Twelfth USA/Europe Air Traffic Management Research and Development Seminar (ATM2017)

Aircraft Boarding – Data, Validation, Analysis

Subtitle as needed *(paper subtitle)*

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***Abstract*—The aircraft boarding is always on the critical path of the turnaround. Efficient boarding procedures have to consider both operational constraints and the individual passenger behavior. In contrast to the processes of fueling, catering and cleaning the boarding is mainly driven by passengers not by airport or airline employees. There are several approaches to model and simulate the aircraft boarding. In this paper a microscopic approach is used to model the passenger behavior, where the passenger movement is defined as a one dimensional, stochastic, and time/space discrete transition process. To validate the research results achieved in the past years, field trials of boarding procedures and measurements of specific processes are recorded, analyzed and transferred to the simulation environment.**

Keywords-boarding; simulation; field trials; validation; improvement

I. INTRODUCTION

Operational systems have to be efficient in both cost and operational strategies. The passenger handling at airports mainly aims at reliable on-time performance for the boarding process. At the aircraft boarding a specific amount of passenger trajectories (path along handling stations and corresponding timestamps [1]) and the associated aircraft trajectory is brought together in one point of space and time. The boarding is the final passenger process at the airport with a significant potential for influencing the future aircraft trajectory. During aircraft turnaround, the aircraft will deboarded, cleaned, (un-) loaded, and refueled. Finally the passengers enter the airplane. From an operational point of view the passenger boarding is getting more important, if an aircraft demands a short turnaround time (e.g. delayed flight, slot adherence)[2]. For the ATM system the turnaround holds the potential to compensate delays and provide a reliable basis for operational planning procedure at the day of operations. From the airline perspective, the boarding process contains a product (cf. priority boarding, passenger convenience) which allows for a specific pricing strategy to improve revenues.

This paper provides a fundamental dataset to model the airplane boarding. In the last years more than 400 flights are recorded with different level of details: passenger processes (e.g. store baggage, seat taking), arrival rates at the aircraft, boarding time using different boarding strategies. The recorded data are systematically analyzed and used to calibrate the stochastic model of the boarding process. The recorded operational scenarios are implemented in the existing simulation environment and the results will be compared against the field measurements. Finally, operational improvements (focusing hand baggage), minimal boarding time, deboarding and infrastructural changes are addressed.

A. Status quo

In the following section a short overview about scientific research on aircraft boarding is given. This overview extends the modelling background already presented in [18].

Common goal of those examinations doing simulations is to minimize the time that is required for passenger boarding. Taking into account different boarding patterns a study by Van Landeghem and Beuselinck [3] investigates to what extent boarding time can be reduced by applying optimal versus current boarding strategies. A similar approach is done by Ferrari, P. and Nagel, K. [4] with special emphasis on disturbances, such as a certain number of passengers not follow their boarding group but boarding earlier or later. The results show improved values for the typical *back-to-front* boarding in case of passengers not boarding to their previously assigned boarding groups. In contrast, Bachmat and Elkin [5] support the classical *back-to-front* policy in comparison to *random* boarding strategy. On the basis of the individual boarding strategy proposed by Steffen, J.H. [21] which considers the time a passenger need to store baggage, the model developed by Milne and Kelly [6] assigns passengers to seats so that their hand baggage is distributed evenly throughout the plane. A more practical approach to airplane boarding is done by Chung [7] as this study points out that boarding times significantly depend on the aircraft seating design and total loading times can be significantly reduced. A link between the efficiency of airlines boarding policies and the airplane design parameters such as distance between the rows is given in a study by Bachmat et al. [8]. In this study, results show a higher attractiveness of *random* boarding among row-based policies. Focusing on the simulation of deplaning strategies (by group and/or column) several equipment types are tested in a study by Wald [9].

Relevant studies about aircraft boarding strategies include but are not limited to the following examples. Picking up the idea of boarding groups, a study based on an analytical model by van den Briel et al. [10] show a significantly improved boarding time by group boarding policies over the traditional method from back to front. Based on a mathematical model that is related to the 1+1 polynuclear growth model with concave boundary conditions Bachmat et al. [11] study all airplane configurations and boarding group sizes. Results show that effectiveness of *back-to-front* boarding can be increased compared to *random* boarding but drops when having more than two boarding groups. Assessing the effectiveness of boarding strategies is also a core part of a study by Soolaki et al. [12]. Based on an integer linear programming approach together with a genetic algorithm they analyze different boarding strategies and to assess the effectiveness of their model.

The interference of passengers when boarding an airplane is in the focus of a study by Bazargan [13]. The mathematical model´s output aims to minimize the interferences and to speed up the boarding time as interferences may lead to delays especially in single aisle aircraft. The interactions of passengers during boarding process (e.g. occupied aisle) are also in the focus of a study by Frette and Hemmer [14] and Tang et al. [15]. Based on a dynamical model Frette and Hemmer calculate the average boarding time when all permutations of N passengers are given equal weight. Tang et al. concentrate on passengers individual properties and apply this knowledge to their numerical model in order to evaluate the benefit of different boarding strategies. An experiment conducted in a mock Boeing 757 was performed by Steffen, J.H. and Hotchkiss, J. [16]. They tested different boarding methods and described the potential savings to airline companies due to less boarding times.

B. *Model and Simulation*

The proposed dynamic passenger movement model for the boarding simulation is based on the asymmetric simple exclusion process (ASEP). The ASEP was successfully adapted to model the dynamic passenger behavior in the airport terminal [1][17]. In this context, the passenger boarding is assumed to be a stochastic, forward directed, one dimensional, and discrete (time and space) process. To provide both an appropriate set of input data and an efficient simulation environment the aircraft seat layout is transferred into a regular grid with aircraft entries, the aisle(s) and the passenger seats as shown in fig. 1(reference: Airbus 320, 29 rows, 174 seats). This regular grid consists of equal cells with a size of 0.4 x 0.4 m, whereas a cell can either be empty or contain exactly one passenger.

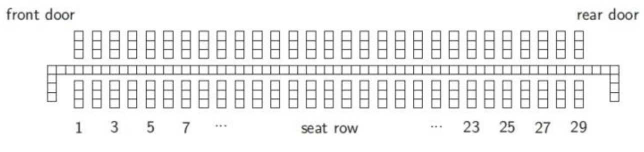

Figure 1. Grid based simulation environment – Airbus A320 as reference

The boarding progress consists of a simple set of rules for the passenger movement: a) enter the aircraft at the assigned door (based on the current scenario), b) move forward from cell to cell along the aisle until reaching the assigned seat row, and c) store the baggage (aisle is blocked for other passengers) and take the seat. The movement process only depends on the state of the next cell (empty or occupied). The storage of the baggage is a stochastic process and depends on the individual amount of hand luggage. The seating process is stochastically modeled as well, whereas the time to take the seat depends on the already used seats in the corresponding row.

The stochastic nature of the boarding process requires a minimum of simulation runs for each selected scenario to derive reliable simulation results. In this context, a simulation scenario is mainly defined by the underlying seat layout, the number of passengers to board (seat load factor, default: 85%), the arrival frequency of the passengers at the aircraft (default: 14 passengers per minute), the number of available doors (default 1 door), the specific boarding strategy (default: *random*) and the conformance of passengers to follow the current strategy (default: 85%). Further details about the model and the simulation environment are available in [18]. To model different boarding strategies the grid based approach enable both the individual assessment of seats and classification/aggregation according to the intended strategy. In fig. 2 the seats are color coded (gray-scale) and aggregated to superior structures (blocks). The boarding takes place in the order of the gray-scale value.

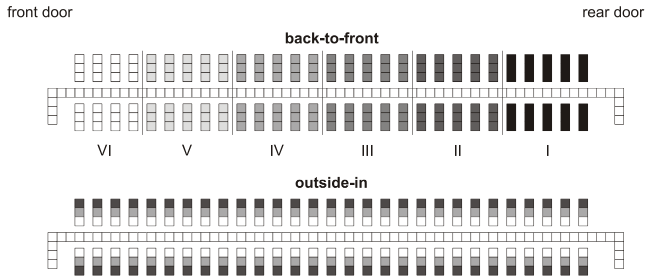

Figure 2. Example for *back-to-front* and *outside-in* boarding strategy (darker seats are boarded first) modelled in the simulation environment

II. MEASUREMENTS

Addressing the bilateral agreements with the concerned airlines and airports, the data sets are appropriately aggregated to be used in this research context. This section will provide an overview about boarding times, boarding/deboaring rates, and measurements about the individual passenger behaviors inside the aircraft (seat interactions and baggage storage).

A. *Boarding Times*

In figure 34 the measurements of 282 boarding events at single aisle aircraft (Airbus 320, Boeing 737) are shown, with a minimum of 29 passengers (pax) and a maximum of 190 pax. Assuming a linear boarding progress, the boarding time increases for each passenger by 4.5 s with an additional offset of 2.3 min at average (bold regression line in fig. 3). If the boarding time only depends on the amount of passengers (no offset) a rate of 5.5 s/passenger has to be used (thin regression line in fig. 3). To derive a more sophisticated understanding of boarding times the boarding time t_B is weighted by the amount of passengers n_p, so the boarding rate is $t_{nB} = t_B/n_p$.

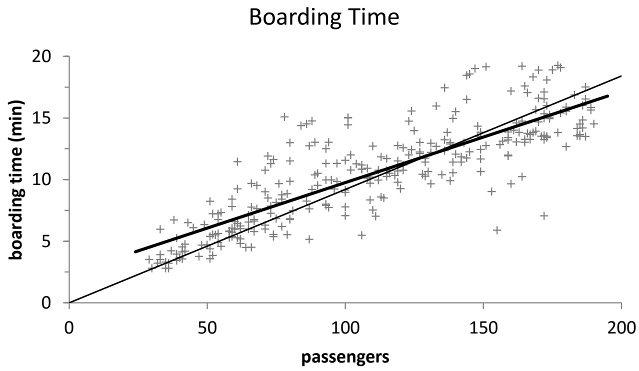

Figure 3. Boarding times (282 measured flights)

In a descriptive statistic summary, t_{nB} can be characterized by the following quantiles Q.10, Q.25, Q.50, Q.75, and Q.90 with values of 4.5 s/pax, 5.0 s/pax, 5.6 s/pax, 6.5 s/pax, and 8.0 s/pax respectively (positive skew). This descriptive summary points out that 80% of t_{nB} is in the range of 4.5s/pax and 8.0 s/pax (between Q.10 and Q.90). According to the median (Q.50 = 5.6 s/pax) this is a spread of the boarding time from -19% to +44%. For a detailed analysis the linear boarding progress is compared against the boarding measurements a Q-Q plot is used (see fig. 4). In a Q-Q plot the probability function of two distributions are compared using a diagonal line as a reference. If the two distribution are the (nearly) the same, all plotted points should be on this diagonal line. Comparing the expected (linear function with t_B = 5.5 s/pax * n_p) and the measured distribution of the boarding time, an entire linear correlation seems not to be a valid assumption.

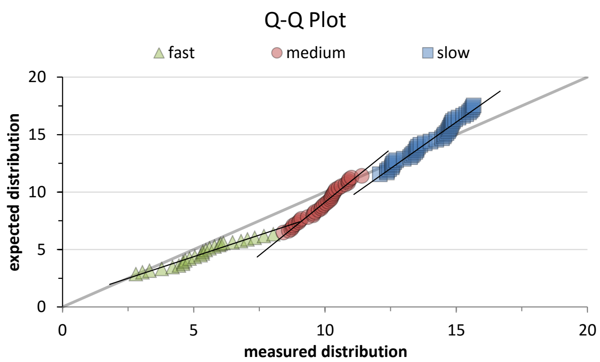

Figure 4. Q-Q plot of boarding time percentiles against a linear boarding progress with tnB = 5.5 s/pax

The Q-Q plot indicates a classification into three sectors: fast, medium, and slow boarding progress. In fig. 4 two prominent coordinates could be observed at 8.4 min and 12.1 min at the measured distribution. At 8.4 min the boarding time per passenger decreases after a section of a nearly constant rate and at 12.1 min an offset indicates a new section of boarding rate. If these values are used as section dividers, three sections with different boarding rates could be introduced. At fig. 5 the result of the classification is shown.

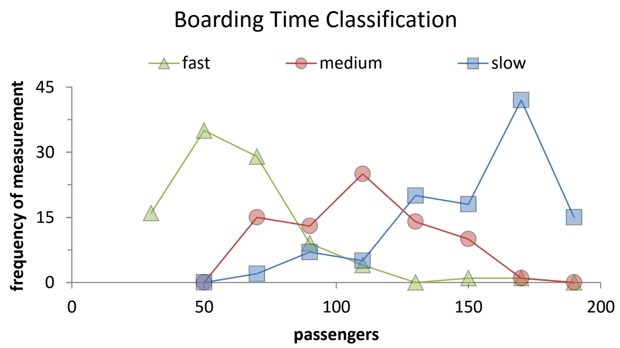

Figure 5. Boarding time classification (fast. medium. slow boarding progress).

On the left side the observed boarding times are separated according to the fast, medium and slow boarding progress. On the right side the characteristics regarding to the amount of passengers according to the classification is pointed out (95 measurement with fast, 78 with medium, and 109 with slow boarding rates). Following the initial approach of linear correlation between the amount of passengers and the boarding time (defined by slope and constant offset), the accompanied slope values are 1.0 s/pax, 1.2 s/pax, 2.2 s/pax and the constant offset are 12.3 min, 8.2 min, and 3.5 min respectively for the slow, medium and fast classification. In the following tab. I the results of the classification are summarized and exemplarily chosen to point out the consequence of using a common average for scenarios with 80, 110, 140, and 170 passengers. According to fig. 5, these scenarios consist a chance to be classified as boarding with fast, medium or slow progress. Depending on both the scenario and the classification the boarding time could accordingly deviate within a corridor of ± 5.3 min (170 pax: 15.0 min at slow, 9.7 min at fast).

TABLE I. BOARDING TIME USING DIFFERENT CLASSIFICATIONS OF LINEAR BEHAVIOR (SLOW, MEDIUM, FAST, AVERAGE)

	Boarding time (min)					
	pax / s	***offset (min)***	***passengers***			
			80	***110***	***140***	***170***
slow	1.0	12.3	13.6	14.0	14.5	15.0
medium	1.2	8.2	9.9	10.5	11.1	11.7
fast	2.2	3.5	6.4	7.5	8.6	9.7
average	5.5	0	7.3	10.1	12.8	15.6
*average	4.5	2.3	8.3	10.5	12.7	15.0

To emphasize the different boarding progress, three boarding scenarios are selected from the recorded data. These scenarios reflect one specific flight with nearly the same amount of passengers: 99, 104, 100 for scenario A, B, and C respectively (see fig. 6). Due to the different arrival of passengers, the boarding is completed after 7 minutes at scenario A, after 11 minutes at scenario B, and after 15 minutes at scenario C. Obviously, late passengers will significantly extend the boarding process (scenario C). But also a (constant) lower arrival rate of passengers at the aircraft impacts the boarding progress negatively.

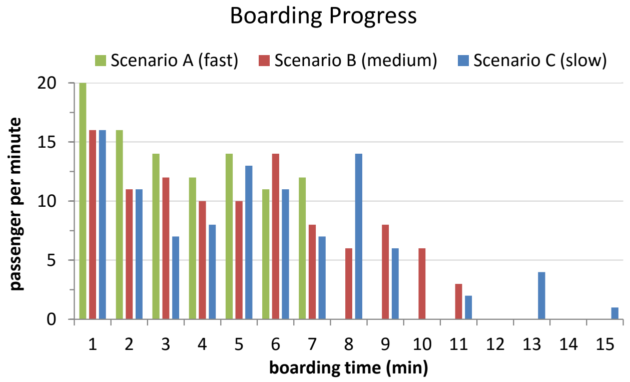

Figure 6. Boarding progress at different recorded scenarios

The arrival rate of passengers at the aircraft is mainly triggered by the presence of passengers at the boarding gate and the service rate at boarding card control. As a consequence, an airline should balance the effort/benefit ratio between introducing new boarding procedures and faster dispatch/ higher availability of passengers at the boarding gate.

B. Boarding and Deboarding Rates

As already shown in fig. 6 the arrival of passengers at the aircraft mainly drives the boarding time. In the recorded data 188 flights are available for an analysis of the arrival time at boarding and 186 flights for deboarding in a higher level of detail. Fig. 7 points out that the arrival rate is not constant over the time: the arrival rate decreases during the boarding progress. This behavior is shown by using the 25%, 50%, and 75% quantiles (Q.25, median, and Q.75), the mean value (μ) and the rates of covered flights (after 10 min approx. 50% of flights already completed their boarding, right scale).

In the first minute 14 pax/min arrive the aircraft (median value) with Q.25 = 12 pax/min and Q.75 = 18 pax/min. These ratios decrease to 3 pax/min, 6 pax/min, and 11 pax/min in the 17th minute for Q.25, median, and Q.75 respectively. At this time the boarding is finished at 91% of all recorded flights finished. The remaining data possess only a limited significance (only few samples per time period) and are not included in fig. 6.

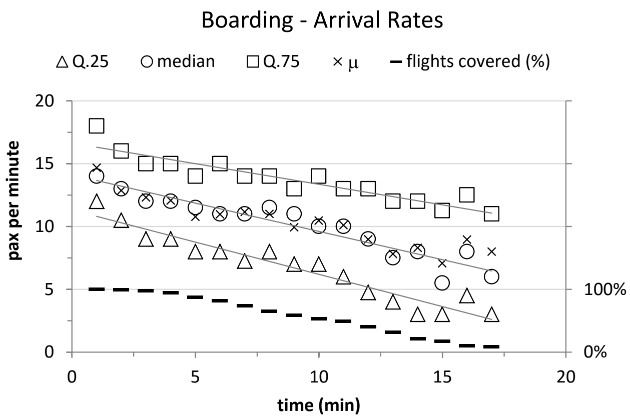

Figure 7. Decrease of the arrival rates during aircraft boarding

The linear lines for in Q.25, median, and Q.75 in fig. 6 emphasize the declining trend and the increasing spread of the arrival rates. If the median is used as a reference with a linear behavior, the arrival rate decreases by 0.45 pax/min starting at 14.1 pax/min.

An in-depth analysis of interarrival times (the times between successive arrivals) provides an additional approach to cover the individual passenger behavior during the arrival process. In the context of airport operations many processes could be mathematically described using a queuing theory approach. This is caused by the nature of the specific handling processes, which are typically structured by sequential/parallel services. Following the queuing approach, the passenger arrival at the aircraft door can be modelled as M/M/1 queue with a single server and exponential distributed arrival times. As a consequence the arrivals will be defined by a Poisson process.

The cumulative distribution function of the exponential distribution is given by (1) where λ is the rate parameter defined by $\lambda = 1 / \mu_{\text{interarrival time}}$.

$$F(x;\lambda) = \begin{cases} 1 - e^{-\lambda x} & x \geq 0, \\ 0 & x < 0. \end{cases} \tag{1}$$

The corresponding cumulative distribution function of the Poisson distribution is given by (2) where in this case the rate parameter λ is defined as the reciprocal value of the average amount of passengers expected in a given time interval.

$$F(x,\lambda) = e^{-\lambda} \sum_{i=0}^{k} \frac{\lambda^i}{i!} \tag{2}$$

To confirm the M/M/1 approach the inter-arrival times of 128 passengers are recorded and evaluated. The results of the evaluation are shown at fig. 8, where the inter-arrival times are clustered in intervals of 5 seconds. An appropriate fitting of the measured values is achieved with an exponential distribution using $\mu_{\text{interarrival time}} = 3.7$ s, which results in a chi-squared test value of 0.64 (acceptance level of 14.07, using significance level of 5% and 7 degrees of freedom).

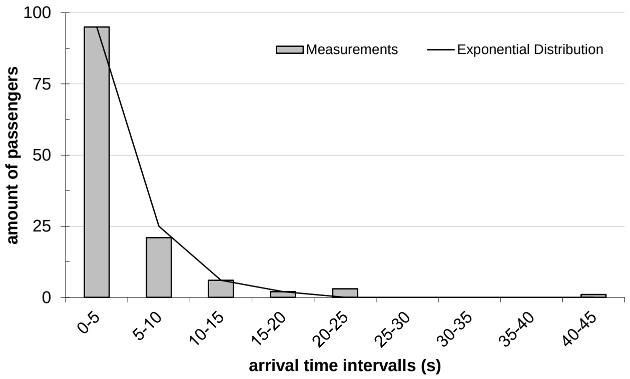

Figure 8. Interarrival times clustered in 5 s intervals

Using this quite good fitting result for the interarrival times as a basis, the corresponding Poisson distribution is shown in fig. 9. The λ value of 0.74 is calculated by 3.7 s average interarrival time divided by a 5 s interval (reciprocal value of 1.35 average passenger arrivals in the 5 s interval). As fig. 9 qualitatively emphasizes, the associated Poisson distribution with a chi-squared test value of 67.2 is not an appropriate candidate to describe the measured data (acceptance level of 11.07 using significance level of 5% and 5 degrees of freedom).

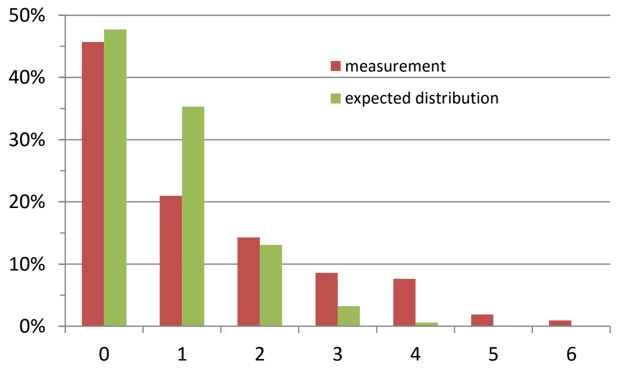

Figure 9. Expected arrivals in a 5 s interval

Whereas the probability of 0 arrivals and 2 per interval corresponds to the Poisson distribution, the arrival of 1 pax per interval indicates a much higher probability and lower probabilities for more than 2 arrivals regarding to the recorded dataset. Fig. 9 points out that the observed groups of passengers in the airport terminal (cf.[1][17]) also influencing the boarding process. Further on it points out the limitation of the standard queueing theory (non-group arrival is required) in the context of passenger arrivals (also see group extension of M/M/1 approach [Zhu1991]).

The analysis of the deboarding regarding to the measured outflow rates will only focus on the aggregated flow rate level. In contrast to the boarding process, the outflow rates at the deboarding start are significantly higher level with 18 pax/min, 23 pax/min, and 29 pax/min for Q.25, median, and Q.75 respectively (see fig. 10).

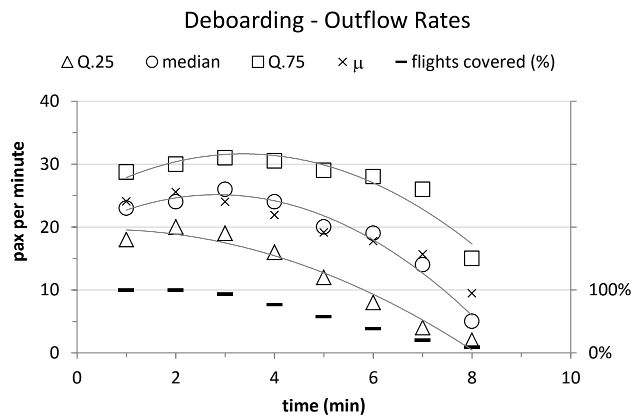

Figure 10. Outflow rates from the aircraft during the deboarding

The outflow rate increases at the first three minutes. After 8 min at 91% of the recorded flights, the deboarding is finished (this level was reached after 17 min at the boarding, so deboarding is 53% faster than boarding).

C. Seat Interactions

Regarding to the possible conditions of the seat rows, a different amount of time to coordinate the positions changes (seat shuffle) is need. In the worst case, the aisle and the middle seat are already used and the arriving passenger wants to seat at the window seat. For this constellation 9 movements are need for stepping out of the row, (re) enter the row and unblock the aisle. The other seat occupation patterns demand for 4 (aisle seat blocked) and 5 movements (center seat is block and windows seat is the target). If the passenger can enter his seat without any interference, the time for enter the seat row is defined with 1 movement. The characteristics of the accompanied time need to finally unblock the aisle are shown in fig. 11. The gray color indicate the measurement the green color the results of the modeled distribution [18]. Further on, the colored area represents 50% of all values (measured or calculated) bounded by the accompanied Q.25 and Q.75 quantiles. Around these colored areas additional areas are defined by bars to cover 80% of all values (with Q.10, Q.90).

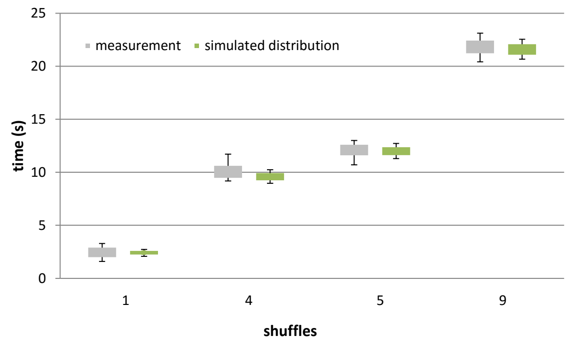

Figure 11. Seat interferrence: measurement vs simulation

During the field trials only a minor quantity of specific movements could be recorded (between 10 and 15 measures per category). This is mainly caused by the observation position at the front/back door of the aircraft, the unpredictable seating progress of a specific row and the ability to clearly define start and end of the seating process. As a consequence, the observers could only concentrate to a limited set of seat rows. However, the recorded measurements qualitatively confirm the proposed model to calculate the time need to unblock the aisle. As a side note, the cabin crews approve the order of magnitude of the gathered data as well, but point out that specific events during the boarding regularly disturb the progress. But these events will not be covered in the model. Considering both, the minor quantity of measurements and the same order of magnitude of the results, the initial distribution for the seat shuffle points out to be an acceptable approach and will be still used in the following simulations.

D. Baggage Storage

The baggage storage process is parameterized by the time to store one piece and the individual amount of baggage pieces.

During the field trials 323 values are manually recorded. The record starts by the time the passenger reaches his seat row and finishes if the passenger enters the set row. To mathematically fit the measurements the Weibull distribution is used (3) with the scale parameter α and the shape parameter β. Since the minimum time x_{min} to store the baggage is zero no offset is needed to derive the distribution parameter ($x_{min} = 0$).

$$F(x, \alpha, \beta, x_{min}) = 1 - e^{-\left(\frac{x - x_{min}}{\beta}\right)^{\alpha}} \tag{3}$$

With the parameter α = 1.7 and β = 16.0 s the Weibull distribution points out an appropriate level of correlation with a chi-squared test value of 3.65 (acceptance level of 12.6. using significance level of 5% and 6 degrees of freedom). The prior used triangular distribution (see [18]) describes the qualitatively the shape of the recorded data, but over estimates the time for the baggage storage. The expected average time to store the baggage is 13.9 s for the recorded data and 17.5 s for the triangular distribution. At fig. 12 the recorded data, the results of the fitted Weibull distribution and the prior used triangular distribution are shown. In the first section (0-5 s) the triangular distribution indicates no values, where the recorded data indicate a probability of 12 %. The sections 10-15 s, 20-25 s, and 25-30 s point out a deviation of 5 % at average.

As a result of this analysis, further simulations will use the derived Weibull distribution with the parameter set α = 1.7 and β = 16.0 s.

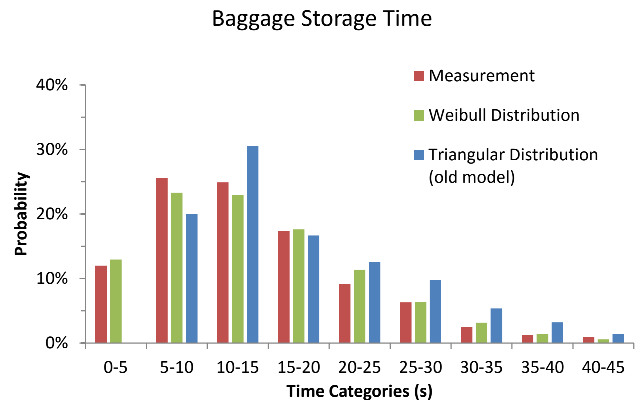

Figure 12. Measurements of baggage storage times

III. SIMULATION

A. Validation of prior Results

Since the field measurements of the specific sub processes of the boarding are analyzed in detail and used to calibrate the simulation environment, the validity of the prior simulation results will be checked (see [18]). For this purpose the additional input parameter are seat load factor (85%) and passenger conformance rate according to the assigned seat (85%). The *random* strategy is used as baseline but with the calibrated input values, the boarding time and the standard deviation changes. So the calibrated *random* strategy is 8.4% faster accompanied with a 5.9% lower standard deviation. The following table II points out that the differences of the boarding times between non-calibrated and calibrated simulation runs are not significant (< 1.5%). As all strategies show a minor improvement, the relative order of the strategies is still valid. As it was expected, the standard deviations of the boarding strategies increase, caused by a higher bandwidth of the baggage distribution and the non-constant arrival distribution observed in the field.

TABLE II. COMPARISSON OF BOARDING PROGRESS USING REAL DATA FOR CALIBRATION

Boarding Strategies		**Boarding time (%)**			
		random	***outside-in***	***back-to-front***	***block***
1 door		100.0	80.9	110.5	96.2
	real	100.0	79.5	109.2	95.3
2 doors		74.2	63.8	75.3	76.2
	real	74.1	62.5	75.0	76.2
		Standard Deviation (%)			
1 door		7.1	5.5	7.9	6.6
	real	7.3	5.7	8.1	6.9
2 doors		4.6	2.9	4.8	5.3
	real	5.9	5.5	5.9	5.5

IV. MEASUREMENTS VS SIMULATION

A. Airline Trials 1

Field measurements with an Airline focusing on efficient boarding to ensure a convenient boarding procedure accompanied with a faster progress. A new strategy was developed and tested to emphasize the operational benefits under operational condition. Beside the common approach of group boarding (*back-to-front* with 4 blocks, airline-S1 in fig. 13) a new *outside-in* strategy was developed (airline-S2 in fig. 13) to figure out potential operational benefits.

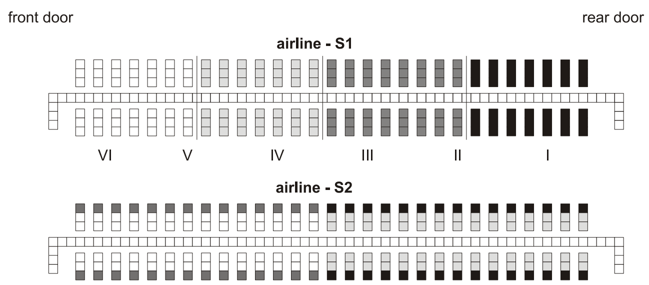

Figure 13. Airline boarding strategies for validation trials

These measurements are conducted in 2014 aiming at business routes with the following restrictions: families were not separated, aircraft at gate position, and A320/B738 aircraft. The average seat load factor of the 13 recorded flights was 76%. Since the test based on non-operational strategies the boarding progress and group assignment was directly supported by the ground staff.

To allow for an internal comparison the airline linear normalized all results to a seat load factor of 90%. But, at the prior studies about the impact of the seat load factor on the boarding progress ([18]), it was emphasized that the *block* boarding strategy (including *back-to-front*) shows no linear behavior.

To allow a reliable comparison of the field trials with the simulation results two approaches are used. The first simulation trial starts with a seat load factor of 90% and the second trial starts with 76% SLF with an equal distributed variation of ±5% to cover the expected deviation from the average load. All simulation uses the validated values for arrival times, seat interaction, and baggage storage from section II.

The results of the simulation runs are listed in the following tab. III, where the simulation results consist of mean values and standard deviation (SD) of the boarding time as well as a five-number-summary of the boarding time distribution (Quantiles: Q.10, Q.25, Q.50, Q.75, Q.90). At the first scenario with 90% SLF, the baseline boarding strategy (*random*) points out only minor differences (1%) and the *outside-in* strategy also indicate a reliable simulation approach (4% difference). A different picture is given at the *back-to-front* strategy, where the simulated boarding times are 12% higher than the measured times at the field trials.

Considering scaling to 90% SLF, the measured boarding times are linearly (re-) scaled down to the initial average SLF of 76% and additionally simulated with an assumed equal distributed variation of ±5% to cover the assumed operational bandwidth. This second approach results in an appropriate consistency of field measurements and simulation results. The differences of the *random* and *outside-in* strategies are slightly increased but now, the *back-to-front* strategy shows the same order of magnitude.

As a side note, the tested *outside-in* could result in faster boarding times, if the 4 blocks are aggregated to 3 blocks (see fig. 13, combining the two gray blocks to one gray block). This strategy **outside-in* leads to additional improvement of approx. 3% boarding time and 0.6% standard deviation.

TABLE III. COMPARISSON OF BOARDING PROGRESS USING REAL DATA FOR CALIBRATION

Boarding Strategies	**Boarding time (%)**							**SD (%)**
	data	***sim.***	***diff.***	***Q.10***	***Q.25***	***Q.75***	***Q.90***	***sim.***
random	101.4	100.0	*1.4*	-8.6	-4.6	4.9	9.5	7.0
back-to-front	93.7	104.5	*-10.8*	-9.3	-5.1	5.2	10.2	7.5
outside-in	87.0	83.8	*3.2*	-7.4	-4.0	4.4	8.4	6.2
**outside-in*		80.5						5.6
	Seat Load Factor 76% ± 5%							
random	102.6	100.0	2.6	-10.6	-5.7	6.2	11.8	8.7
back-to-front	94.8	98.7	-3.9	-11.5	-6.3	6.6	12.7	9.4
outside-in	88.0	83.4	4.6	-8.9	-4.8	5.2	10.2	7.4
**outside-in*		80.8						6.8

Finally, the simulation runs using the calibrated values and cover the observed boarding times at the field. The observed times are within the ± 25% environment (between Q.25 and Q.75) which emphasizes the validity of the developed model.

B. *Airline Trials 2*

During second airline trial 64 boarding progresses are recorded aiming at a deeper understanding of how passengers influence the boarding process. The particular trial mainly focusses on two strategies (*back-to-front* with 4 blocks and *outside-in*), two configurations (one door and two doors), and A320/B738 aircraft (180-210 seats). For the analysis the flights are separated by the seat load factor in three groups: A with 60%-80% (27 flights), B with 80%-90% (20 flights) and C with more than 90% (17 flights). Additionally, for each flight the aircraft position (remote, gate, apron), the categorization (tourist, EU, Germany) and the amount of pre-boarding passengers was recorded (see figure 14).

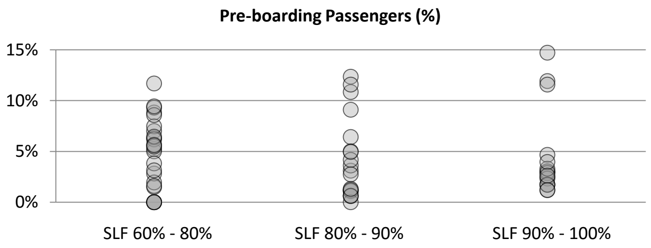

Figure 14. Amount of pre-boarding passengers

The position of the aircraft determines the mode of transfer: bus shuttle, gangway or walk boarding (see tab. IV).

TABLE IV. FLIGHT CLASSIFICATION

	Transfer Mode			**Destination**			
	bus	***gangway***	***walk***	***tourist***	***EU***	***Germany***	***no tag***
A	1	14	13	7	7	12	2
B	0	4	16	6	5	6	4
C	0	7	10	6	5	5	1

In contrast to the first measurement campaign the simulation results point out a different view. The recorded boarding times show high deviations which are not covered by the simulation results. In fig. 15 the simulation results are marked with circles with an error bar indicating the 10% and 80% quantile. The blue cross mark the *block* strategy (*back-to-front* with 4 blocks) and the red plus mark the *outside-in* strategy separated by one/door configuration.

In particular, the *outside-in* strategy is not showing the expected benefit. Due to the fact that there are several impact factors could influence the result (e.g. aircraft position or destination), the number of 64 recorded flights is not sufficient for a deeper analysis. As tab. IV shows, only the separation into destination or transfer mode leads to classes with less than 10 values.

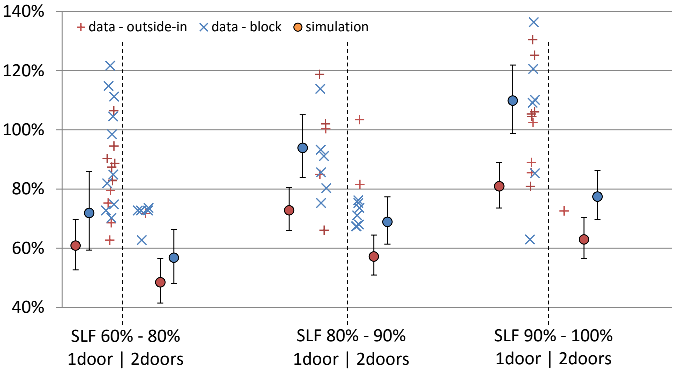

Figure 15. Comparission of simulation results and recorded boarding times

V. New Procedures and Infrastructure

At prior research the results of the B777 and A380 boarding confirm the general findings of the A320 analyses (cf. [18]), so only the A320 will be used for the following investigations. The first approach aims to analyze the impact if a 'no hand baggage' rule is applied by an airline or if passengers with a higher amount of baggage pieces have to board at the rear part of the aircraft. Secondly, a new seat design is focused, which changes the infrastructure of the aircraft by providing a wide aisle during the boarding. Finally, the minimal boarding time will be analyzed.

A. *Hand Baggage*

A frequently upcoming statement is that passengers with no hand baggage will immediately result in a faster boarding progress. The prior analysis mainly focusses on the sequence optimization to prevent unfavorable seat row states (see [18]). The amount of baggage was taken as an external parameter. Besides the negative impact on the individually perceived level of service and the need for parallel baggage loading process (in some circumstances additionally accompanied by a baggage check-in/out procedure), the potential savings in the boarding time will be addressed in this section. The initial approach assumed at least one piece of baggage per passenger and a probability rates for one piece, two pieces, and three pieces with 60%, 30%, and 10% respectively [18]. These values are taken as baseline with the aim to stepwise reduce the amount of baggage from 1.5 to 0 pieces per passenger on average (see tab. V).

TABLE V. Baggage Scenarios

	Scenarios (probability %)					
bags	***B1***	***B2***	***B3***	***B4***	***B5***	***B6***
0	0	15	30	50	70	100
1	60	55	50	40	30	0
2	30	25	20	10	0	0
3	10	5	0	0	0	0
avg. amount of bags	1.5	1.2	0.9	0.6	0.3	0.0

The proposed baggage scenarios are simulated using the default set of parameters (1 door configuration). In fig. 16 the achieved simulation results are shown. The *random* and *block* boarding nearly linearly benefit from the decreased amount of baggage pieces with a slope of 23.5% reduced boarding time per piece of bag. The *outside-in* boarding shows a declining behavior of the boarding time between 8.1% and 4.4 % changing from scenario B1 to B2 and B5 to B6 respectively.

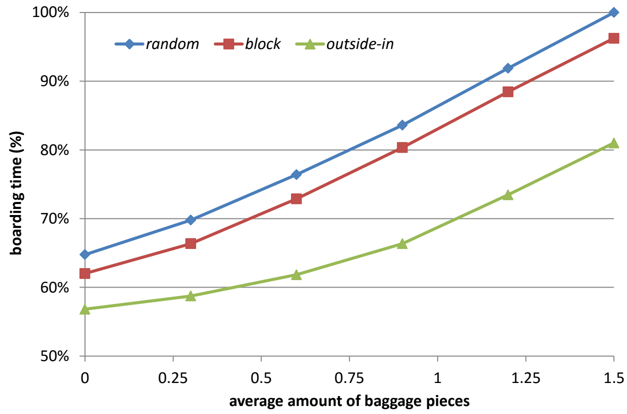

Figure 16. Reduction of hand baggage

Finally, if passengers have no baggage to store in the overhead compartments, the boarding time reach a minimum of 65% for *random*, 62% for *block* and 57% for *outside-in* boarding accompanied with a minimum variance of 2.9%, 2.6%, and 1.5%. Addressing an operational implementation the strict reduction to one piece per passenger could result in 5%-15% benefits (scenario S2 and S3) and the avoidance of suitcases (only allow few small bagpacks, shoulder bags, or similar) result in 20% - 25% benefits (scenario B4 and B5).

Beside the potential to reduce the amount of baggage pieces another boarding strategy regarding to the storage of baggage could be to reduce the negative impact to other passengers. All following passengers will be negatively influenced if the storage process of an individual passenger consumes a significant amount of time. The resulting waiting queues could be prevented or reduced to a minimum, if the passengers with a high amount of baggage pieces seat in the rear part of the aircraft. This strategy is a kind of *back-to-front* strategy, but not in terms of the passenger arrival sequence. A dedicated pricing strategy could be the precondition of this particular baggage distribution in the aircraft. Passengers seated in front of the airplane are only allowed to have one piece of hand baggage. If a passenger wants to have more than one, he has to seat in the rear part of the aircraft. The simulation runs points out the clear advantage if passengers are allocated according to their amount of baggage. The introduced boarding strategies benefit within a range of 6-9%.

B. *Minimum Boarding Time*

To determine the absolute minimum of the boarding time the *individual* strategy points out to be the right candidate. Using the prior introduced approach to minimize the time consuming baggage storage (no hand baggage will be allowed in the aircraft), the *individual* strategy results in a minimum of

55.1% boarding time and standard deviation of 1.4% (measured in units of *random* boarding time). A reliable indicator for the minimum boarding time is that the application of the second boarding door not results in further improvements (see tab. VI).

Reaching a minimum of the boarding time consequently demands for an overall picture of passenger process at the aircraft which includes the *deboarding* of the passengers as well. The *deboarding* process needs no arrival and conformance rates. As an assumption, each passenger picks his baggage using the same probability density function as for the storage process but with reduced values for the triangular distribution (4) {min, mode, max} with {2 s, 4 s, 6 s}.

$$F(t) = \begin{cases} \frac{(t-min)^2}{(max-min)(mode-min)}, \text{if } min \le t \le mode \\ 1 - \frac{(max-t)^2}{(max-min)(max-mode)}, \text{if } mode < t \le max. \end{cases} \quad (4)$$

This reduction reflects the normal behavior that passengers could take their baggage even if they are standing at their seats, accompanied with the fact that no additional time for baggage rearrangements at occupied overhead compartments are needed. Since the interaction between the passengers are reduced to a minimum (no seat interferences), only an additional rule regarding to the right of way between aisle and row movements has to be defined. Because there are no strong arguments for the prioritization of aisle or row movements, it is defined that passengers follow a balanced approach. This approach is implemented by an equally distributed choice of prioritization at each crossing of aisle and row. At tab. VI the boarding time and corresponding standard deviation is shown for the *individual* strategy [21] and for aircraft *deboarding*. An optimal flow is established, if during the *deboarding* no hand baggage is available.

TABLE VI. MINIMUM BOARDING TIME FOR BOARDING AND DEBOARDING

Boarding strategies	**Boarding time and standard deviation (%)**			
	1 door		***2 doors***	
	time	***SD***	***time***	***SD***
random	100.0	7.1	74.1	4.7
individual (no bags)	55.1	1.4	55.1	1.4
deboarding	43.0	2.4	23.8	1.6
deaboaring (no bags)	12.6	0	6.7	0

C. Side-Slip Seat

Standard approaches to fasten the boarding process mainly addresses to manage passenger behavior by generating boarding sequences or reducing the amount of baggage. In the prior evaluation the use of a second door the board the passenger could be understand as a significant change of the infrastructure. The most prominent effect on the boarding time is accompanied with a blocked aisle due to passengers storing baggage or entering their seat row. With the innovative approach of a side-slip seat [19], the available infrastructure could be dynamically changed to support the boarding process by providing an extra space to allow two passengers to pass each other in a convenient way. As fig. 17 points out, the aisle seat could be moved in the direction of the center seat. The aisle seat will be in the initial position until one passenger wants to access the center or aisle seat.

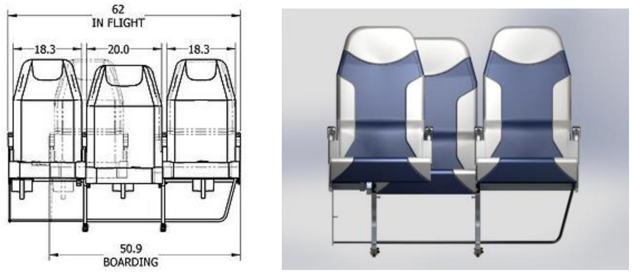

Figure 17. Infrastructural changes using a side-slip seat configuration [2]

The developed simulation environment has to be adapted to allow movements of two passengers along the aisle. Furthermore, the dynamic status of the seat row (folded/unfolded) is implemented to enable/disable the parallel movement of two passengers (see fig. 18). If both sides of the aisle are 'open', a second passenger can pass without reducing the speed. If only one side is 'open', the speed is reduced by 50%. If no side is 'open' only one passenger is allowed to move at the aisle. At fig. 18 the following passenger can pass the orange passenger on the left side, while the orange passenger store his belongings and take the seat (orange indicates that the passengers wants to take the window seat).

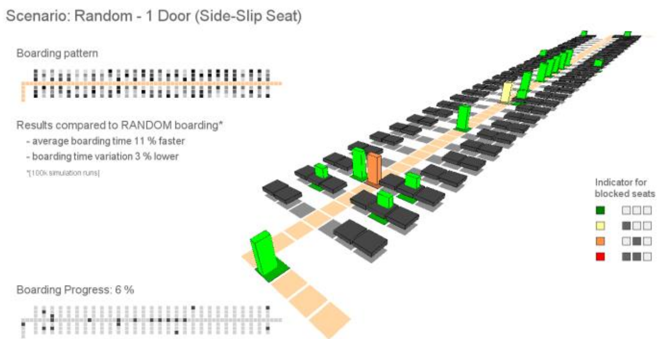

Figure 18. Modell extension to cover new side-slip seat operations [20]

To evaluate the benefit of the side-slip seat configuration, boarding strategies are analyzed using the default values for a one and two configuration. Each analyzed boarding strategy significantly benefit from this infrastructural change. The specific benefit reaches from 3.0% up to 15.0% reduced boarding time using one boarding door with regards to the boarding strategy without the side-slip seat. Since the use of the second door already realizes significant improvements of the boarding progress, the new seats enable additional benefits from 0.5% up to 6.4% reduction of the boarding time. The standard deviations of the boarding times are also positively affected by the new seat configuration.

The implementation of the side-slip seat holds the potential of additional boarding time savings of the order of 10% (one door configuration) accompanied with a reduced standard deviation. These savings are smaller, when the boarding strategy already possesses are higher degree of complexity (e.g. individual sequencing or use of two doors). It is expected that a combination of the side-slip technology in association with a less complex boarding strategy could reliably reduce the boarding time even under operational conditions.

VI. Outlook

The simulation environment and the aircraft boarding model are continuously developed. Currently more than 10 basic boarding strategies are implemented, which can be combined to new strategies (e.g. *block* + *alternation*, fig, 19) in different scenarios (e.g. procedure/technology changes, fig. 20).

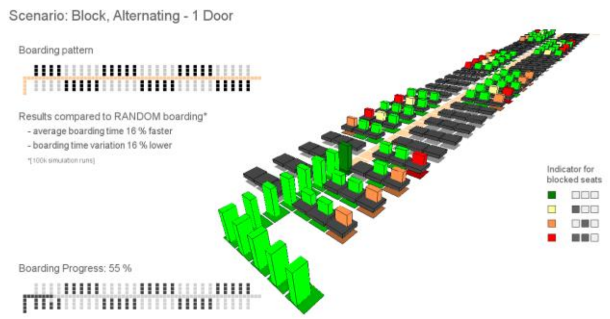

Figure 19. Combination of strategies (*block* + *alternation*)

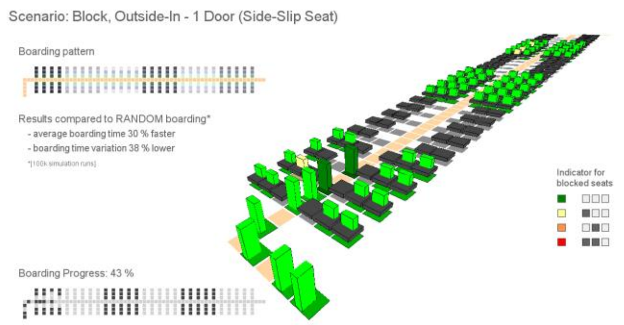

Figure 20. Combination of strategies and technologies (*block* + *ouside-in* + *side-slip seat*)

At standard PC hardware the simulation engine can calculate 100.000 simulation runs for one scenario in 2 min. Visualization and analysis modules are available for fast post-processing. In a next step, the gathered experience will be used in operational environments to develop dynamic approaches supporting airline and airport management systems.

Further on, the validation of different boarding strategies will be focused, but with a more specific level of detail. In this process the simulation are used as a pre-check environment to identify valuable operational scenarios.

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