[EN-A-011] Reliable Aircraft Boarding for Fast Turnarounds

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Abstract: This paper provides an overview about the research done in the field of aircraft boarding focusing on fast and reliable progress. Since future 4D aircraft trajectories demand the comprehensive consideration of environmental, economic, and operational constraints, a reliable prediction of all aircraft-related processes along the specific trajectories is essential for punctual operations. The necessary change to an air-to-air perspective, with a specific focus on the ground operations, will provide key elements for complying with the challenges over the day of operations. Mutual interdependencies between airports result in system-wide, far-reaching effects (reactionary delays). The ground trajectory of an aircraft primarily consists of the handling processes at the stand (deboarding, catering, fueling, cleaning, boarding, unloading, and loading), which are defined as the aircraft turnaround. To provide a reliable prediction of the turnaround, the critical path of processes has to be managed in a sustainable manner. The turnaround processes are mainly controlled by the ground handling, airport or airline staff, except the aircraft boarding, which is driven by the passengers' experience and willingness or ability to follow the proposed procedures. In this paper a reliable, validated, stochastic aircraft boarding model is introduced, as well as results from three different research activities: application of Side-Slip Seat, interference potential as metric to evaluate the boarding progress, and capabilities of a future connected cabin.

Keywords: aircraft boarding, ground handling, validation, optimization, infrastructure, connected cabin

1. INTRODUCTION

ICAO provides with the Aviation System Block Upgrades (ASBU) a timeline to implement efficient flight paths by full 4D trajectory-based operations (ICAO, 2013). In the ASBU Block 0 (available) improved airport operation through Airport Collaborative Decision Making (A-CDM, Eurocontrol/IATA/ACI, 2014) are a mandatory element. The A-CDM concept aims at an information-based decision management by online sharing of operational milestones among all stakeholders. It is expected that the common awareness results in improved processes and a balanced utilization of both local and network resources. Thus, the prediction and reliability of the TOBT (Target Off Block Time, SESAR 2014) are getting essential towards the challenged high arrival punctuality at the destination (Tobaruela, 2014). The next ASBU Block 1 (2018-2023) necessarily demands for performance improvements through the application of SWIM (System Wide Information Management, see ICAO, 2016) and an increased interoperability through flight and flow information for a collaborative environment (ICAO, 2012) application before departure. Since information and data management is becoming more important for the efficiency of the global air traffic management system (ICAO, 2005), SWIM is one of the key elements of the US NextGen and Single European Sky initiatives.

From an air transportation system view, a flight could be seen as a gate-to-gate or an air-to-air process, where the gate-to-gate is more focused on the aircraft trajectory flown, the air-to-air process concentrates on the airport ground operations to enable efficient flight operations proving reliable departure times. Typical standard deviations for airborne flights are 30 s at 20 minutes before arrival (Bronsvoort et al., 2009), but could increase to 15 min when the aircraft is still on the ground (Mueller and Chatterji, 2002). As Figure 1 demonstrates, the average time variability (measured as standard deviation) is in flight phase (5.3 min) higher than in the taxi-out (3.8 min) and taxi-in (2.0 min) phase but significantly lower than the variability of both variabilities departure (16.6 min) and arrival (18.6 min) (Eurocontrol, 2017). If the aircraft is departing at the airport, changes with regards to the arrival time are comparatively small (Tielrooij et al., 2015). Thus, the arrival punctuality is clearly driven by the departure punctuality (Eurocontrol, 2017).

Punctual air traffic operations depend on the performance of all involved parties (airlines, airport, network management, air navigation service provider). To achieve a target value of punctuality, airlines implement time buffers to compensate deviations on the operational level. In 2016 only 80.5% of the flights were punctual (delay smaller than 15 minutes) with a decreasing trend since 2013 with 84% punctuality (Eurocontrol, 2017).

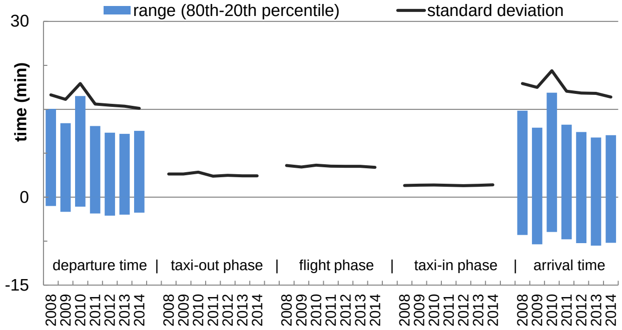

Figure 1. Variability of ground and flight phases on intra-European flights from 2008-2014 (Eurocontrol, 2017)

In Figure 2 the departure delay is analyzed and broken down to four delay groupings: airline, reactionary, enroute (ATFM) and weather (other than ATFM, but ATFM delays due to weather at destination) delays. This grouping is based on the standard IATA delay codes defined in the Airport Handling Manual (IATA, 2017). The airline delay causes are ranging from delay code 11 'late check-in (passenger and baggage)' up to delay code 69 'captain request for security check'. The reactionary delay (code 91-96) considers causes of load connection, through check-in error, rotation (aircraft, crew, cabin crew) and operations control.

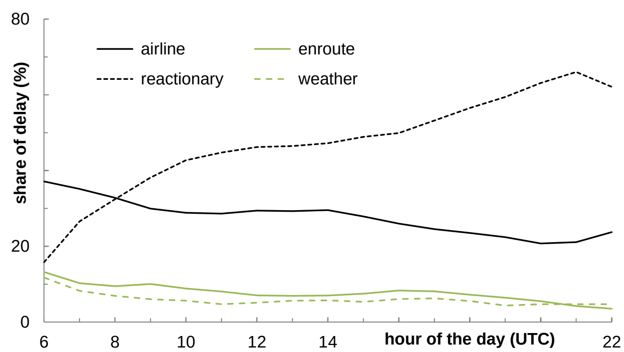

Figure 2. Average departure delay per flight by hour of the day (Eurocontrol, 2016).

The reactionary delay starts at 18% and reaches the maximum of 66% and 2100 UTC. During that time the airline delay decreases from 37% to 21%. The delay caused by enroute and weather impacts has only a minor influence indicated by a relative stable, average share of 8% and 6% respectively. The local turnaround delays, caused by airlines, airport operators, ground handlers and other parties accounted for 35.2% of all departure delays in 2016, where the average departure delay per flight reaches 11.2 min. (Eurocontrol, 2017). All this demands for a sustainable improvement of the turnaround efficiency and predictability, supported by local initiatives, such as A-CDM or APOC (Airport Operations Centre), a platform for stakeholder communication and coordination (SESAR, 2015).

The turnaround consists of five major tasks: deboarding, catering, cleaning, fueling and boarding as well as the parallel processes of unloading and loading. From the operator perspective, all these aircraft handling processes will follow defined procedures and are mainly controlled by the ground handling, airport or airline staff (Fricke and Schultz, 2008, 2009). As an exception, the boarding process is driven by the passenger's experience and willingness or ability to follow the proposed procedures (e.g. late arrivals, no-shows, amount of hand luggage, status passengers). To provide a reliable time stamp for the TOBT, the critical path of the turnaround has to be under the control of the operational entities. Especially the stochastic and passenger-controlled progress of the aircraft boarding makes it difficult to reliably predict the turnaround time, even if the boarding is already in progress.

1.1 Status quo

In the following section, a short overview concerning scientific research on aircraft boarding problem is given. Relevant studies concerning aircraft boarding strategies include but are not limited to the following examples. More comprehensive overviews are provided by Jaehn and Neumann (2015) for the boarding and by Schmidt (2017) for the aircraft turnaround.

Milne and Kelly (2014) develop a method, which assigns passengers to seats so that their luggage is distributed evenly throughout cabin assuming a less time consuming process for finding available storage in the overhead bins. Qiang et al. (2014) proposed a boarding strategy, which prioritize passengers with a high number of hand luggage to board first. Milne and Salari (2016) assign passengers to seats according to the number of hand luggage and propose that passengers with few pieces should be seated closed to the entry. Kierzkowski and Kisiel (2017) provide an analysis covered the time needed to place items in the overhead bins depending on the availability of seats and occupancy of the aircraft. Zeineddine (2017) emphasizes the importance of groups when traveling with the aircraft and propose a method, where all group member should board together, assuming a minimum of individual interference ensured by the group itself.

Fuchte (2014) focusses on the aircraft design and, in particular, the impact of aircraft cabin modifications with regard to the boarding efficiency and Schmidt et al. (2015, 2017) evaluate novel aircraft layout configurations and seating concepts for single- and twin-aisle aircraft with 180-300 seats.

1.2 Objectives and Structure of the Document

The paper provides an overview about the current status of passenger boarding research, as an important process of the aircraft turnaround. After introducing a stochastic approach to consider the individual passenger behavior during aircraft boarding (Schultz et al. 2008, 2013), the field measurements to validate the model (Schultz, 2017a), and investigations into procedural/infrastructural changes (Schultz, 2017b), two topics in the context of aircraft boarding will be focused upon: the prediction of the boarding time using sensor information (Schultz, 2017c) and the capabilities of a future connected cabin.

2. Stochastic Boarding Model

The most scientific approaches do not reflect the operational aircraft/airline conditions (e.g. seat load factor, conformance to the boarding procedure) or the non-deterministic nature of the underlying processes (e.g. amount and distribution of hand luggage). Furthermore, there is a 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 (Schultz et al., 2008, 2013).

2.1 Model

The proposed dynamic model for the boarding simulation is based on an asymmetric simple exclusion process (ASEP, cf. Schultz, 2014). The ASEP was successfully adapted to model the dynamic passenger behavior in the airport terminal environment (Schultz et al., 2008; Schultz and Fricke 2011). 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.

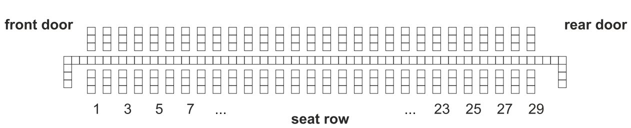

Figure 3. Grid-based simulation environment - Airbus A320 as reference.

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 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 in order 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 provided by Schultz et al. (2008, 2013).

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 color-coded (grey-scale) and aggregated to superior structures with three blocks of seats (per row and per designation). The boarding takes place in the order of the grey-scale value, from the back to the front (back-to-front sequence I-II-III) in the first example and from the outer to the inner seat designation (window to aisle, outside-in) in the second example. In this context, random boarding means that all passengers possess a seat, but the chronological order of the arrival of passengers is not defined. Block boarding stands for an optimized block sequence, which is, in the case of 6 equal blocks (numbered from the back to the front by I, II, III, IV, V, VI), II-IV-VI-I-III-V. Schultz et al. (2008) and Bachmat et al. (2013) demonstrate that the back-to-front policy is only favorable for a 2-block configuration.

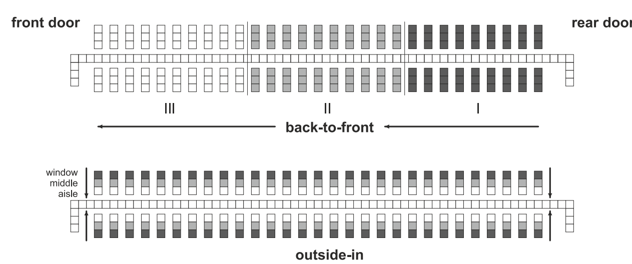

Figure 4. Example for back-to-front and outside-in boarding strategy (darker seats are boarded first, block sequence is I-II-III) modelled in the simulation environment.

Furthermore, the operational constraints are implemented in the stochastic boarding model (see Fig. 5). In particular, these constraints consist of priority boarding (e.g. first/business class), conformance of passengers to the provided boarding strategy (e.g. late arrivals), seat load factor of a specific flight, and group patterns (e.g. families).

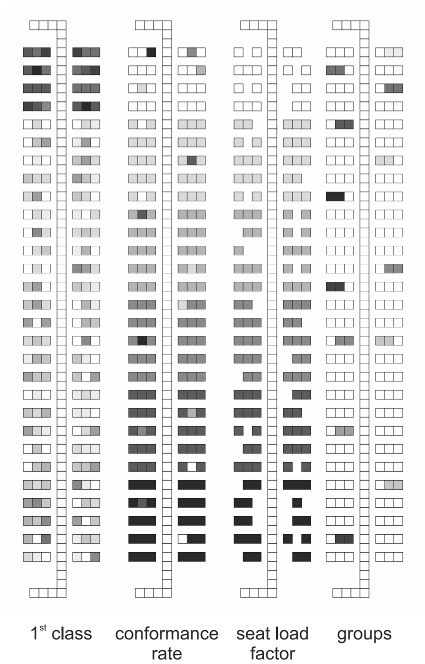

Figure 5. Consideration of operational constraints

The develop boarding model does not address unruly passenger or system behavior or counterflow passenger movements, which may arise from individual problems in finding the assigned seat or blocked overhead compartments. In particular, the problem of blocked overhead compartments could not be solved by operational strategies, but with increased compartment capacity or a more restrictive airline policy regarding the amount of allowed hand luggage. If the airline does not react to high numbers of hand luggage items, Milne and Kelly (2014) provide a boarding approach to allow for evenly distributed hand luggage throughout the cabin.

2.2 Field measurement and calibration

This section provides an overview about the results of the field measurements and boarding trials. Further details are available at Schultz (2017a). In Fig. 6, the measurements of manually measured 282 boarding events for single-aisle aircraft (Airbus 320, Boeing 737) are shown, with a minimum of 29 passengers and a maximum of 190 passengers.

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. 6). 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. 6).

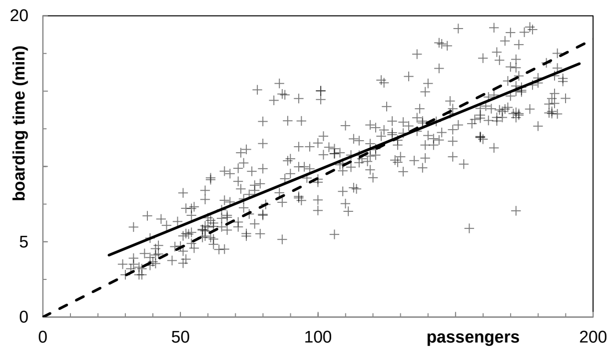

Figure 6. Boarding times of 282 measured flights with different amount of passengers assuming a linear correlation between passengers and boarding time with both defined offset (bold line) and no offset (thin line).

Using a data classification based on a Q-Q-plot, the boarding times could be separated into three classes of fast medium, and slow boarding times. The characteristics regarding the amount of passengers according to the classification are shown in Fig. 7 (95 measurements with fast, 78 with medium, and 109 with slow boarding rates).

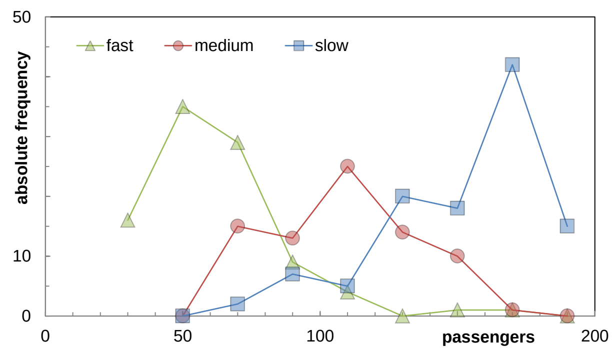

Figure 7. Boarding time classification of fast, medium, and slow boarding progress.

To emphasize the different boarding progresses, three boarding scenarios are selected exemplarily from the recorded data. These scenarios reflect a single specific flight with nearly the same number of passengers to board the aircraft: 99, 104 and 100 for scenarios A, B, and C, with fast, medium and slow arrival behavior respectively (see Fig. 8). Due to the different passengers' 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. 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.

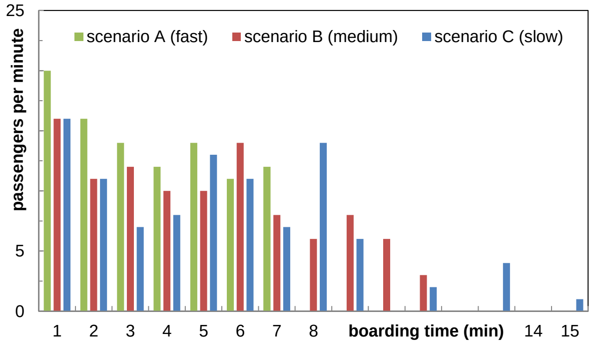

Figure 8. Boarding progress in different recorded scenarios.

For the boarding model the following input parameter could be measured in the field.

- Distribution of time needed to store the hand luggage
- Distribution of time for seat shuffle (interactions during the seating)
- Distribution of passenger arrival
- Distribution of walking speed in the aisle

Finally, the recorded field data are used to calibrate the (sub) processes of a stochastic aircraft boarding model, which finally results in a model accuracy of ±5%, as maximum difference between measured and simulated boarding times (Schultz 2017a).

3. Applications for Aircraft Boarding

The stochastic boarding model is implemented in a simulation environment, which allows evaluating specific boarding scenarios with different procedures and technologies. An additional visualization module is developed to demonstrate the working principle of the analyzed boarding scenarios (see Fig. 9).

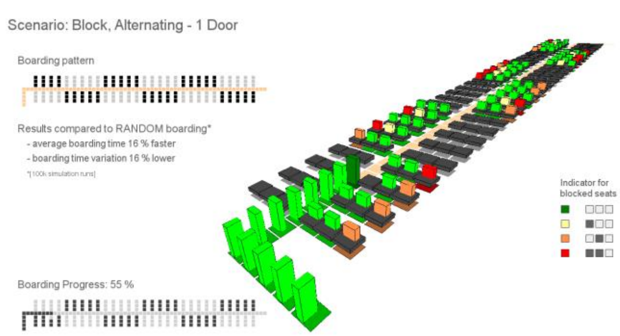

Figure 9. Comprehensive stochastic simulation environment with visualization capabilities

In this section, the results of three different applications of the boarding model will be shown. The first application focusses on the Side-Slip Seat as an innovative infrastructural technology to fasten the aircraft boarding (Schultz, 2017b). The second application aims at a reliable prediction of the boarding progress using a developed interfering potential for evaluation of the current boarding status (Schultz, 2017c). The connected cabin is briefly introduced as a third application to emphasize the operational feasibility of the developed methods and technologies to ensure a reliable and fast aircraft boarding.

3.1 Side-Slip Seat

Standard approaches to accelerating the boarding process mainly address the management of passenger behavior by providing airline specific boarding sequences (e.g. boarding by zones, e.g. Air Canada) or reducing the amount of hand luggage (only one piece per passenger). Only the use of the rear door of the aircraft to board the passengers could be understood as a significant change in the infrastructure. The most prominent negative effect on the boarding time is accompanied with a blocked aisle due to passengers storing their hand luggage or entering their seat row. With the innovative technology of the Side-Slip Seat (see Fig. 10). Here, the available infrastructure could be dynamically changed to support the boarding process by providing a wider aisle, which allows two passengers to pass each other in a convenient way.

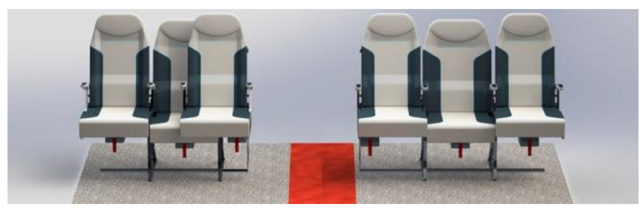

Figure 10. Side-Slip Seat provides a wider aisle for boarding: seat in initial condition (left) and unfolded operational condition (Molon Labe Seating 2017)

Two additional benefits come with this new technology: the wider aisle allows airlines to offer full-size wheelchair access down the aisle and the middle seat is two inches wider than the aisle and window seats (aisle and window seats retain their standard width). Fig. 3 demonstrates the staggered seat approach: the aisle seat is initially positioned over middle seat and will be moved in flight position if a passenger wants to use the middle or aisle seat.

The stochastic boarding model is adapted to allow a parallel movement of two passengers along the aisle. Furthermore, the dynamic status of the seat row (folded/unfolded) is implemented to enable/disable this parallel movement. The implementation of these new dynamic aircraft seats demand for an appropriate adapted boarding strategy. To identify an optimal boarding sequence, the stochastic simulation model (Schultz et al., 2008, 2013) was used as a reliable basis for an evolutionary algorithm, which continuously improves an initial set of boarding sequences (see Fig. 11). A detailed description of the method and results is provided by Schultz (2017b).

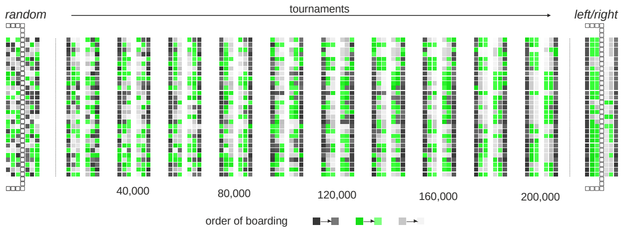

Figure 11. Evolution of boarding sequence from random sequence to a left/right sequence (Schultz, 2017b).

The evolutionary algorithm demonstrates that a boarding sequence which differentiates between the left and the right side of the aircraft will benefit most from the innovative Side-Slip Seat technology. Using the reference A320 layout, a random boarding strategy with calling in the left (right) side of the aircraft first results in a 19% faster boarding accompanied with a more reliable progress (10% smaller value for the standard deviation of boarding time).

3.2 Interfering Potential as Metric for Progress Prediction

Addressing the fact that boarding is on the critical path of the aircraft 4D trajectory and not controlled by the operators, a scientific approach is needed for a real-time evaluation of the boarding progress using the capabilities of a future connected cabin (e.g. sensor environment). Therefore a set of indicators is developed for depicting the real-time status of the boarding progress as a fundamental basis for the prediction of the boarding time (Schultz, 2017c). In this context, the aircraft seats are used as a sensor network with the capability to detect the seat status: free or occupied. The seat status is the basis for the calculation of an aircraft-wide interference potential as the major indicator for the boarding time. In combination with an integrated airline/airport information management (e.g. sequence of boarding passengers), the boarding progress will be transformed from a black box to a transparent progress with the operator’s real-time ability to react to significant deviations from the planned progress. Thus, the research results provide a fundamental contribution towards the derivation of the crucial aircraft departure time.

To predict the duration of aircraft boarding, the stochastic simulation model could be used with specific assumptions for the day of operations such as the position of the aircraft (apron, gate), doors to be used, boarding counters, aircraft type (e.g. A31x, A32x, B737), amount of passengers booked (e.g. seat load factor, specific seats used), characteristics of passengers (e.g. premium, eco, hand luggage), or boarding sequence. Finally, this specific parameter set is implemented into the simulation environment and results in both an average boarding time and a corresponding standard deviation.

During the course of boarding, the number of passengers seated in the aircraft increases constantly and the stochastic component of the boarding time has a decreasing influence on the final boarding time. In Fig.12, the implication of the decreasing uncertainty during the course of boarding is shown, indicated by higher values of the corresponding probability density function (PDF), exemplarily using a progress of the boarding of 0%, 50% and 80% with a realized progress time t_r. In this case, the prediction of the expected boarding time t_b starts at 1103 s (0% progress, 100% stochastic share) and the last prediction (80% progress, 20% stochastic share) results in 1021 s, with standard deviations of 78 s and 35 s respectively.

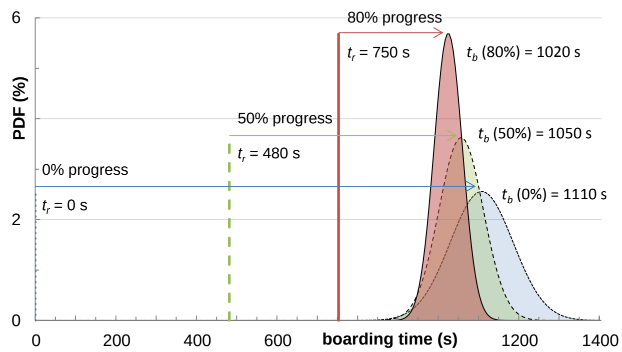

Figure 12. Evaluation of boarding time distribution during the aircraft boarding based on a realized boarding progress of 0%, 50% and 80% (Schultz, 2017c).

Furthermore, the boarding time could be predicted with a higher level of reliability if the exact sequence of passengers is known beforehand. But the boarding times still consist of a normal distributed characteristic, as Fig. 13 demonstrates using PDF and CDF (cumulative density function), for the boarding time distribution.

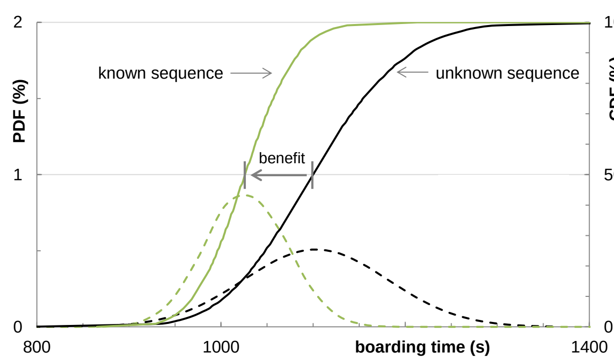

Figure 13. Boarding time distribution with unknown and known sequence of passengers (Schultz, 2017c).

Nevertheless, it is expected that a future connected cabin could provide additional data to further improve the prediction of boarding time. Thus, a metric was developed to evaluate the current status of boarding considering the allocation of used seats in the aircraft cabin. The main idea is that a scenario where all aisle seat are used, will lead to significant longer boarding times in comparison to a scenario where all window seats are used (both cases contain the same number of passengers). In the case of the used aisle seats, these passengers have to stand up first before the next passenger could take seat. In the case of the used window seats no further interactions will arise from this scenario. The possible interactions between the passengers are aggregated to an interference potential for the whole seat configuration in the aircraft.

In Fig. 14 the progress of the interference potential and the seat load are shown. The grey, vertical line labels a point in time, where the progress of the seat load provides no clear indication, which boarding will be faster. But the new developed interference potential demonstrates that the boarding scenario marked with a solid line consists of a significant lower value for the interference potential leads to a shorter boarding time.

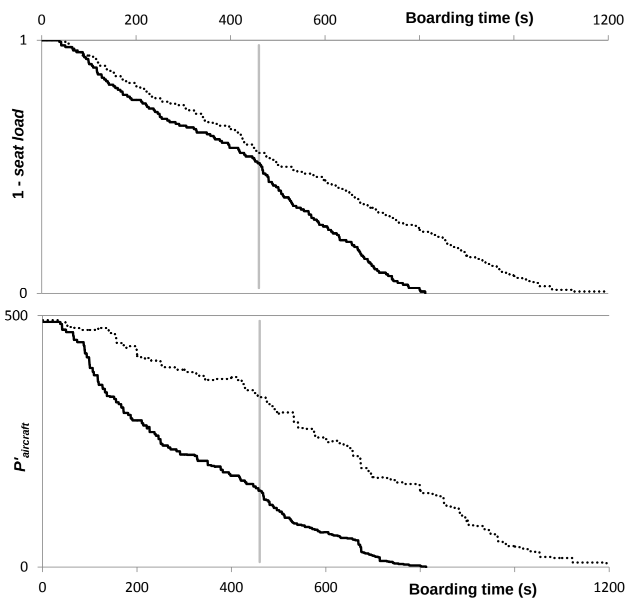

Figure 14. Different indicators for the evaluation of the progress of two boarding scenarios: seat load and aggregated interfering potential $P'_{aircraft}$ (Schultz, 2017c).

3.3 Connected Cabin

The set of indicators are extend to a complexity metric (passenger interactions) and are part of a hardware prototype environment. This environment was used in field trials within a close co-operation with Eurowings. In Fig. 15, the field test setup is shown with seat sensors from the automotive industry. This sensor network was successfully tested in a mockup environment previously. The individual seat sensors could efficiently indicate the seat status and an aggregated seat row condition was sent to the central processing unit. Furthermore, a sensor floor was installed in the aisle of the aircraft to detect the specific passenger density (congestion) and walking speeds in the aisle.

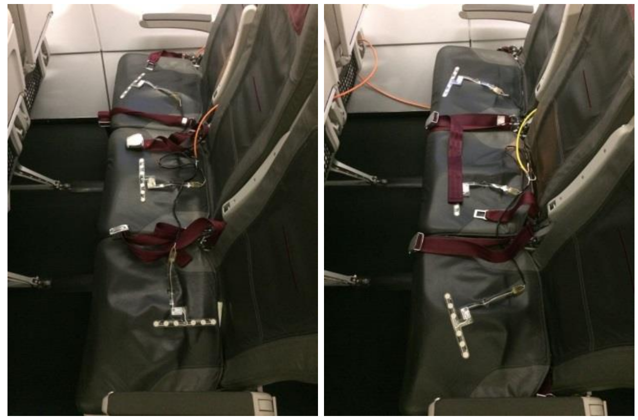

Figure 15. Seat sensors in a field trial environment (Schultz, 2017c).

In Fig. 16 the sensor results of two different boarding scenarios are exemplarily shown: random and outside-in boarding (see Fig. 4). In Fig. 16 the x-axis shows the position inside the aircraft and the y-axis shows the time. Consequently, this kind of representation allows determining the unconstraint, maximum speed in the aisle and an indication of congested areas. The random boarding scenario clearly consists of more congested areas (waiting queues), which indicate a longer boarding progress.

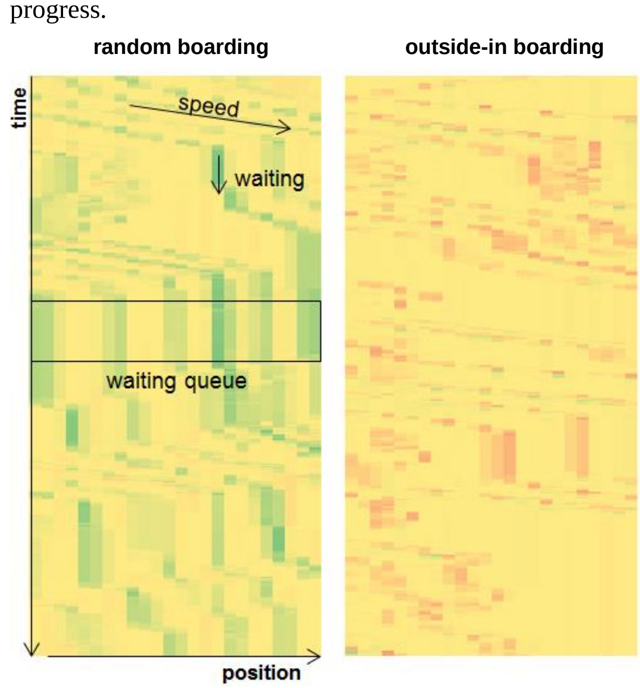

Figure 16. Feedback from the floor sensors indicating walking speeds and passenger queues in the aircraft cabin.

A first analysis of the average unconstraint, maximum speed of passengers results in 0.78 m/s with a standard deviation of 0.31 m/s for the case of boarding and a speed of 0.99 m/s with 0.24 m/s for deboarding.

4. Summary and Outlook

In the paper an overview about the status quo of the current activities regarding to a fast aircraft turnaround is given, focusing the aircraft boarding. Therefore the developed stochastic boarding model is introduced and results of field trials to provide calibration measurements are emphasized. This section is followed by an introduction of three different types of applications of the stochastic boarding model: infrastructural changes enabled by the Side-Slip Seat, development of an interference potential to evaluate the boarding progress in real-time, and capabilities of future connected cabin.

As part of a future cabin management system, the integration of the aircraft boarding time prediction into a comprehensive turnaround monitor is planned in upcoming projects.

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