

Aircraft Boarding: When the Fastest Method Changes

An Agent-Based Simulation of Boarding Strategies Under Different Operating Conditions

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1 Executive Summary

Aircraft boarding is a moving congestion problem inside one of the narrowest spaces encountered in routine transport operations.

Passenger walking, luggage stowage, seat interference, boarding order, non-compliance, travel groups and aircraft-door configuration interact to determine the total boarding time.

The final experiment contained **66,000 simulation runs**: 11 boarding policies $\times$ 3 operating scenarios $\times$ 2,000 Monte Carlo trials. Across the audited model-development history, **523,460 simulation rows** were actually



written to result workbooks.

Single door

CRBF

13 min 55 sec

Dual door

Steffen-Lug

16 min 05 sec

Operational stress

CRBF

29 min 43 sec

The primary result is therefore not simply that one strategy won.

The optimal boarding strategy changed when operating conditions changed.

2 Explore the Boarding Process

The visualization below uses representative deterministic runs from the same V3.1.2 simulation engine used in the final experiment.

The animation is illustrative. The reported statistical conclusions are based on 2,000 Monte Carlo trials per strategy-scenario combination.

The HTML edition includes an interactive aircraft-cabin explorer where the reader can switch between boarding strategies and operating scenarios and observe passenger movement, luggage stowage and seating.

3 1. Introduction

Aircraft boarding appears simple from the passenger perspective: enter the aircraft, find a seat, store luggage and sit down.

Operationally, however, each passenger becomes part of a dynamic queue inside a narrow single aisle.

The effectiveness of a boarding strategy therefore depends on how well it distributes passenger activity through the aircraft while preventing local bottlenecks.

4 2. Why Boarding Strategy Matters

Common sources of delay include:

- walking through the aisle,
- luggage stowage,
- limited aisle width,
- simultaneous use of nearby overhead bins,
- passengers blocking one another,
- seat interference,
- travel groups,
- deviations from the prescribed boarding order,
- and front/rear door infrastructure.

The optimization objective is not simply to create an orderly queue.

It is to maximize useful parallel activity inside the cabin.

5 3. Boarding Strategies

The final comparison included seven academic or optimization-oriented methods:

- CRBF
- Steffen
- Steffen-Lug
- Reverse Pyramid (adapted)
- WilMA
- Random
- Back-to-Front

and four simplified airline-like structures:

- Ryanair-like
- easyJet-like
- Lufthansa-like
- US Network-like

The airline-like policies are structural approximations for comparative simulation and are not exact reconstructions of every real-world boarding procedure.

6 4. Model Development

The project contains **19 named simulation script files representing 18 unique executable versions**. `boarding_simulation_v3.py` and `boarding_simulation_v3_0.py` are byte-identical aliases and share the same V3.0 result workbook, so they are counted once rather than double-counted.

The counts below were audited against each script’s loop structure and the row count of the corresponding **All Runs** worksheet. They are recorded executions, not estimates.

Version	Main change / research question	Trials and design	Simulations	Cumulative
V1.0	Baseline 26-row, 156-passenger agent model; Random, Back-to-Front, WilMA and Steffen.	100 per strategy	400	400
V1.1	Diagnostic validation: distributions, stowing, blocking, seat interference, throughput and experimental comparison.	100 per strategy	400	800

Version	Main change / research question	Trials and design	Simulations	Cumulative
V1.2	Cabin-length replication test: 26-row baseline versus the 12-row, 72-passenger experimental geometry.	100×2 geometries $\times$ 4 strategies	800	1,600
V1.3	Movement-realism sensitivity: entry headway, aisle spacing, restart delay and combined configurations.	100×2 geometries $\times$ 12 configs $\times$ 4	9,600	11,200
V1.4	Exact literature-oriented Steffen order and luggage-stowing footprint sensitivity.	100×2 geometries $\times$ 2 footprints $\times$ 5	2,000	13,200
V1.5	Concurrent luggage-stowing sensitivity across seven proximity/penalty configurations.	100×2 geometries $\times$ 7 configs $\times$ 4	5,600	18,800
V1.6	Final calibration and robustness validation of continuous nearby-stower interference.	500×23 calibration configs $\times$ 4	46,000	64,800
V2.0	Operational experiment begins: load-factor and carry-on-luggage intensity scenarios.	500×7 scenarios $\times$ 4	14,000	78,800
V2.1	Passenger compliance and travel-group cohesion added as behavioural dimensions.	500×9 scenarios $\times$ 4	18,000	96,800

Version	Main change / research question	Trials and design	Simulations	Cumulative
V2.2	First dual-door infrastructure model with front and rear passenger streams.	500×2 door scenarios $\times 4$	4,000	100,800
V2.3	Deterministic paired infrastructure validation and balanced front/rear assignment.	500×3 infrastructure modes $\times 4$	6,000	106,800
V2.4	Full load-factor $\times$ cabin-occupancy $\times$ door- infrastructure factorial sensitivity.	$500 \times 3 \times 3 \times 3 \times 4$	54,000	160,800
V3.0	Frozen physical engine and six final production scenarios (v3.py is an identical alias).	$5,000 \times 6$ scenarios $\times 4$	120,000	280,800
V3.0.1	Targeted validation of entry release, walking/spacing and seat-interference overlap.	$1,000 \times 10$ configs $\times 4$	40,000	320,800
V3.0.2	External replication of the 72-passenger Steffen- Hotchkiss experiment.	$1,000 \times 4$ strategies	4,000	324,800
V3.1	Seven academic and four airline-like policies compared in three final scenarios.	$2,000 \times 3$ scenarios $\times 11$	66,000	390,800
V3.1.1	Methodological audit corrected CRBF, Reverse Pyramid and Steffen-Lug im- plementations.	$2,000 \times 3$ scenarios $\times 11$	66,000	456,800

Version	Main change / research question	Trials and design	Simulations	Cumulative
V3.1.2	Final policy definitions; verified smoke run followed by the final 2,000-trial experiment.	20 smoke + 2,000 final; each $\times 3 \times 11$	66,660	523,460

The cumulative total is **523,460 simulations**. This includes the V3.1.2 smoke test (660 runs) and its separate final run (66,000 runs).

The development path moved from baseline mechanics, through experimental replication and sensitivity analysis, into behavioural and infrastructure scenarios. V3.0 froze the physical engine; V3.1–V3.1.2 then concentrated on policy breadth and literature-correct definitions. Reverse Pyramid remains reported as **Reverse Pyramid (adapted)** because its published A320 zones were proportionally adapted to a 26-row all-economy cabin.

7 5. Experimental Design

Scenario	Doors	Luggage	Compliance	Travel groups
Single door	Front	Baseline	100%	0%
Dual door	Front + rear	Baseline	100%	0%
Operational stress	Front	High	75%	25%

Each strategy was evaluated with **2,000 Monte Carlo trials per scenario**.

The final dataset therefore contains **66,000 simulations**. `TRIALS_PER_SCENARIO` is a single explicit builder parameter. Setting it to 5,000 is prepared for a future matching result workbook, but this builder never reruns the simulation automatically.

8 6. Statistical Analysis

Because policies within each trial were evaluated using matched passenger realizations, strategy comparisons were paired.

The statistical analysis included:

- paired t-tests,
- Wilcoxon signed-rank tests,
- Holm multiple-comparison correction,
- Cohen’s d_z ,
- 95% confidence intervals,
- win probabilities,
- P95 boarding times,
- and variability measures.

With 2,000 trials, small effects can become statistically significant.

Operational interpretation therefore prioritizes:

1. absolute time difference,
2. percentage difference,

3. effect size,
4. win probability,
5. P95 performance.

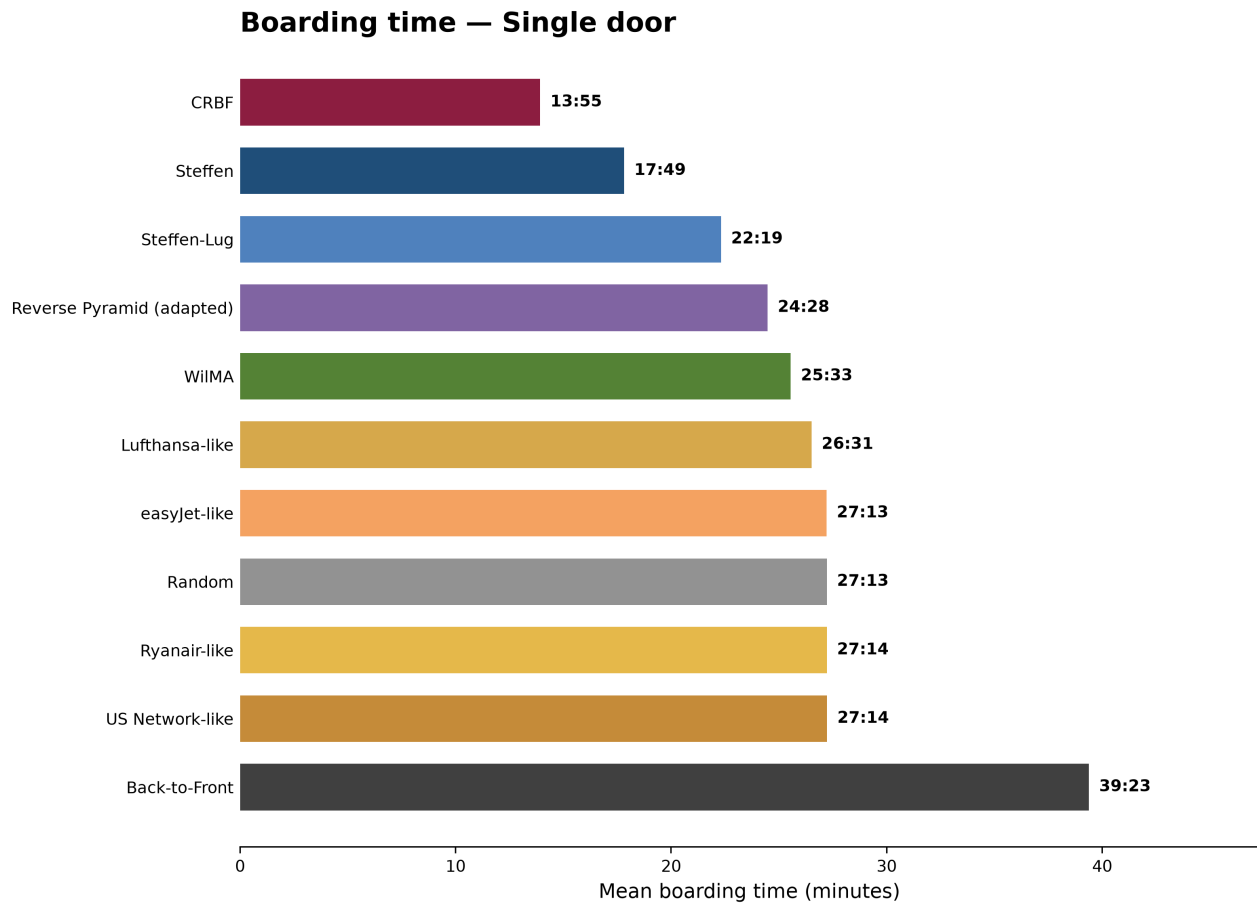
8.1 6.1 Convergence check from the existing final runs

A post-hoc running-mean check used the existing 66,000 `All Runs` rows; no simulation was rerun. Across all 33 scenario $\times$ policy groups, the median absolute change from 500 to 2,000 trials was **1.59 seconds** and the largest was **7.48 seconds**. From 1,500 to 2,000 trials, the median change was **1.18 seconds** and the largest was **9.04 seconds**.

At 2,000 trials, the median Monte Carlo 95% half-width for a mean was **4.14 seconds**; the maximum was **7.26 seconds**. These diagnostics support the stability of the reported mean estimates at the seconds-to-low-tens-of-seconds scale. A 5,000-trial run would reduce Monte Carlo standard errors to about 63.2% of their present size, but it is not required to reinterpret the existing results as valid.

9 7. Results

9.1 7.1 Single-door scenario



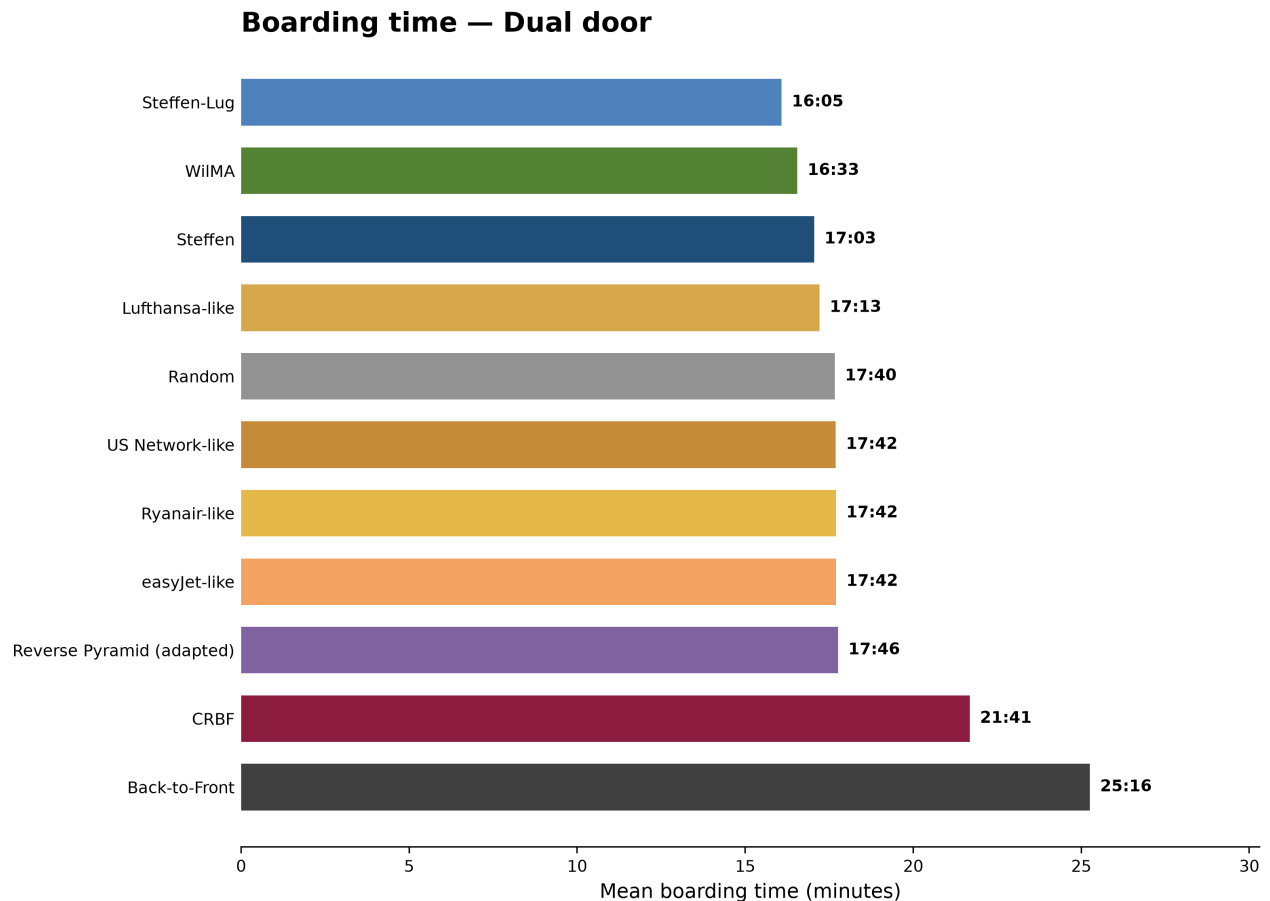
Rank	Strategy	Mean	P95	SD
1	CRBF	13 min 55 sec	14 min 52 sec	0.54 min
2	Steffen	17 min 49 sec	19 min 04 sec	0.74 min
3	Steffen-Lug	22 min 19 sec	24 min 26 sec	1.24 min

Rank	Strategy	Mean	P95	SD
4	Reverse Pyramid (adapted)	24 min 28 sec	26 min 58 sec	1.39 min
5	WilMA	25 min 33 sec	28 min 02 sec	1.45 min
6	Lufthansa-like	26 min 31 sec	29 min 17 sec	1.59 min
7	easyJet-like	27 min 13 sec	29 min 57 sec	1.55 min
8	Random	27 min 13 sec	30 min 00 sec	1.60 min
9	Ryanair-like	27 min 14 sec	29 min 58 sec	1.60 min
10	US Network-like	27 min 14 sec	29 min 51 sec	1.61 min
11	Back-to-Front	39 min 23 sec	42 min 42 sec	1.96 min

CRBF was the fastest strategy in the clean single-front-door scenario, averaging **13 min 55 sec**.

Its performance was associated with extremely low aisle blocking and high parallel luggage-stowage activity.

9.2 7.2 Dual-door scenario



Rank	Strategy	Mean	P95	SD
1	Steffen-Lug	16 min 05 sec	17 min 44 sec	0.95 min
2	WilMA	16 min 33 sec	18 min 26 sec	1.07 min
3	Steffen	17 min 03 sec	18 min 52 sec	1.13 min

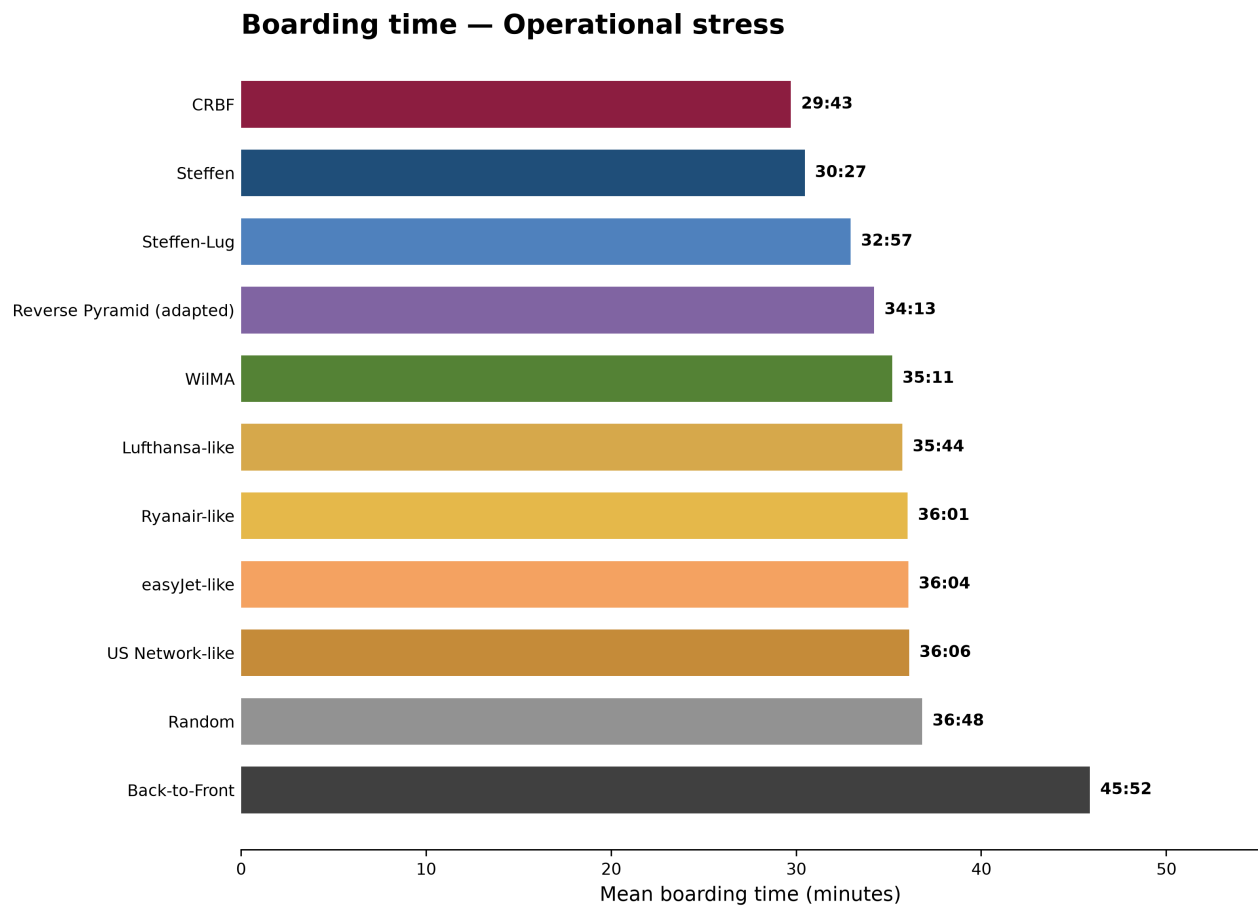
Rank	Strategy	Mean	P95	SD
4	Lufthansa-like	17 min 13 sec	19 min 08 sec	1.12 min
5	Random	17 min 40 sec	19 min 40 sec	1.16 min
6	US Network-like	17 min 42 sec	19 min 52 sec	1.19 min
7	Ryanair-like	17 min 42 sec	19 min 47 sec	1.15 min
8	easyJet-like	17 min 42 sec	19 min 43 sec	1.17 min
9	Reverse Pyramid (adapted)	17 min 46 sec	19 min 42 sec	1.10 min
10	CRBF	21 min 41 sec	23 min 57 sec	1.36 min
11	Back-to-Front	25 min 16 sec	27 min 57 sec	1.57 min

Opening both the front and rear doors changed the ranking.

Steffen-Lug became the fastest method at **16 min 05 sec**.

This demonstrates that the fastest strategy cannot be identified independently of aircraft infrastructure.

9.3 7.3 Operational stress



Rank	Strategy	Mean	P95	SD
1	CRBF	29 min 43 sec	33 min 00 sec	1.93 min
2	Steffen	30 min 27 sec	33 min 51 sec	1.93 min

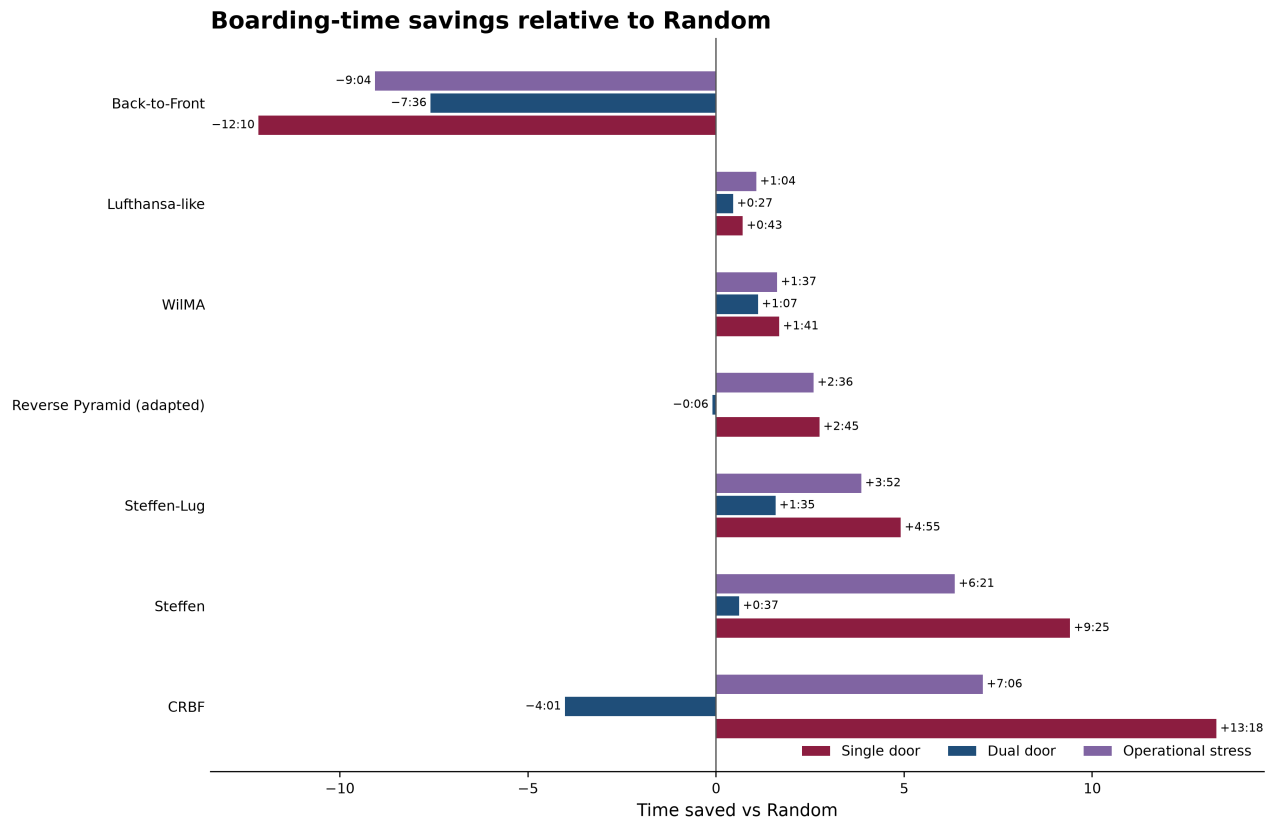
Rank	Strategy	Mean	P95	SD
3	Steffen-Lug	32 min 57 sec	36 min 13 sec	1.98 min
4	Reverse Pyramid (adapted)	34 min 13 sec	37 min 43 sec	2.09 min
5	WilMA	35 min 11 sec	38 min 47 sec	2.14 min
6	Lufthansa-like	35 min 44 sec	39 min 40 sec	2.26 min
7	Ryanair-like	36 min 01 sec	39 min 47 sec	2.26 min
8	easyJet-like	36 min 04 sec	40 min 00 sec	2.24 min
9	US Network-like	36 min 06 sec	40 min 03 sec	2.28 min
10	Random	36 min 48 sec	40 min 44 sec	2.31 min
11	Back-to-Front	45 min 52 sec	50 min 32 sec	2.76 min

Under high luggage volume, 75% compliance and travel-group disruption, CRBF again produced the lowest mean boarding time: **29 min 43 sec**.

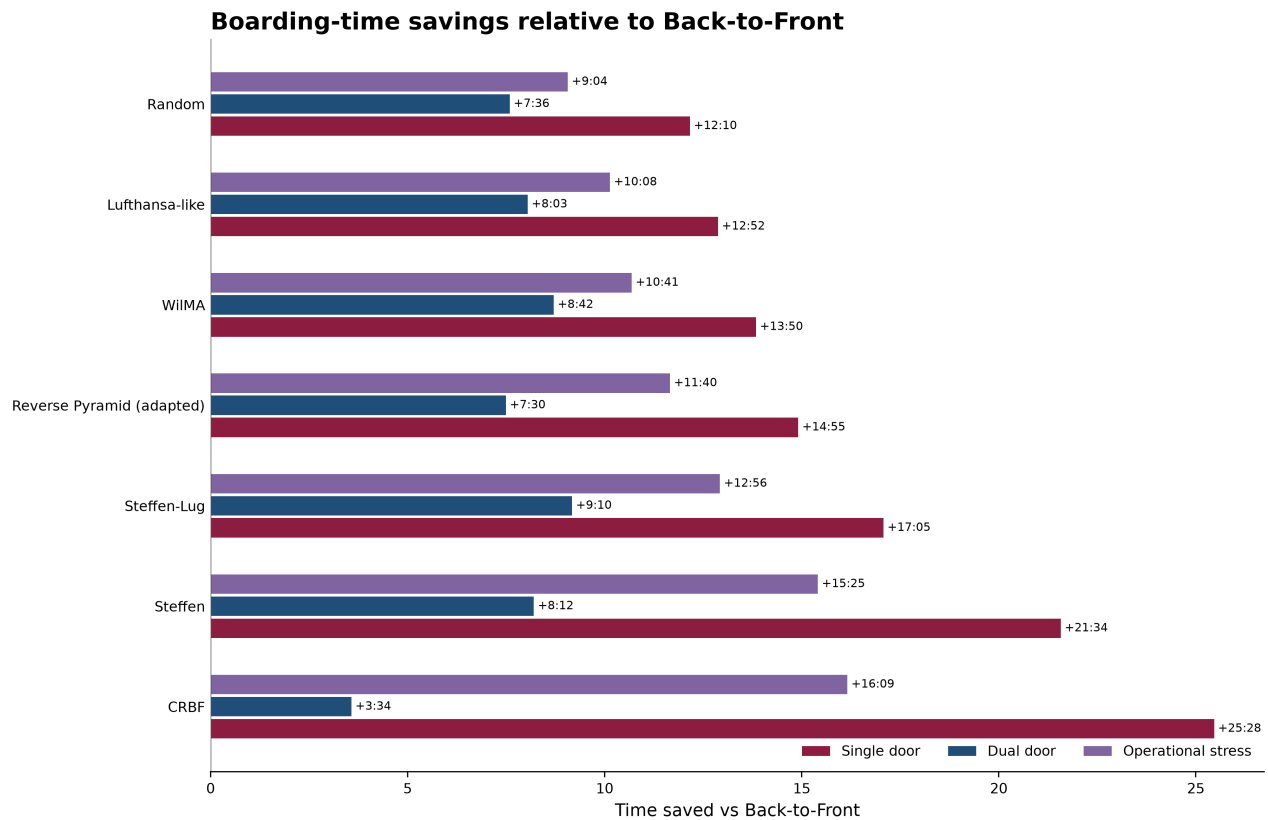
However, the difference between the best strategies became much smaller than under the clean single-door condition.

10 8. Time Savings

10.1 8.1 Relative to Random boarding



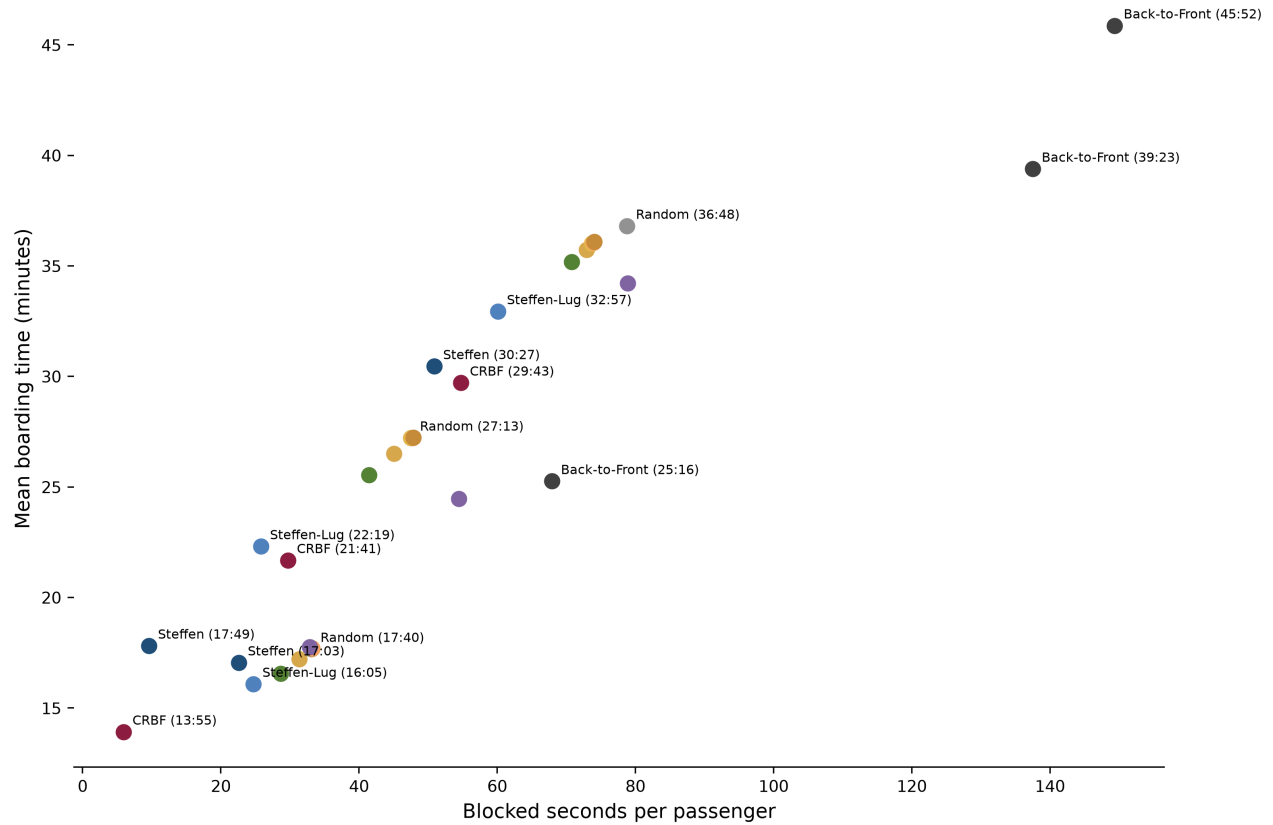
10.2 8.2 Relative to Back-to-Front



The largest improvements appeared when highly structured methods were compared with Back-to-Front boarding. This is consistent with the model mechanism: Back-to-Front concentrates passengers in similar cabin regions and therefore creates substantial local aisle congestion.

11 9. Why the Strategies Behave Differently

Aisle blocking and total boarding time

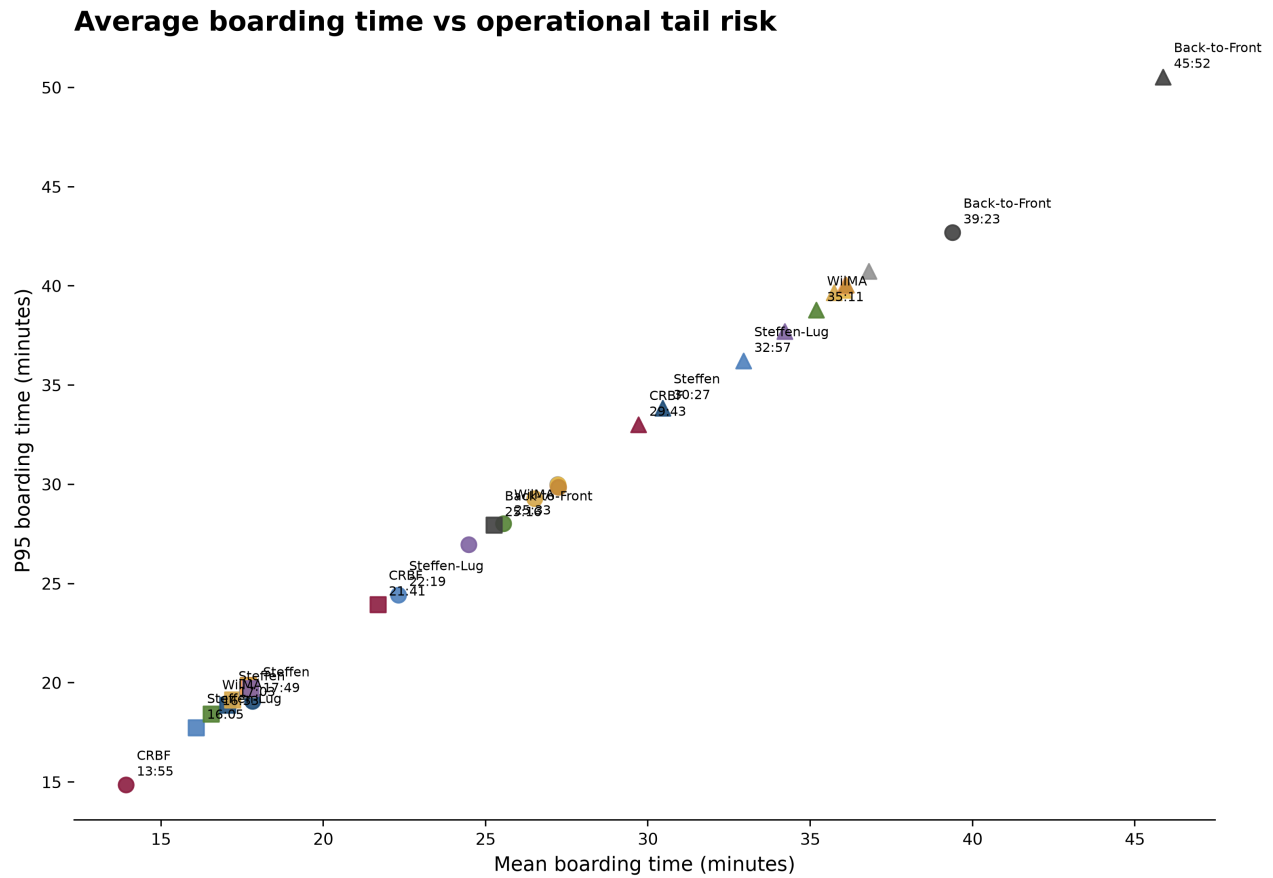


Aisle blocking provides an important explanation for the differences between policies.

Methods such as CRBF and Steffen create spatial separation and allow multiple passengers to perform useful work simultaneously.

Methods that concentrate passengers into adjacent rows create moving bottlenecks.

12 10. Reliability

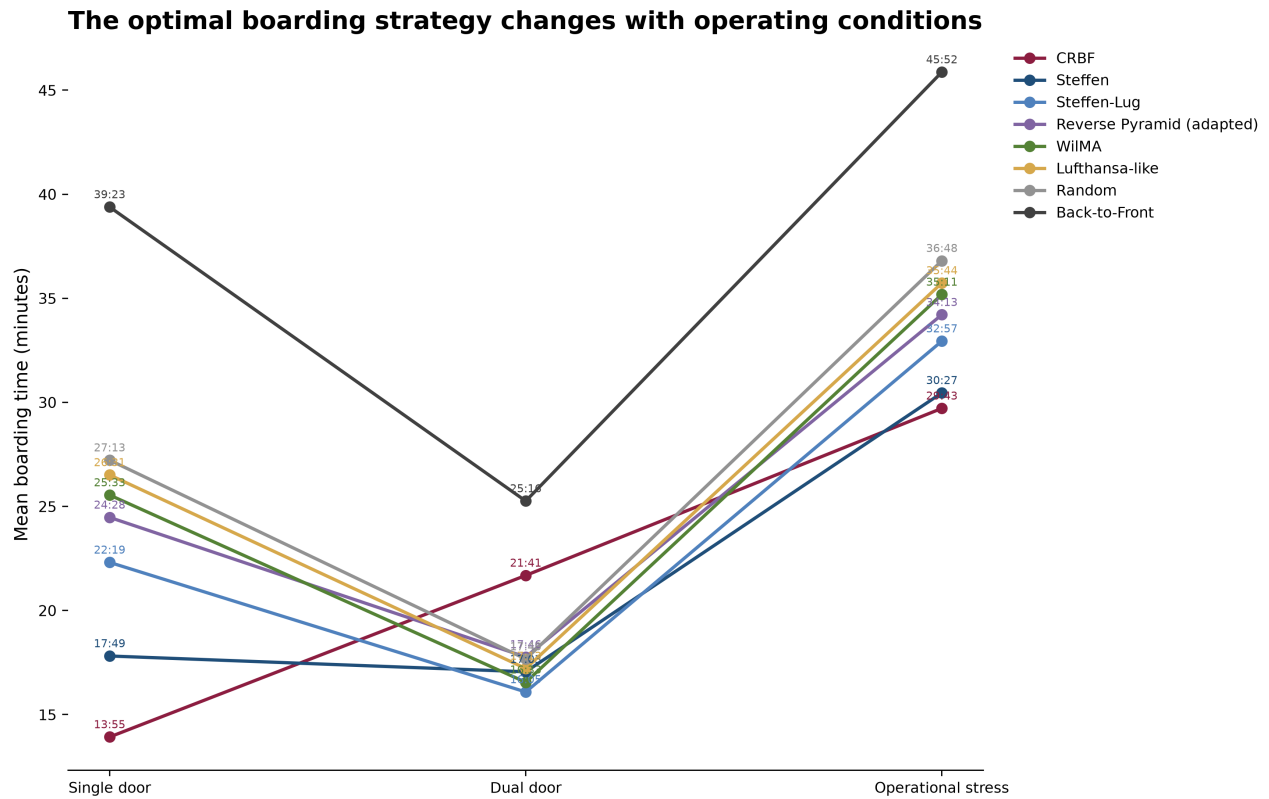


Mean boarding time describes average performance.

P95 provides a more operational interpretation: a boarding time exceeded by only approximately 5% of simulated runs.

For schedule planning, a strategy with slightly slower average performance may still be attractive if it provides lower tail risk.

13 11. Scenario Sensitivity

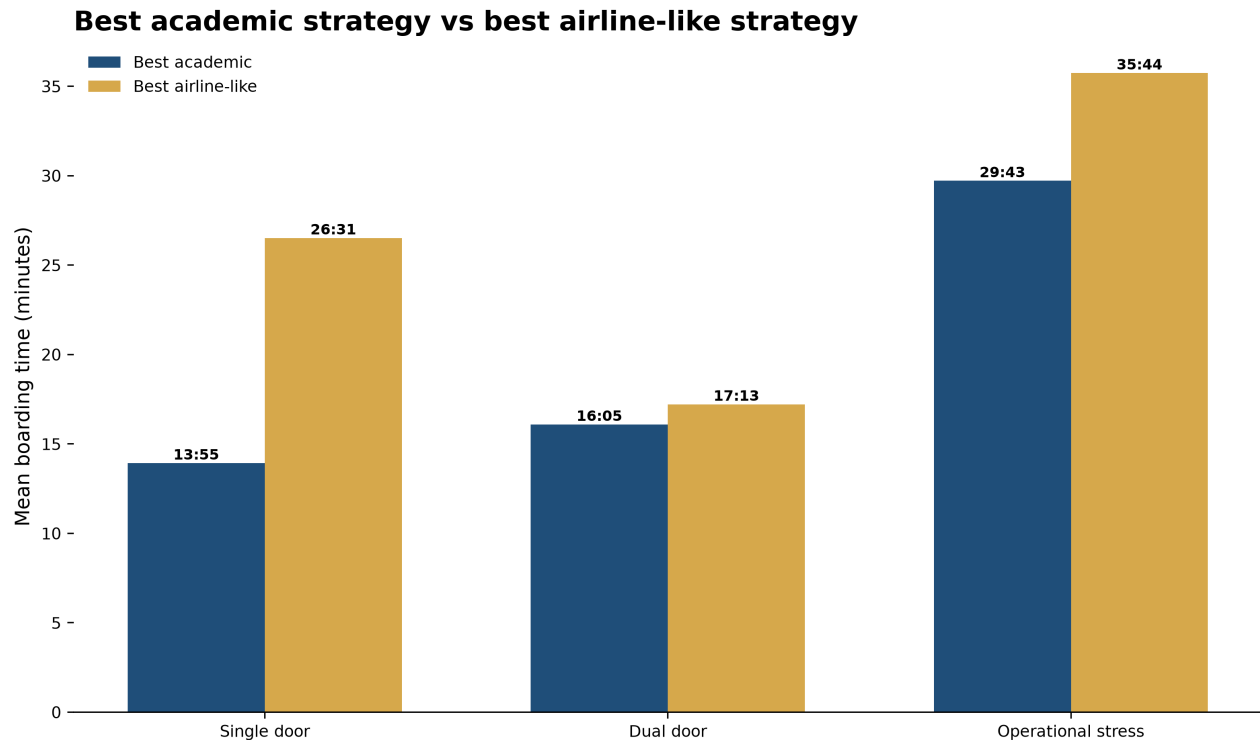


The ranking changes substantially between operating scenarios.

CRBF was exceptionally strong with a single front door but lost much of its advantage under the fixed dual-door split.

Steffen-Lug moved in the opposite direction and became the fastest dual-door strategy.

14 12. Academic vs Airline-Like Boarding



Strongly spatial academic strategies generally outperformed the simplified airline-like structures in pure boarding-flow efficiency.

This does not imply that airlines are necessarily using inferior commercial policies.

Real airline boarding must balance additional objectives such as:

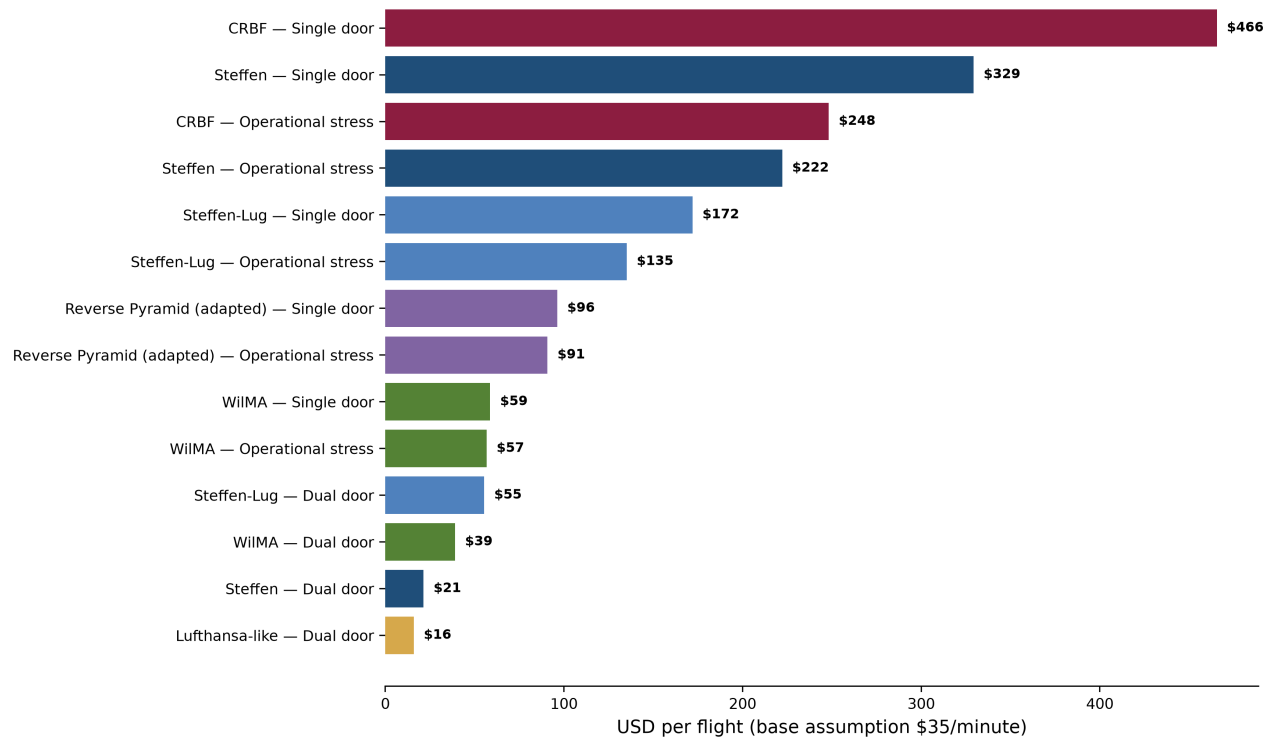
- premium products,
- accessibility,
- families,
- loyalty status,
- passenger comprehension,
- enforcement complexity,
- gate configuration,
- and revenue.

15 13. Economic Interpretation

The economic dataset is now a directed **all-vs-all comparison of all 11 strategies**. It contains 363 rows: 11×11 choices $\times$ 3 scenarios. This includes $A = B$ comparisons (zero difference) and both directions of every pair. Excluding self-comparisons and reverse duplicates, there are 55 unique pairs per scenario and 165 across the study.

The chart below retains Random as one readable cross-section of the larger all-vs-all dataset; Random is not treated as the only benchmark.

Illustrative gate-time value saved per flight



The economic layer applies an illustrative gate-time value of:

- **\$30/minute** — low
- **\$35/minute** — base
- **\$40/minute** — high

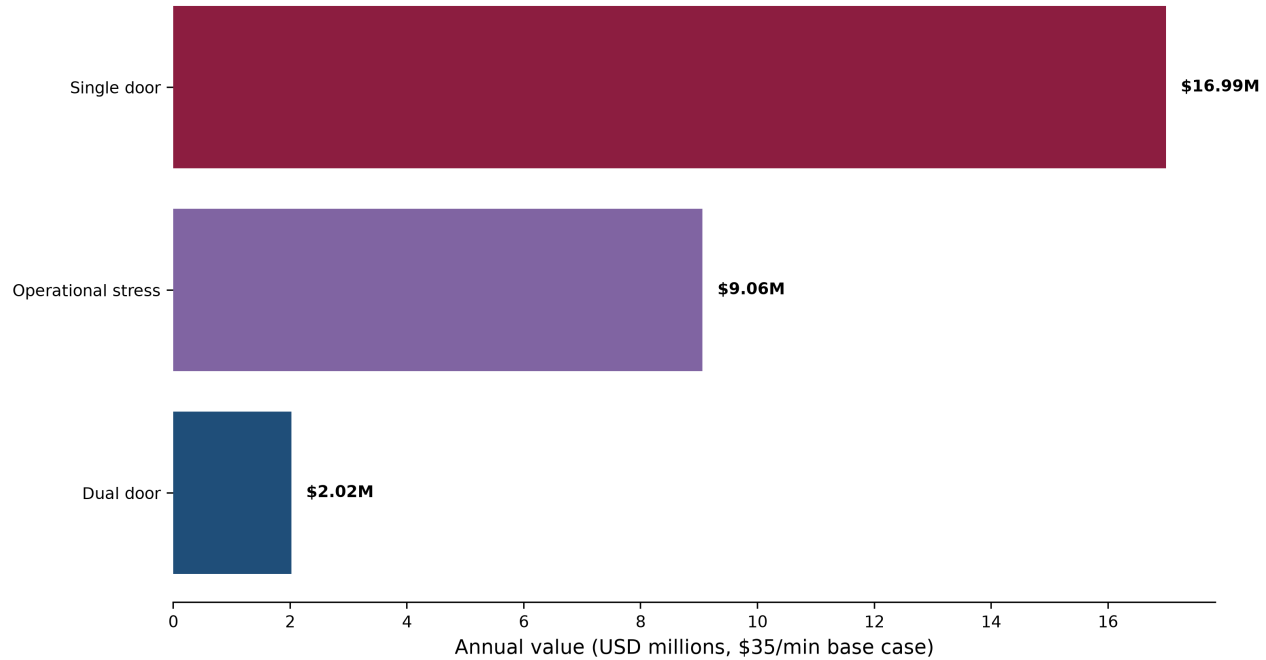
The calculation is:

$$\text{Value per flight} = \text{boarding minutes saved} \times \text{assumed cost per minute}$$

Illustrative operating value, not profit.

15.1 13.1 Annualized operating scale

Illustrative annual gate-time value at 100 flights per day



The time-saving effect can also be extrapolated across repeated daily operations.

The calculation is:

$$\text{Annual value} = \text{minutes saved per flight} \times \text{cost per minute} \times \text{flights per day} \times 365$$

For a compact operational table, every strategy is shown against Back-to-Front at 10 flights per day. The interactive calculator and exported economic workbook allow any of the full 11×11 choices.

Scenario	Strategy A	Reference B	Time difference/flight	Base value/flight	Annual base value at 10 flights/day
Single door	CRBF	Back-to-Front	+25 min 28 sec	\$891	\$3,253,056
Single door	Steffen	Back-to-Front	+21 min 34 sec	\$755	\$2,755,964
Single door	Steffen-Lug	Back-to-Front	+17 min 05 sec	\$598	\$2,181,423
Single door	Reverse Pyramid (adapted)	Back-to-Front	+14 min 55 sec	\$522	\$1,905,168
Single door	WilMA	Back-to-Front	+13 min 50 sec	\$484	\$1,767,974
Single door	Lufthansa-like	Back-to-Front	+12 min 52 sec	\$451	\$1,644,649
Single door	Ryanair-like	Back-to-Front	+12 min 10 sec	\$426	\$1,553,646
Single door	easyJet-like	Back-to-Front	+12 min 10 sec	\$426	\$1,555,205
Single door	US Network-like	Back-to-Front	+12 min 09 sec	\$425	\$1,551,957
Single door	Random	Back-to-Front	+12 min 10 sec	\$426	\$1,553,861
Single door	Back-to-Front	Back-to-Front	0 min 00 sec	\$0	\$0
Dual door	CRBF	Back-to-Front	+3 min 34 sec	\$125	\$456,597
Dual door	Steffen	Back-to-Front	+8 min 12 sec	\$287	\$1,048,041
Dual door	Steffen-Lug	Back-to-Front	+9 min 10 sec	\$321	\$1,171,900

Scenario	Strategy A	Reference B	Time difference/flight	Base value/flight	Annual base value at 10 flights/day
Dual door	Reverse Pyramid (adapted)	Back-to-Front	+7 min 30 sec	\$262	\$957,249
Dual door	WilMA	Back-to-Front	+8 min 42 sec	\$305	\$1,112,331
Dual door	Lufthansa-like	Back-to-Front	+8 min 03 sec	\$282	\$1,028,022
Dual door	Ryanair-like	Back-to-Front	+7 min 33 sec	\$264	\$965,175
Dual door	easyJet-like	Back-to-Front	+7 min 33 sec	\$264	\$964,709
Dual door	US Network-like	Back-to-Front	+7 min 34 sec	\$265	\$966,327
Dual door	Random	Back-to-Front	+7 min 36 sec	\$266	\$969,906
Dual door	Back-to-Front	Back-to-Front	0 min 00 sec	\$0	\$0
Operational stress	CRBF	Back-to-Front	+16 min 09 sec	\$566	\$2,064,097
Operational stress	Steffen	Back-to-Front	+15 min 25 sec	\$539	\$1,968,913
Operational stress	Steffen-Lug	Back-to-Front	+12 min 56 sec	\$452	\$1,651,342
Operational stress	Reverse Pyramid (adapted)	Back-to-Front	+11 min 40 sec	\$408	\$1,489,354
Operational stress	WilMA	Back-to-Front	+10 min 41 sec	\$374	\$1,365,019
Operational stress	Lufthansa-like	Back-to-Front	+10 min 08 sec	\$355	\$1,294,612
Operational stress	Ryanair-like	Back-to-Front	+9 min 51 sec	\$345	\$1,258,422
Operational stress	easyJet-like	Back-to-Front	+9 min 48 sec	\$343	\$1,252,913
Operational stress	US	Back-to-Front	+9 min 46 sec	\$342	\$1,247,968
Operational stress	Network-like	Back-to-Front	+9 min 04 sec	\$317	\$1,158,046
Operational stress	Random	Back-to-Front	+9 min 04 sec	\$317	\$1,158,046
Operational stress	Back-to-Front	Back-to-Front	0 min 00 sec	\$0	\$0

The annual values are **scenario extrapolations**.

They do not include:

- aircraft utilization effects,
- network recovery,
- crew costs,
- passenger connections,
- schedule redesign,
- revenue implications,
- or actual airline accounting costs.

16 14. Interactive Results Table

17 15. Discussion

Three findings dominate the study.

17.1 15.1 Spatial organization matters

The fastest policies were not simply priority systems.

They controlled where passengers were located inside the aircraft and therefore how many passengers could walk, stow luggage or sit down simultaneously.

17.2 15.2 Infrastructure changes the optimum

The same policy can perform very differently when the boarding infrastructure changes.

The strong decline in CRBF performance under dual-door boarding is one of the clearest examples.

17.3 15.3 Statistical significance is not operational significance

With 2,000 paired trials, relatively small differences can become statistically significant.

A difference of several seconds or tens of seconds should therefore be interpreted differently from a saving of several minutes.

18 16. Limitations

The results should be interpreted within the model boundary.

Important limitations include:

- simulation rather than direct live-airline observation,
- representative passenger distributions,
- simplified airline-like procedures,
- fixed 26-row narrow-body geometry,
- adapted Reverse Pyramid zoning,
- simplified behavioural assumptions,
- limited gate-area modelling,
- no direct revenue optimization,
- and no airline network simulation.

The economic section represents illustrative operating-value scenarios, not an accounting forecast.

19 17. Conclusion

The study does not identify one universally optimal aircraft boarding strategy.

Instead, boarding performance depends on the interaction between:

- passenger sequencing,
- aisle congestion,
- luggage,
- behavioural compliance,
- and aircraft infrastructure.

In the final simulation:

CRBF was fastest with a single front door.



Steffen-Lug was fastest with dual-door boarding.

CRBF was fastest under operational stress.

The practical question for an airline is therefore not simply:

Which boarding strategy is fastest?

It is:

Which boarding strategy is fast, robust, understandable and operationally compatible with the environment in which it must actually be used?

20 18. References

The bibliography below is limited to sources present in the supplied literature folder and verified from the documents' actual title pages or publisher records. Two differently named supplied PDFs contain the same Coppens et al. article; it is listed once.

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21 Appendix A — Interactive Strategy Explorer

22 Appendix B — Economic Assumptions

Parameter	Assumption
Low	\$30/minute
Base	\$35/minute

Parameter	Assumption
High	\$40/minute