Delta x_i, \Delta v_i\right) = F_{\max} = -m_i \cdot \frac{\Delta v_i^2}{2l}$$

Also, **the force will continue to act until the passenger stands still.**

$f_{\cup}\left(t,i\right)$ is rather hard to quantify. Since the passenger i cannot see passenger $i+1$ directly behind him, $f_{\cup}\left(t,i\right)$ should be smaller than $f_{\cap}\left(t,i\right)$.

When $\Delta x_{i+1} > d_{\min}$, we simply define $f_{\cup}\left(t,i\right) = 0$. The distance is simply to big fot the preceding passenger to be affected.

When $\Delta x_{i+1} \le d_{\min}$, the expression is related with $F_{\max}$. We assume that the influence coefficient is c, when $c < 1$. That is:

$$f_{\cup}\left(t,i\right) = c \cdot \left(-F_{\max}\right) = c \cdot m_i \frac{\Delta v_i^2}{2l}$$

When defining $f_W(t,i)$, we can regard the wall as a "person" that doesn't move. Then:

$$\begin{cases} f_W(t,i) = -m_i \dfrac{v_i^2}{2\left(\Delta x_i - d_{\min}\right)} \cdot S, & \text{when passenger is adjacent to the wall} \\ f_W(t,i) = 0, & \text{when passenger isn't adjacent to the wall} \end{cases}$$

Above all, we can get:

$$\frac{dv_i(t)}{dt} = \frac{v_i^0 - v_i(t)}{\tau_i} + \frac{f_{\cap}\left(t,i\right) + f_{\cup}\left(t,i\right) + f_W(t,i)}{m_i}$$

$$= \frac{v_i^0 - v_i(t)}{\tau_i} + \frac{f_W(t,i)}{m_i} + \begin{cases} 0 & \Delta v_i \ge 0, \Delta x_{i+1} > d_{\min} \\ c \cdot \dfrac{\Delta v_i^2}{2l} & \Delta v_i \ge 0, \Delta x_{i+1} \le d_{\min} \\ -\dfrac{\Delta v_i^2}{2 \cdot \max\left\{\dfrac{\Delta x_i - d_{\min}}{S}, l\right\}} & \Delta v_i < 0, \Delta x_{i+1} > d_{\min} \\ -\dfrac{\Delta v_i^2}{2 \cdot \max\left\{\dfrac{\Delta x_i - d_{\min}}{S}, l\right\}} + c \cdot \dfrac{\Delta v_i^2}{2l} & \Delta v_i < 0, \Delta x_{i+1} \le d_{\min} \end{cases}$$

In order to maintain the integrity of the formula, $f_w(t,i)$ is not expanded. See above for its definition.

5.2 Model reliability test

In order to ensure that the mathematical model is reasonable and reliable, we performed a computational simulation to verify the model's reliability.

We set $v_i^0 \in (0.7\text{m/s}, 0.9\text{m/s})$ Another look at the pedestrian walking speed[8]. We take $\tau = 0.8$, $S = 1.3$, $c = 0.2$.

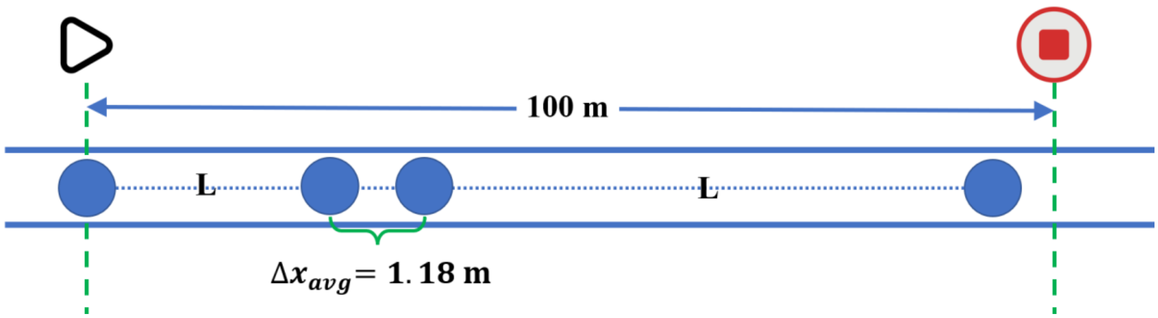

Figure 2 Airplane aisle2

The track is 100 meters long. We generate a passenger at the start every 1.8 ± 0.5 seconds. Their initial velocity $v_i(t) = v_i^0 - 0.2$ m/s. As soon as one reaches the finish, it's removed from the track. After performing the method 1000 times, we get the average distance between two adjacent passengers $\Delta x_{avg} = 1.18$ m.

Next, we tested the authenticity of the model in simulating the formation and evacuation of blockages.

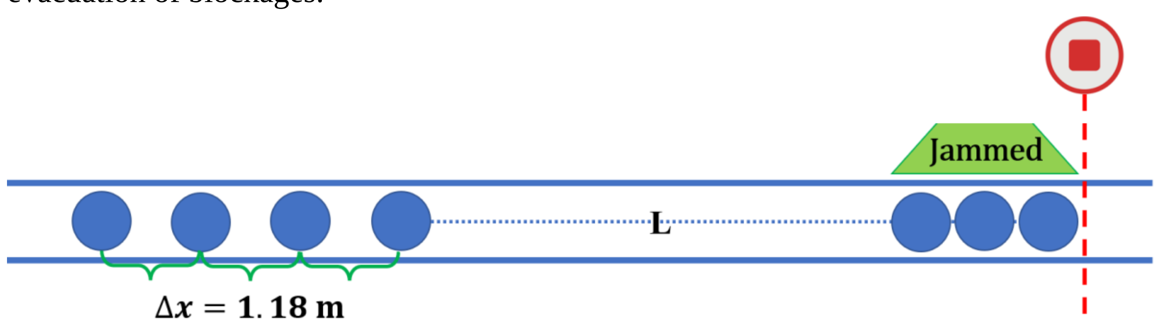

Figure 3 Another situation of airplane aisle3

We make the passengers distributed evenly on the track with a spacing of 1.18 meters, which is the Δx_{avg} obtained above. Their initial velocity $v_i(t) = v_i^0 - 0.2$ m/s.

We make the first one-stop with a braking force of $F_{\max} = -m_i \cdot \dfrac{\Delta v_i^2}{2l}$. This way, the congestion is formed. After $t_{occupation}$, release the first passenger. Congestion time $t_{congestion}$ starts when $\Delta x_i \le d_{\min}$ is triggered and ends when $\forall i, \Delta x_i > d_{\min}$.

The relationship between $t_{occupation}$ and $t_{congestion}$ is shown in the following figure:

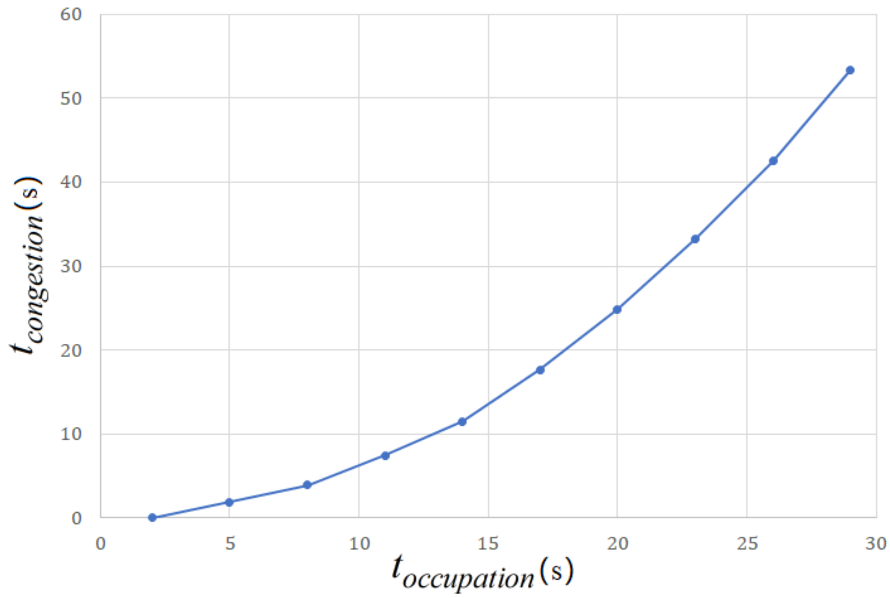

Figure 4 The relationship between $t_{occupation}$ and $t_{congestion}$ 4

6. A measurement model of boarding interference based on integer planning

6.1 Grouping of passengers

In order to facilitate subsequent analysis of seat interference to obtain the impact of different boarding strategies on the total length of boarding, we need to pre-process the passengers. So we grouped them: set the passenger in Row A Seat B to $P_{a,b}$, where $a \in \{1,2,3,\cdots,33\}$ and $b \in \{\mathrm{A,B,C,D,E,F}\}$. We then divided the passengers into n groups. And:

$$\begin{cases} \forall i \neq j, G_i \cap G_j = \varnothing \\ \bigcup_{i=1}^{n} G_i = P \end{cases}$$

for $P_{a,b} \in G_i$, we define $g(a,b) = i, i \in \{1,2,3,\cdots,n\}$. For example, if a passenger belongs to Row 7 Seat D, $g(7,D) = 3$.

6.2 Interference analysis

When a passenger arrives at their seat and intends to take a seat, a seat hindrance occurs. A seat offer can cause blockages in the aisles, resulting in longer boarding times. Therefore, we need to determine the interference with aisle usage and the impact on passenger's passage time caused by offering the seat when another passenger enters the seat. We first set the interference as I_0 when a passenger enters the seat. When someone gives up his seat, we set the disturbance of one passenger moving a distance of one seat as I_1.

Assuming that every passenger places their luggage directly above their seat, we can integrate aisle disturbance into seat interference analysis. We set I_2 as the disturbance of a passenger placing his luggage. It is worth mentioning that we consider a passenger rational, which means that he will utilize waiting time to place his luggage.

To make the model universal, we set the three seats which are on the same side to W, M, A. W refers to Window, M refers to Middle, and A refers to Aisle. Therefore, we use an ordered array (W, M, A) to represent the seating order of the passengers: $W \to M \to A$. We can get the interference of the permutation of W, M, A on the use of the aisle. We use $I((W, M, A))$ to denote the seat interference coefficient produced by (W, M, A). Here are the seat interference coefficients from the six ordering scenarios:

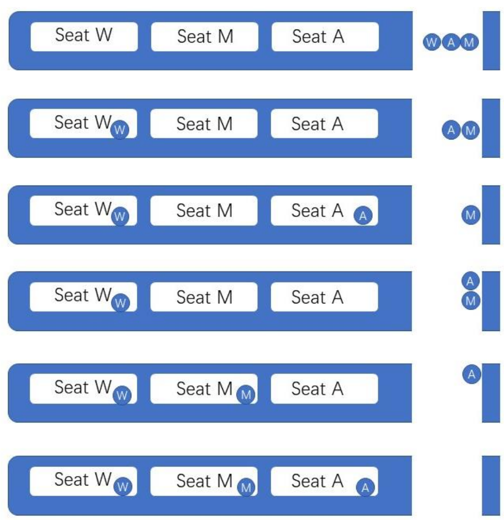

Figure 5 Airplane seating chart

$$I((W, M, A)) = 3I_0 + 3I_2$$

$$I((W, A, M)) = 4I_0 + I_1 + 2I_2$$

$$I((M, W, A)) = 4I_0 + 2I_1 + 2I_2$$

$$I((M, A, W)) = 5I_0 + 2I_1 + 2I_2$$

$$I((A, W, M)) = 5I_0 + 2I_1 + 2I_2$$

$$I((A, M, W)) = 6I_0 + 3I_1 + I_2$$

We set $I_0 = 0.4s, I_1 = 0.9s, I_2 = 2.1s$, and substitute them into the $t_{occupation}$ - $t_{congestion}$ relationship, and set $I\left(\left(W, A, M\right)\right) = 1$. Results are shown here:

$$I\left(\left(W, M, A\right)\right) = 0.26$$

$$I\left(\left(W, A, M\right)\right) = 1$$

$$I\left(\left(M, W, A\right)\right) = 2.86$$

$$I\left(\left(M, A, W\right)\right) = 4.01$$

$$I\left(\left(A, W, M\right)\right) = 4.01$$

$$I\left(\left(A, M, W\right)\right) = 4.97$$

When the three passengers are in different groups, we can obtain their interference straightforward. But when some of them are assigned in the same group, we assume each permutation is assumed to occur with equal probability. For example, when $g\left(7, D\right) = 1, g\left(7, E\right) = 3, g\left(7, F\right) = 3$, we define its interference parameter as $I\left(\left(A, \left[W, M\right]\right)\right)$. Then:

$$I\left(\left(A, \left[W, M\right]\right)\right) = \frac{I\left(\left(A, W, M\right)\right) + I\left(\left(A, M, W\right)\right)}{2}$$

Define $I_{left}\left(i\right)$ as the interference caused by the left side of the row i, and $I_{right}\left(i\right)$ by the right side.

Thus, the sum of interference

$$I_{\sigma} = \sum_{i} I_{left}\left(i\right) + I_{right}\left(i\right)$$

7. Model application to the standard “narrow-body” aircraft

7.1 Analysis of three basic strategies

Based on the above models, we apply it to a "narrow-body" aircraft. To measure the efficiency of the boarding strategy, we define the total boarding time. We divide the passengers into three groups according to the row number of the seat and call the strategy in this state BF3 strategy. We first considered three boarding strategies: Random (unstructured) boarding, boarding by section (examing varying the order of aft section (rows 23-33), middle section (rows 12-22), and bow section (rows 1-11)) and boarding by seat (examing the order of window seats (A and F), middle seats (B and E), and aisle seats (C and D)).

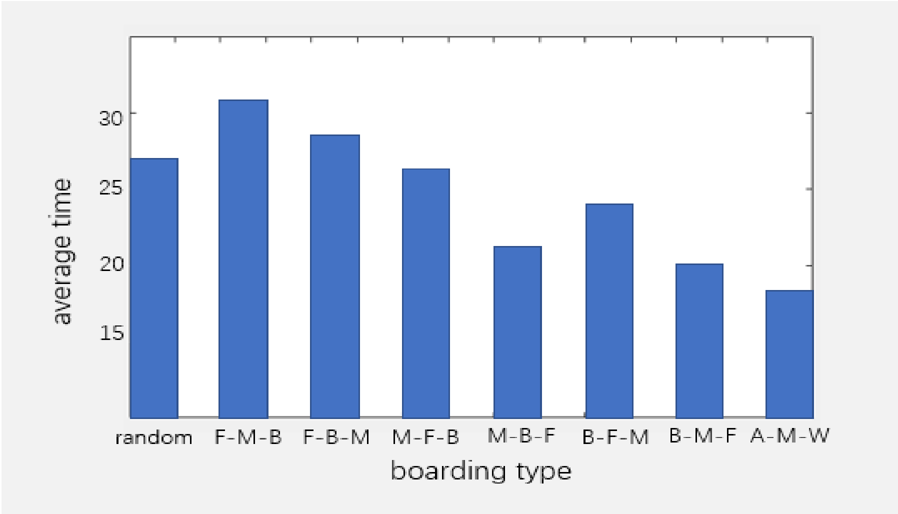

Figure 6 The relationship between time and boarding type

7.1.1 Performing interference analysis

We performed the interference analysis mentioned above, and obtain the I_σ of every scenario. Results are shown below.

Strategy	I_σ	Strategy	I_σ
Random	172.31	M-B-F	139.54
F-M-B	182.68	B-F-M	142.83
F-B-M	174.33	B-M-F	126.22
M-F-B	165.26	A-M-W	107.50

Table 2 Strategies and the time

7.1.2 Computational Emulation

By stimulating cellular automata 1000 times, we obtained the boarding time under these three different strategies.

It is worth noting that through program simulation, we obtain that local congestion occurs in the F-B-M strategy, resulting in an increase in boarding time. Restricting passengers to one section of the cabin greatly increases the number of aisle disturbances and reduces the probability of passengers handling luggage at the same time, thereby increasing boarding time. Noting that the extent of this partial blockage increases as the number of packets increases as well. Therefore, F-M-B is less efficient than F-B-M. Therefore, we can obtain that the OI (Boarding by seat, which is also known as boarding from outside to the inside) boarding strategy takes the shortest time, the partial boarding strategy takes the second place, and the random boarding takes the longest time. According to our analysis, boarding by the seat is the best option when we board the “narrow-body” aircraft.

7.2 Analysis of two more strategies

We then discussed another two possible boarding scenarios. The first one is the OI strategy, that is, outside to the inside. Passengers are divided into three boarding groups according to their reserved seats: window, middle, and aisle. The window seat passengers are the first to get on the plane after boarding begins. The passengers in the middle seats are the second group to board the plane, and the last ones to the board are the passengers in the aisle seats. Passengers in each group have no order control at boarding, it is completely random.

The second strategy is the Reverse Pyramid(RP), which is a mixture of BF (From back to the front) and OI strategies, and passengers board the plane in ascending order of group numbers. Passengers in the rear window and middle seat board first, then passengers in the front window and middle seat, then passengers in the rear aisle, and finally passengers in the front aisle.

Afterward, we still use the cellular automata based on the pedestrian flow model and integer programming for simulation.

Therefore, we can rank the boarding strategies in the case of narrow-body airliners. One of the shortest times is RP. The second one is OI. BF is in third place and random boarding is in fourth place. The strategy that needs the longest time is FB (From front to the back). But it is worth noting that in daily life, "small group" boarding often occurs. It refers to two people who are familiar with each other often boarding together and sitting in the nearby seats. The OI and RP strategies will disassemble the small group, which is not very in line with the actual situation of life.

Based on our model, it is easy to get that the disembarking strategy is almost the same as the boarding strategy, so we won't go into details here. The total time is also only about twice as long as the boarding strategy.

7.3 Sensitivity analysis for the number of luggage

Sensitivity analysis is to set irrelevant variables or secondary variables in the mathematical model unchanged, and only increase the important variables that need to be studied in a progressive proportion at a time, and study the changes in the results after the variable is proportionally changed. In this model, such as the ideal moving speed and the appropriate distance from the predecessors in the pedestrian flow, we have found the appropriate values in previous research or multiple simulations conducted autonomously. Therefore, in this sensitivity analysis, we only analyze the impact of changes in baggage quality onboarding time.

It is worth noticing that since the movement of each person in the pedestrian flow is determined by probability rather than completely fixed after we determine the baggage and boarding method, we simulate the programe 100 times under the same conditions and then take the average value. The reason for not taking 1000 times is that the number of times is too many and unnecessary.

To study the effect of changes in baggage quality onboarding time is to analyze the sensitivity of check-in time. Through such an analysis, the stability of the boarding time can be determined, and it can be further determined whether the appropriate boarding method is suitable for use in the airport.

We use the data from the previous test to scale up and down each passenger's luggage in equal proportions. Baggage information used here may not perfectly match reality. However, it is sufficient to perform the analysis after the sensitivity analysis results have been generated. The result is shown below:

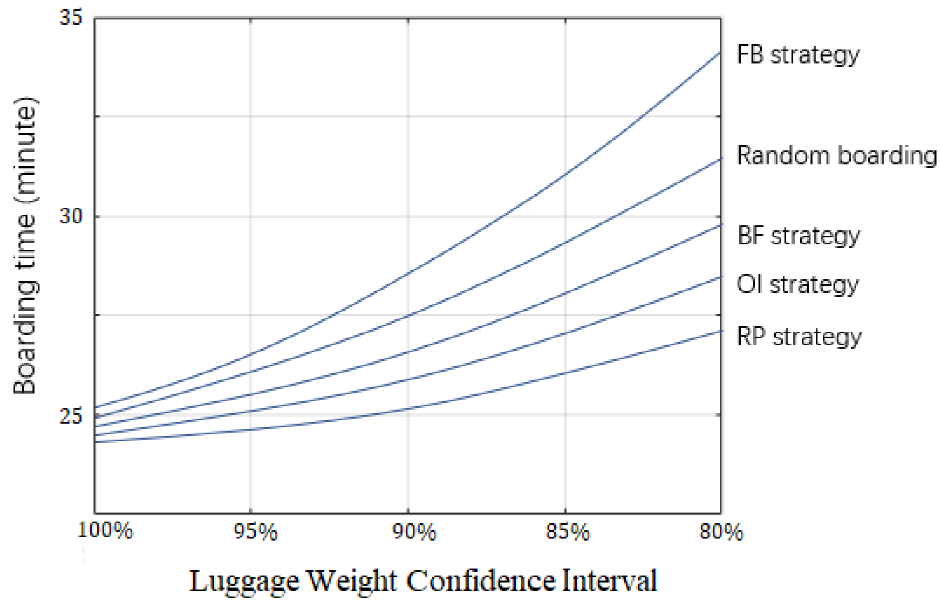

Figure 8 Sensitive analysis of luggage weight

There is a positive correlation between boarding time and the number of luggage carried by passengers, and as the number of luggage carried by passengers increases, the average boarding time also increases. The differences between strategies are small when the number of passengers carrying bags is small but gradually increases as the number of bags an individual is allowed to carry increases. Due to the limited capacity of luggage racks in passenger aircraft cabins, each airline has clear regulations on the number of luggage carried by passengers and the size of luggage. It can be seen that reasonable control of the number of luggage carried by passengers can effectively reduce the average boarding time.

OI and RP strategies both have smaller boarding times under different luggage distributions and show better stability, while FB and random strategies are very sensitive to baggage distribution. At the same time, it is also noticed that if the airline strictly controls passengers to carry a smaller number of luggage, from the perspective of policy implementation, the BF strategy can also be a feasible method.

8. Model extension

We apply a simulation-based cellular automata model to the flying-wings and two-entrance two-aisle aircraft. But the difference is that there are multiple aisles for passengers to choose from, and the grouping strategy is more cumbersome.

8.1 Flying Wings Aircraft

We assume that every passenger tends to walk aisle rather than straddling the seat. We apply the reverse pyramid method to the aircraft. The result is:

$$t = 23.2\,\text{min}$$

8.2 Two-Entrance Two-Aisle Aircraft

We divide the passengers equally between the two entrances. In this case, the inverted pyramid strategy cannot be used. Therefore, we apply a new strategy: separate the body from both sides and apply the inverted pyramid strategy to each. Then, the passenger seat entered by the front entrance is at the front, and the passenger seat entered by the rear entrance is at the rear. But the disordered flow caused great chaos. Thus, it takes even more time than the single entrance boarding method.

$$t = 42.6\,\text{min}$$

9. Boarding and disembarking strategy under capacity limitations

Due to the impact of the epidemic, airlines will take appropriate capacity restrictions. So, we reduced the number of seats available for sale to 30%, 50% and 70%, and got the following conclusions.

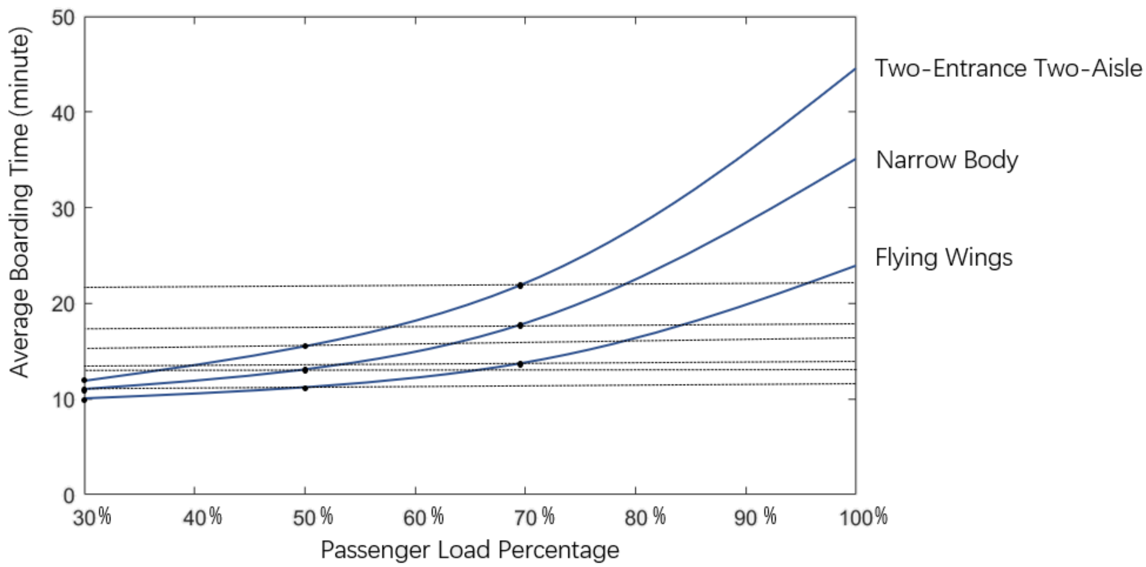

Figure 9 Capacity constraints

Surprisingly, capacity constraints in our model did not have any effect on the boarding strategy. RP is still the best boarding strategy. Likewise, the disembarkation strategy has not changed in any way.

10. A letter to the airline executive

Dear airline executive:

Hello!

We know that time is money in air transport and passengers spend a lot of time getting on and off planes. We've got a general expression for boarding time, you just need to find someone with a little math knowledge and bring in your ideal parameters to get the result you want.

We recommend RP boarding, which consumes the least amount of time compared to other boarding methods and can save you a lot of money.

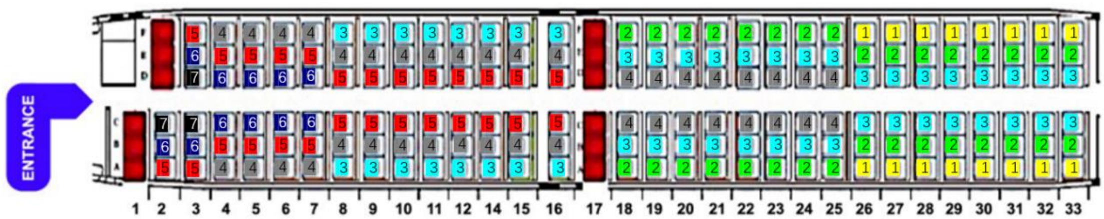

Figure 8 Boarding strategy and disembarking strategy

Therefore, if your passenger aircraft is a narrow-body aircraft, we recommend that you use the Reverse Pyramid (RP) boarding method, which is a mix of BF (back to front) and OI, allowing passengers to board in ascending order of group numbers. Passengers in the rear window and middle seat board first, then passengers in the front window and middle seat, then passengers in the rear aisle, and finally those in the front aisle. To save the most time and maximize airline profits.

Sincerely, Team 22102094

11. Strength and weakness

11.1 Strength

- We use simulation models for cross-validation with linear programming models.
- We took into account complicated movements of pedestrians at slow speeds, making the results more realistic.
- We used cellular automata for boarding simulations to make the conclusions more robust.
- We specifically used a social force model to make the boarding effect more realistic rather than a simple simulation.

11.2 Weakness

- We lack information on specific aircraft types and pedestrians to accurately quantify them.
- Treat the pedestrian's acceleration as a constant number.
- Does not consider the impact of different price zones such as economy class on boarding strategies

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