Aircraft Boarding - Data, Validation, Analysis

Michael Schultz
Institute of Flight Guidance
German Aerospace Center
Braunschweig, Germany
michael.schultz@dlr.de

Abstract—Aircraft boarding is always on the critical path of the turnaround. Efficient boarding procedures have to consider both operational constraints and the individual passenger behaviour. In contrast to the handling processes of fuelling, catering and cleaning, the boarding process is mainly driven by the passenger and not by airport or airline employees. Models for evaluating boarding sequences mainly depend on assumptions concerning the individual passenger processes in the aircraft than on reliable field measurements. This paper provides a comprehensive set of operational data including classification of boarding times, passenger arrival times, time to store hand luggage, and passenger interactions as a fundamental basis for the calibration of boarding simulation models. In this paper, a microscopic approach is used to model the passenger behaviour, where the passenger movement is defined as a one-dimensional, stochastic, and time/space discrete transition process. This model is used to compare measurements from field trials of boarding procedures with simulation results and achieves an accuracy of ± 5%.

Keywords: boarding; simulation; field trials; validation; operational improvements

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. For aircraft boarding, a specific amount of passenger trajectories (path along handling stations and corresponding timestamps [1]) and the associated aircraft trajectory are 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 whole aircraft trajectory. During aircraft turnaround, the aircraft will be deboarded, cleaned, (un-) loaded, and refuelled. Finally, the passengers enter the aircraft. From an operational point of view, passenger boarding becomes 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 for compensating delays and providing a reliable basis for the operational planning procedure on the day of operations. From the airline perspective, the boarding process contains specific airline products (e.g. priority boarding, passenger convenience) which allow for a dedicated pricing strategy to improve the economic revenues of the airline.

This paper provides a fundamental dataset for calibrating models for aircraft boarding. In recent years, more than 400 flights were recorded with different level of details: passenger processes (e.g. store baggage, seating), arrival rates at the aircraft, and boarding time using different boarding strategies. The recorded data are systematically analysed 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 are compared against the field measurements.

A. Status quo

In the following section, a short overview concerning scientific research on aircraft boarding is given. This overview extends the modelling background already presented in [3].

A common goal of these simulation-based evaluations is to minimize the time that is required for passenger boarding. Taking into account different boarding patterns, a study by Van Landeghem and Beuselinck [4] investigates to what extent boarding time can be reduced by applying optimal versus current boarding strategies. A similar approach is made by Ferrari and Nagel [5] with special emphasis on disturbances, such as a certain number of passengers do not follow their boarding group but board earlier or later. The results show improved values for the typical back-to-front boarding in the case of passengers not boarding in their previously assigned boarding groups. In contrast, Bachmat and Elkin [6] support the classical back-to-front policy in comparison to random boarding strategy. A stochastic approach to cover both a stochastic behaviour model and operational constraints was developed by Schultz and Fricke [7]. The aircraft boarding model considers the amount of hand luggage, interarrival times, seat load factors, and passenger conformance to the provided boarding strategies.

On the basis of the individual boarding strategy proposed by Steffen [8], which considers the time a passenger needs to store baggage, the model developed by Milne and Kelly [9] assigns passengers to seats so that their hand luggage is distributed evenly throughout the plane. Chung [10] addresses the aircraft seating layout and indicates that alternative designs could significantly reduce the boarding time. A link between the efficiency of an airline’s boarding policies and the aircraft design parameters, such as distance between the rows, is given in a study by Bachmat et al. [11]. 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 [12].

Relevant studies concerning 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. [13] shows 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. [14] study all aircraft configurations and boarding group sizes. Results show that the 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. [15]. Based on an integer linear programming approach together with a genetic algorithm, they analyse different boarding strategies to assess the effectiveness of their model.

The interference of passengers when boarding an aircraft is in the focus of a study by Bazargan [16]. 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 the boarding process (e.g. occupied aisle) are also in the focus of a study by Frette and Hemmer [17] and Tang et al. [18]. Frette and Hemmer calculate the average boarding time with a dynamical model, assuming that all permutations of the amount of passengers have the same weight. Tang et al. concentrate on the passenger’s individual properties and apply this knowledge to their numerical model in order to evaluate the benefit of different boarding strategies. An experiment was performed by Steffen and Hotchkiss in a mock Boeing 757 [19]. They tested different boarding methods and described the potential savings for airline companies through reduced boarding times. Fuchte [20] focusses on the aircraft design and, in particular, the cabin modifications with regard to the efficiency of the resulting boarding process. Schmidt et al. [21] evaluate novel aircraft layout configurations and seating concepts for single- and twin-aisle aircraft with 180-300 seats.

The most scientific approaches do not reflect the operational conditions (e.g. seat load factor, conformance) or the non-deterministic nature of the underlying processes (e.g. amount of baggage). Furthermore, there is clear lack of reliable data from the aircraft operations and the passenger handling. Assumptions regarding the inner processes are often derived from simplified research environments or gathered in less realistic test setups. To bridge this gap, data from the field are manually recorded during the day of operations to calibrate the sub processes of a stochastic aircraft boarding model.

B. Model and Simulation

The proposed dynamic model for the boarding simulation is based on an asymmetric simple exclusion process (ASEP). The ASEP was successfully adapted to model the dynamic passenger behaviour in the airport terminal [1][22]. In this context, 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.

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 boarding 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 modelled 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 in following the current strategy (default: 85%). Further details regarding the model and the simulation environment are available in [3].

To model different boarding strategies, the grid-based approach enables both the individual assessment of seats and classification/aggregation according to the intended strategy. In Fig. 2, the seats are colour-coded (grey-scale) and aggregated to superior structures (blocks). The boarding takes place in the order of the grey-scale value.
The model does not address unruly behaviour or counterflow passenger movements which may arise from blocked overhead compartments or individual problems in finding the assigned seat. In particular, the problem of blocked overhead compartments could not be solved by operational strategies but with increased compartment capacity or a more restrict airline policy regarding to the amount of allowed hand luggage.

II. MEASUREMENTS AND CALIBRATION

This section will provide an overview of boarding times, boarding/deboarding rates, and measurements regarding the individual passenger behaviours inside the aircraft (seat interactions and baggage storage). Addressing the bilateral agreements with the concerned airlines and airports, the data sets are appropriately aggregated to be used in this research context. The data were manually and specifically recorded addressing the specific process to calibrate. This results in a high level of reliability, since each setup was controlled by the responsible examiner and contains additional descriptions of progress, setup and comments.

A. Boarding Times

In Fig. 3, the measurements of 282 boarding events for 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 on average (bold regression line in Fig. 3). In the simplest case, if the boarding time only depends on the amount of passengers (no offset), a rate of 5.5 s per 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 $t_{ab} = \frac{t_{B}}{n_{p}}$.

![Boarding Time](image)

Figure 3. Boarding times (282 measured flights)

In a descriptive statistic summary, $t_{ab}$ can be characterized by the following quantiles: Q10, Q25, Q50, Q75 and Q90 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 demonstrates that 80% of $t_{ab}$ is in the range of 4.5s/pax and 8.0 s/pax (between Q10 and Q90). According to the median (Q50 = 5.6 s/pax), this is a spread of the boarding time from -19% to +44%. For a detailed analysis, the assumed linear boarding time relation is compared against the boarding measurements; a Q-Q plot is used (see Fig. 4). In a Q-Q plot, the probability functions of two distributions are compared against each other. In the case of similarity, the data points converge to a 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 does not seem to be a valid assumption.

![Q-Q Plot](image)

Figure 4. Q-Q plot of boarding time percentiles against a linear boarding progress with $t_{B} = 5.5$ 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 in 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 can be introduced. In Fig. 5, the result of the classification is shown.

![Boarding Time Classification](image)

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

On the left side, the observed boarding times are separated according to a fast, medium and slow boarding progress. On the right side, the characteristics regarding the amount of passengers according to the classification are shown (95 measurements 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 and 2.2 s/pax and the constant offsets are 12.3 min, 8.2 min and 3.5 min for the slow,
medium and fast classification respectively. 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 of 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 in the slow category and 9.7 min in the fast category).

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

<table>
<thead>
<tr>
<th>boarding time (min)</th>
<th>pax / s</th>
<th>offset (min)</th>
<th>passengers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>80</td>
<td>110</td>
</tr>
<tr>
<td>slow</td>
<td>1.0</td>
<td>12.3</td>
<td>13.6</td>
</tr>
<tr>
<td>medium</td>
<td>1.2</td>
<td>8.2</td>
<td>9.9</td>
</tr>
<tr>
<td>fast</td>
<td>2.2</td>
<td>3.5</td>
<td>6.4</td>
</tr>
<tr>
<td>average</td>
<td>5.5</td>
<td>0</td>
<td>7.3</td>
</tr>
<tr>
<td>*average</td>
<td>4.5</td>
<td>2.3</td>
<td>8.3</td>
</tr>
</tbody>
</table>

To emphasize the different boarding progresses, three boarding scenarios are selected from the recorded data. These scenarios reflect a single specific flight with nearly the same number of passengers: 99, 104 and 100 for scenarios A, B, and C with fast, medium and slow arrival behaviour respectively (see Fig. 6). Due to the different passenger’s arrival times, boarding is completed after 7 minutes in scenario A, after 11 minutes in scenario B and after 15 minutes in scenario C. Obviously, late passengers will significantly extend the boarding process (scenario C). However, a (constant) lower arrival rate of passengers at the aircraft also affects the boarding progress adversely.

![Boarding progress in different recorded scenarios](image)

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 effectively 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 demonstrates that the arrival rate is not constant over the time: the arrival rate decreases during the boarding process. This behaviour 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 at 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 in 91% of all recorded flights. The remaining data possess only a limited significance (only a few samples per time period) and are not included in Fig. 6.

![Decrease of the arrival rates during aircraft boarding](image)

The straight lines of the Q.25, median and Q.75 value in Fig. 6 emphasize a declining trend and the increasing spread of the arrival rates. If the median is used as a reference with a linear behaviour, 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 covering the individual passenger behaviour 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 exponentially distributed arrival times. As a consequence, the arrivals are 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 \( \lambda = 1 / \mu_{	ext{interarrival time}} \).

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

(1)
The corresponding cumulative distribution function of the Poisson distribution is given by (2) where, in this case, the rate parameter \( \lambda \) is defined as the reciprocal value of the average amount of passengers expected in a given time interval.

\[
F(x, \lambda) = e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!}
\]

(2)

To confirm the M/M/1 approach, the interarrival times of 128 passengers are recorded and evaluated. The results of the evaluation are shown in Fig. 8, where the interarrival times are clustered in intervals of 5 seconds. An appropriate fitting of the measured values is achieved with an exponential distribution using \( \mu_{\text{interarrival time}} = 3.7 \text{ s} \), 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).

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 with regard to the recorded dataset. Fig. 9 shows that the observed groups of passengers in the airport terminal (cf.[1][22]) also influence the boarding process. Furthermore, it indicates the limitation of the standard queueing theory (non-group arrival is required) in the context of passenger arrivals (see also group extension of M/M/1 approach [Zhu1991]).

The analysis of deboarding with regard to the measured outflow rates focuses on the aggregated flow rate level. In contrast to the boarding process, the outflow rates at the beginning of deboarding are significantly higher than during the boarding process (18 pax/min, 23 pax/min and 29 pax/min for Q.25, median and Q.75 values respectively, see Fig. 10).

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

C. Seat Interactions

The chronological order of occupying the seat rows affects the boarding time, because of the required coordination of position changes (seat shuffle). In the worst case, the aisle and the middle seats are already occupied and the arriving passenger wants to sit in the window seat. For this constellation, 9 movements are necessary for stepping out of the row, (re-) entering the row and unblocking the aisle. The other seat occupation patterns demand 4 (aisle seat blocked) and 5 movements (middle seat is blocked and window seat is the target). If the passenger can enter his seat without any interference, the time for entering the seat row is defined with 1 movement.

The characteristics of the accompanied time required to finally unblock the aisle are shown in Fig. 11, where grey and black bars indicate the measurement and the results of the modelled distribution respectively [3]. Furthermore, the coloured area represents 50% of all values (measured or calculated) bounded by the accompanied Q.25 and Q.75 quantiles. Around these coloured areas, additional areas are defined by bars to cover 80% of all values (with Q.10, Q.90).
During the field trials, only a minor quantity of specific movements could be recorded (between 10 and 15 measurements 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 on a limited set of seat rows.

However, the recorded measurements qualitatively confirm the proposed model as regards calculating the time required 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 boarding regularly disturb the progress. These events are not covered in the model. Considering both the minor quantity of measurements and the same order of magnitude of the results, the initial distribution of the seat shuffle would appear to be an acceptable approach and will be 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. The prior approach to modelling the time needed to store the hand luggage was based on a triangular distribution (3) with time values for the minimum, maximum and mode for storing one piece of baggage as well as a distribution of the hand luggage per passenger [3].

\[
F(t) = \begin{cases} 
\frac{(t-min)}{(max-min)(mode-min)} & \text{if } min \leq t \leq mode \\
1 - \frac{(max-t)}{(max-min)(max-mode)} & \text{if } mode < t \leq max.
\end{cases}
\]  

(3)

During the field trials, 323 values are manually recorded. The recording starts at the time the passenger reaches his seat row and ends when the passenger enters the set row. To mathematically fit the measurements, the Weibull distribution is used (4) with the scale parameter \( \alpha \) and the shape parameter \( \beta \). Since the minimum time \( x_{\text{min}} \) to store the baggage is zero, no offset is required to derive the distribution parameter \( x_{\text{min}} = 0 \).

\[
F(x, \alpha, \beta, x_{\text{min}}) = 1 - \left(\frac{x - x_{\text{min}}}{\beta}\right)^{\frac{1}{\alpha}}
\]  

(4)

With the parameter \( \alpha = 1.7 \) and \( \beta = 16.0 \) s, the Weibull distribution demonstrates 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). Although the previously used triangular distribution (see [3]) qualitatively describes the shape of the recorded data, it over-estimates the time for the baggage storage. The expected average time for storing the baggage is 13.9 s for the recorded data and 17.5 s for the triangular distribution. In Fig. 12, the recorded data, the results of the fitted Weibull distribution and the probability values of the previously used triangular distribution are shown.

![Figure 11. Seat interference: measurement vs simulation](image)

![Figure 12. Measurements of times needed to store the hand luggage](image)

In the first section (0-5 s), the triangular distribution indicates no values, whereas the recorded data indicate a probability of 12%. The sections 10-15 s, 20-25 s and 25-30 s exhibit a deviation of 5% on average. As a result of this analysis, further simulations will use the derived Weibull distribution with the parameter set \( \alpha = 1.7 \) and \( \beta = 16.0 \) s.

E. Simulation - Validation of Prior Results

Since the field measurements of the specific sub-processes of boarding are analysed in detail and used to calibrate the simulation environment, the validity of the prior simulation results will be checked (see [3]). For this purpose, the additional input parameters 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. The calibrated random strategy is therefore 8.4% faster accompanied with a 5.9% lower standard deviation. The following Table II demonstrates that the differences in 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 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.
III. FIELD TRIALS VS. SIMULATION

The previous chapter was aimed at the validation of the simulation environment through the calibration of the sub-processes of the boarding model. In a next step, the calibrated simulation environment is used to simulate whole boarding scenarios which were set up in operational field trials. The first airline trial evaluates the performance of two advanced boarding scenarios as a proof of concept. The second trial extends the initial concept and integrates the boarding scenarios into the airline operations, which cover different seat loads and the use of one/two doors.

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

<table>
<thead>
<tr>
<th>Boarding Strategies</th>
<th>random</th>
<th>outside-in</th>
<th>back-to-front</th>
<th>block</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 door</td>
<td>100.0</td>
<td>80.9</td>
<td>110.5</td>
<td>96.2</td>
</tr>
<tr>
<td>calibrated</td>
<td>100.0</td>
<td>79.5</td>
<td>109.2</td>
<td>95.3</td>
</tr>
<tr>
<td>2 doors</td>
<td>74.2</td>
<td>63.8</td>
<td>75.3</td>
<td>76.2</td>
</tr>
<tr>
<td>calibrated</td>
<td>74.1</td>
<td>62.5</td>
<td>75.0</td>
<td>76.2</td>
</tr>
<tr>
<td>standard deviation (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 door</td>
<td>7.1</td>
<td>5.5</td>
<td>7.9</td>
<td>6.6</td>
</tr>
<tr>
<td>calibrated</td>
<td>7.3</td>
<td>5.7</td>
<td>8.1</td>
<td>6.9</td>
</tr>
<tr>
<td>2 doors</td>
<td>4.6</td>
<td>2.9</td>
<td>4.8</td>
<td>5.3</td>
</tr>
<tr>
<td>calibrated</td>
<td>5.9</td>
<td>5.5</td>
<td>5.9</td>
<td>5.8</td>
</tr>
</tbody>
</table>

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 realized savings under operational conditions. Besides the common approach of group boarding (back-to-front with four blocks, airline - S1 in Fig. 13), a new outside-in strategy was tested (airline - S2 in Fig. 13) to determine potential operational benefits.

![Figure 13. Airline boarding strategies for validation trials](image)

These measurements were conducted in 2014, aiming at business routes with the following restrictions: families are not separated, the aircraft stands at gate position, and an A320/B738 aircraft is used. The average seat load factor of the 13 recorded flights was 76%. Since the test is based on non-operational strategies, the boarding progress and group assignment were directly supported by the ground staff. To allow for an internal comparison, the airline linearly normalized all results to a seat load factor of 90%. In prior studies of the impact of the seat load factor on the boarding progress [3], it was emphasized that the block boarding strategy (including back-to-front) shows a nonlinear behaviour.

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 simulations use the validated values for arrival times, seat interaction, and baggage storage from section 0. The results of the simulation runs are listed in the following Tab. III, where mean values and standard deviation (SD) of the boarding time as well as a five-number-summary of the boarding time distribution are shown (Quantiles: Q.10, Q.25, Q.50, Q.75, Q.90). In the first scenario with 90% SLF, the baseline boarding strategy (random) exhibits only minor differences (1%) and the airline - S2 strategy also indicates a reliable simulation approach (4% difference).

A different picture is given for the airline - S1 strategy, where the simulated boarding times are 12% higher than the measured times at the field trials. Considering a 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 airline - S2 strategies are slightly increased, but now the airline - S1 strategy shows the same order of magnitude.

As a side note, the tested airline - S2 could result in faster boarding times, if the 4 blocks are aggregated to 3 blocks (see Fig. 13, combining the two grey blocks to one grey block – window seats in the front and middle/aisle seats in the back). This strategy *airline - S2 leads to an additional improvement of approx. 3% boarding time and 0.6% standard deviation.

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

<table>
<thead>
<tr>
<th>Boarding Strategies</th>
<th>data</th>
<th>sim.</th>
<th>diff.</th>
<th>Q.10</th>
<th>Q.25</th>
<th>Q.75</th>
<th>Q.90</th>
</tr>
</thead>
<tbody>
<tr>
<td>random</td>
<td>101.4</td>
<td>100.0</td>
<td>1.4</td>
<td>-8.6</td>
<td>-4.6</td>
<td>4.9</td>
<td>9.5</td>
</tr>
<tr>
<td>airline - S1</td>
<td>93.7</td>
<td>104.5</td>
<td>-10.8</td>
<td>-9.3</td>
<td>-5.1</td>
<td>5.2</td>
<td>10.2</td>
</tr>
<tr>
<td>airline - S2</td>
<td>87.0</td>
<td>83.8</td>
<td>3.2</td>
<td>-7.4</td>
<td>-4.0</td>
<td>4.4</td>
<td>8.4</td>
</tr>
<tr>
<td>*airline - S2</td>
<td>80.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Seat Load Factor 76% ± 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>random</td>
</tr>
<tr>
<td>airline - S1</td>
</tr>
<tr>
<td>airline - S2</td>
</tr>
<tr>
<td>*airline - S2</td>
</tr>
</tbody>
</table>

Finally, the results of simulation runs with the calibrated values 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 the second airline trial, 64 boarding progresses are recorded, aiming at a deeper understanding on how passengers influence the boarding process. The particular trial mainly focusses on two strategies (airline - S1 with 4 blocks and airline - S2), 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 categorisation (tourist, EU, Germany) and the amount of pre-boarding passengers are recorded (see Figure 14).

![Figure 14. Amount of pre-boarding passengers](image)

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

<table>
<thead>
<tr>
<th>Transfer Mode</th>
<th>Destination</th>
</tr>
</thead>
<tbody>
<tr>
<td>bus</td>
<td>gangway</td>
</tr>
<tr>
<td>A</td>
<td>1</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
</tr>
<tr>
<td>C</td>
<td>0</td>
</tr>
</tbody>
</table>

In contrast to the first measurement campaign, the simulation results present 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 crosses mark the block strategy (airline - S1 with 4 blocks) and the red plus signs mark the airline - S2 strategy separated by one door/two door configuration. In particular, the airline - S2 (outside-in) strategy does not show the expected benefit. Due to the fact that several impact factors could influence the result (e.g. aircraft position or destination), the quantity of 64 recorded flights is insufficient for a deeper analysis. As Tab. IV shows, only the separation into destination or transfer mode leads to classes with less than ten values.

![Figure 15. Comparison of simulation results and recorded boarding times using the tested block (airline - S1) and outside-in (airline - S2) boarding strategies](image)

IV. Conclusion and Outlook

This paper provides a comprehensive set of operational data including classification of boarding times, passenger arrival times, time to store hand luggage, and passenger interactions as a fundamental basis for the calibration of boarding simulation models. The recorded field data are used to calibrate the (sub) processes of the stochastic aircraft boarding model, which finally results in a model accuracy of ±5% (maximum difference between measured and simulated boarding times).

The simulation environment and the aircraft boarding model are being continuously developed in order to enable both scientific and operational assessments of aircraft boarding scenarios. In the context of specific research projects, the simulation environment is extended with evolutionary algorithms to search for optimal strategies under certain airline requirements.

In close co-operation with Eurowings, a new operational concept is being developed to significantly improve aircraft boarding. In this context, the validated aircraft boarding model is used to prove the initial concept. In a next step, this proven concept will be tested in an operational environment (A319) at Cologne Bonn Airport (EDDK).

REFERENCES