AIRCRAFT BOARDING AS PART OF AN EFFICIENT 4D TRAJECTORY

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Abstract

Ground operations are an essential part of the 4D aircraft trajectory. The ground trajectory of an aircraft primarily consists of the handling processes at the stand, defined as the aircraft turnaround, which are mainly controlled by operational experts. Only the aircraft boarding, which is on the critical path of the turnaround, is driven by the passengers' experience and willingness or ability to follow the proposed procedures.

1 Introduction

From an air transportation system view, a flight could be seen as a gate-to-gate or an air-to-air process. Whereas the gate-to-gate is more focused on the aircraft trajectory flown, the air-to-air process concentrates more on airport ground operations. Typical standard deviations for airborne flights are 30 s at 20 minutes before arrival [1], but could increase to 15 min when the aircraft is still on the ground [2]. The average time variability (measured as standard deviation, see Fig. 1) is in the flight phase (5.3 min) higher than the variability of both departure (16.6 min) and arrival (18.6 min) [3]. If the aircraft is departing from one airport, changes with regards to arrival time at the next are comparatively small [4]. This is why current research in the field of flight operations addresses economic, operational and ecological efficiency [5-16]. To evaluate these operational deviations in the economic context, reference values are provided for the cost of delay to European airlines [17]. The aircraft turnaround on the ground consists of five major ground handling operations at the stand: deboarding, catering, cleaning, fueling and boarding as well as the parallel processes of (un-) loading [18].

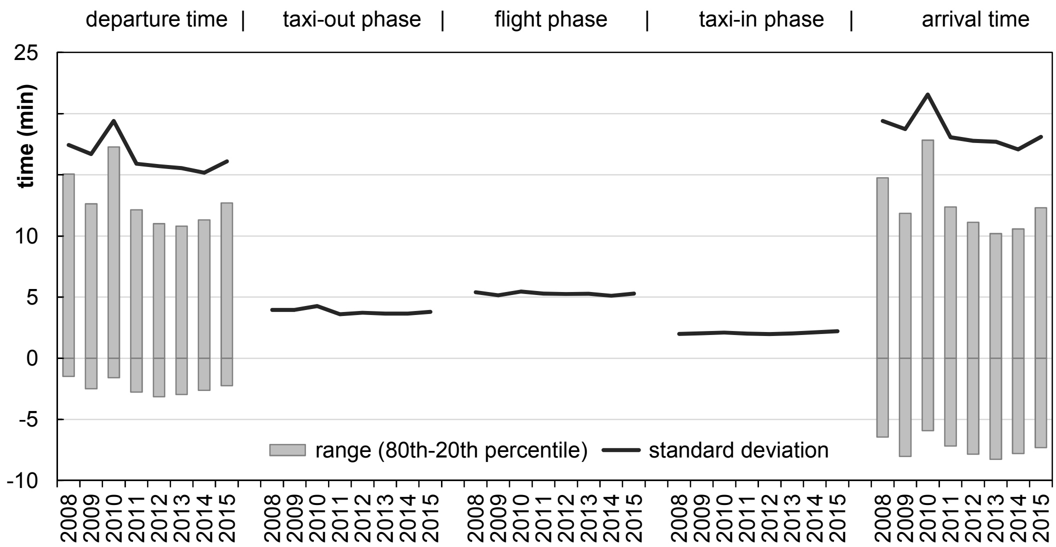

Fig. 1 Variability of ground and flight phases on intra-European flights from 2008-2015 [3]

All these handling processes follow clearly defined procedures and are mainly controlled by ground handling, airport or airline staff [19, 20]. But in particular, aircraft boarding is driven by passengers' experience and willingness or ability to follow the proposed procedures and is disturbed by individual events, such as late arrivals, no-shows, specific (high) numbers of hand luggage items, or priority passengers (privileged boarding). To provide reliable values for the target off-block time, which is used as a planning time stamp for the subsequently following departure procedures, all critical turnaround processes are subject to prediction. In this context, complex, stochastic, and passenger-controlled boarding makes it difficult to reliably predict turnaround times, even if boarding is already in progress.

1.1 Status Quo

The research presented is connected to three different topics: aircraft turnaround, passenger behavior, and machine learning. Comprehensive overviews are provided for aircraft turnaround [21], for boarding [21], and for the corresponding economic impact [17, 23, 24]. Relevant studies include, but are not limited to, the following current examples.

The aircraft turnaround, as part of the aircraft trajectory over the day of operations, has to be part of optimization strategies for minimizing flight delays [25] and ensuring flight connection considering operational uncertainties [26, 27]. In this context, turnaround absorbs inbound delay [20] and could enhance slot adherence at airports [28] or mitigate problems of push-back scheduling [29]. A microscopic turnaround model provides an open and closed-loop process control for higher automation levels in turnaround management [30]. The inter-aircraft propagated delay is focused at [31], since individual delays could result in parallel demand of turnaround resources (personnel, space, and equipment). Furthermore, delayed use of infrastructure may cause excessive demand in later time frames, and both turnaround stability and resource efficiency will provide significant benefits to airline and airport operations [20, 32]. The compatibility with airline operations, existing ground handling procedures and airport infrastructure requirements were analyzed in the context of alternative energy concepts [33].

With a focus on efficient aircraft boarding, Milne and Kelly [34] develop a method that assigns passengers to seats so that their luggage is distributed evenly throughout the cabin, assuming a less time-consuming process for finding available storage in the overhead bins. Qiang et al. [35] propose a boarding strategy that allows passengers with a large amount of hand luggage to board first. Milne and Salari [36] assign passengers to seats according to the number of hand luggage items and propose that passengers with few pieces should be seated close to the entry. Zeineddine [37] emphasizes the importance of groups when traveling by aircraft and proposes a method whereby all group members should board together, assuming a minimum of individual interferences in the group.

Fuchte [38] addresses aircraft design and, in particular, the impact of aircraft cabin modifications with regard to the boarding efficiency. Schmidt et al. [39, 40] evaluate novel aircraft layout configurations and seating concepts for single- and twin-aisle aircraft with 180–300 seats. The innovative approach to dynamically changing the cabin infrastructure through a Side-Slip Seat is evaluated [41]. Gwynne et al. [42] perform a series of small-scale laboratory tests to help quantify individual passenger boarding and deplaning movement considering seat pitch, hand luggage items, and instructions for passengers. Schultz [43, 44] provides a set of operational data including classification of boarding times, passenger arrival times, time to store hand luggage, and passenger interactions in the aircraft cabin as a fundamental basis for boarding model calibration.

1.2 Scope and Structure of the Document

The paper provides a general overview about aircraft boarding with a specific focus on a stochastic approach to cover both individual passenger behavior and operational constraints. This stochastic approach and the simulation environment are briefly introduced, followed by a description of field trials to provide reliable input data for calibration and validation. Furthermore, the Side-Slip Seat shows operational benefits due to innovative adaptation of the aircraft cabin infrastructure. The prototype of a connected cabin is represented to emphasize the potential of future digital infrastructures.

2. Boarding Model

The proposed dynamic model for the boarding simulation is based on an asymmetric simple exclusion process (ASEP, cf. [45, 46]). The ASEP was successfully adapted to model the dynamic passenger behavior in the airport terminal environment [47-49]. 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. 2 (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 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), the arrival frequency of the passengers at the aircraft door, the number of available doors, the specific boarding strategy and the compliance of passengers in following the current strategy. Further details regarding the model and the simulation environment are provided in [50-52]. To model different boarding strategies, the grid-based approach enables the individual assessment of seats as well as classification/ aggregation according to the intended boarding strategy.

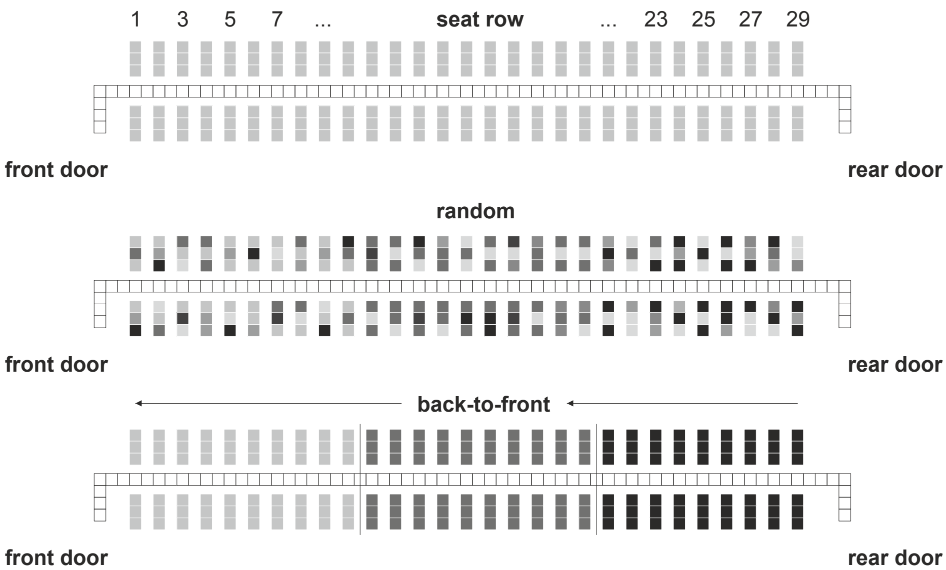

Fig. 2 Grid-based model environment using single aisle reference layout [53]

Furthermore, the operational airline/ airport constraints are implemented in the stochastic boarding model. In particular, these constraints consist of priority boarding (e.g. first/business class), conformance of passengers to follow boarding strategy (e.g. late arrivals), seat load factor (ratio of booked to available seats), and group patterns (e.g. families).

3 Simulation Environment

The stochastic boarding model is implemented in a simulation environment (see Fig. 3), which allows for evaluating specific boarding scenarios with different procedures and technologies. In the simulation environment, the boarding process is implemented as follows. Depending on the seat load, a specific number of randomly chosen seats are used for boarding. For each seat, a passenger (agent) is created. The agent contains individual parameters, such as number of hand luggage items, maximum walking speed in the aisle, seat coordinates, time to store the hand luggage and arrival time at the aircraft door. Further on, several process characteristics could be saved during the simulation runs (e.g. waiting times, number of interactions). To create the time needed to store the hand luggage, a Weibull distribution provides a stochastic time value depending on the number of items [43, 44]. The agents are sorted with regard to their seats and the current boarding strategy. From this sequence, a given percentage of agents (conformance rate) are taken out of the sequence and inserted into a position, which contradicts the current strategy (e.g. inserted into a different boarding block). According to the arrival time distribution (e.g. linear or exponential) and the boarding sequence, each agent gets a timestamp to appear on the aircraft door queue.

When the simulation starts, the first agent of the queue always enters the aircraft by moving from the queue to the entry cell of the aisle grid (aircraft door), if this cell is free. In each simulation step, all agents located in the row are moved to the next cell, if possible (free cell and not arrived at the seat row), using a shuffled sequential update procedure (emulate parallel update behavior [46, 47]. If the agent arrives at the assigned seat row, he waits on the cell according to the time needed to store the hand luggage. Depending on the seat row condition (e.g. blocked aisle or middle seat or both), an additional time is stochastically generated to wait in the aisle to perform the seat shuffle. During the whole waiting process, no other agent can pass. If the waiting process finally finishes, the agent is set to the seat and the aisle cell is set free.

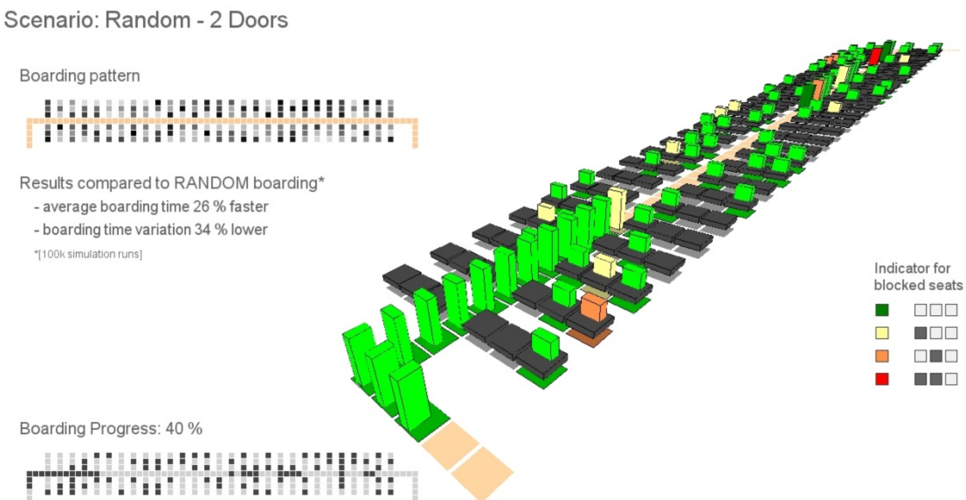

Fig. 3 Visualization of the boarding process, using a random strategy with two doors as an example and indicating passenger interaction during the seating process (color coded from red (many interactions) to green (no interactions).

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, an adopted boarding approach could result in evenly distributed hand luggage throughout the aircraft cabin [34, 52, 54].

The model was primarily developed to analyze the A320 reference layout in an efficient way, by means of calculation times and consideration of relevant operational constraints. Nevertheless, the model was extended to be used for twin-aisle configuration [51], implementation of infrastructural changes such as the Side-Slip Seat [55], development and optimization of appropriately adapted boarding strategies [41, 52], to derive a complexity metric to predict boarding progress [56, 57], and to predict the aircraft boarding progress (real-time) [58, 59]. An additional visualization module is developed to demonstrate the working principle of the analyzed boarding scenarios (see Fig. 3).

4 Model Validation - Field Trials

In the context of input data for boarding models, there are only limited datasets available to provide reliable input for boarding models. These datasets are from experimental mock-ups [60], observations during boarding operations [61, 62], and small scale experiments [42, 63]. Thus, to calibrate and validate the stochastic boarding model, data from more than 400 flights were manually recorded in recent years with a different focus and level of details: passenger processes (e.g. time to store hand luggage or time needed to take the seat), arrival rates at the aircraft, and boarding time using different boarding strategies.

The data were recorded at several field measurements during actual aircraft turnarounds of Airbus A320 and Boeing B737/B738. Each measurement campaign aimed at different aspects of the individual boarding behavior of passengers and realized in close cooperation with the corresponding airlines, ground handling agents, and airport operators. While passenger arrival/departure rates could be measured from outside the cabin by recording the individual time stamps of passengers passing the aircraft door, the hand luggage storage time and passenger interactions during the seating (seat shuffle) were recorded from positions inside the narrow aircraft cabin. Particularly, the specific seat shuffles are required special attention and a close observation position, which results only in a limited number of measurements.

The first field measurements aimed to record the passenger boarding time and determine the correlation to the number of passengers boarded, which should be used as an input for an aircraft turnaround model [30]. The boarding time was defined as time between first passengers enters the aircraft (pass the aircraft door) and last passenger is seated. The boarding times were recorded at different German airports with different airlines during the summer periods 2010-2015. The observer cooperates closely with the ground handling companies and stands near the aircraft door, where the (inter-arrival) times between the passengers during boarding and deboarding could be additionally measured. The analysis of the boarding times shows a positive correlation, but different categories of boarding speed exists (slow, medium, fast boarding), which are not indicated by the number of passengers. In the context of the aircraft turnaround, the boarding time consists of additional dependencies, which are mainly driven by the individual passenger behavior.

To cover this expected individual behavior during the passenger boarding process, the existing stochastic aircraft boarding model was planned to be calibrated with data from additional field trial measurements. Since inter-arrival times of passengers are already covered by the prior measurements passenger interactions are focused, particularly the time to store the hand luggage and time for the seating process. The measurements were taken in the summer period of 2012. For each flight, two observers were positioned inside the cabin to separately cover the front and rear part of the aircraft cabin. Therefore the observers stand near the first and the last seat row or used not booked seats.

To proof the reliability of the calibrated stochastic model, a third field measurement with a German airline was setup, to compare simulated boarding times with the actual boarding times of newly introduced boarding strategies. Thus the airline prepared an operational test phase in summer 2014 with the developed boarding strategies and recorded both the boarding time and the number of passengers. The latest airline trials in 2015 and 2016 mainly focusses on the impact boarding strategies, operational configurations (one door and two doors), seat load factor, transfer mode (walk, bus shuttle, gate), and destination. Finally, the calibrated boarding model was used for validation. The simulation of different boarding scenarios showed deviations of ±5% between simulation results and boarding times measured in the field [43, 44].

5. Adaptive Infrastructure

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) or reducing the amount of hand luggage (only one piece per passenger). The most prominent negative effect on the boarding time is a blocked aisle due to passengers storing their hand luggage or entering their seat row. With the innovative Side-Slip Seat, 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 (see Fig. 4). 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. 4 demonstrates the staggered seat approach: the aisle seat is initially positioned over the middle seat and will be moved into flight position if a passenger wants to use the middle or aisle seat [41, 55].

Fig. 4 Side-Slip Seat provides a wider aisle and enables a faster aircraft boarding: passengers could pass each other in the aisle or people with reduced mobility could easily reach their seat row (https://www.airlineseats.biz/).

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 was used as a reliable basis for an evolutionary algorithm, which continuously improves an initial set of boarding sequences. The evolutionary algorithm leads stepwise to a boarding strategy, where passengers on one side of the aisle should be boarded first. A detailed description of the method and results is provided at [41]. 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 a reference A320 layout, a random boarding strategy results in a 19% faster boarding accompanied with a more reliable progress (10% smaller standard deviation (SD) of boarding time).

6 Connected Aircraft Cabin

A hardware prototype environment of a connected aircraft cabin was developed and used in field trials in close cooperation with Eurowings at Cologne/Bonn airport. This prototype was used to proof the concept of boarding time prediction (during active operations) and the potential of a dynamic seat allocation. In Fig. 5, 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 efficiently indicate the seat status (free, occupied). During the field trial the current seat conditions were sent to a central processing unit, which shows aircraft-wide status information to the airline operator. Furthermore, a sensor floor was installed in the aircraft aisle to additionally detect specific passenger positions (density, congestion) and walking speeds in the aisle (free flow, jam). As a result, the average unconstrained (maximum) walking speed of passengers results in 0.78 m/s (0.31 m/s SD) during boarding and 0.99 m/s (0.24 m/s SD) during deboarding [53, 64].

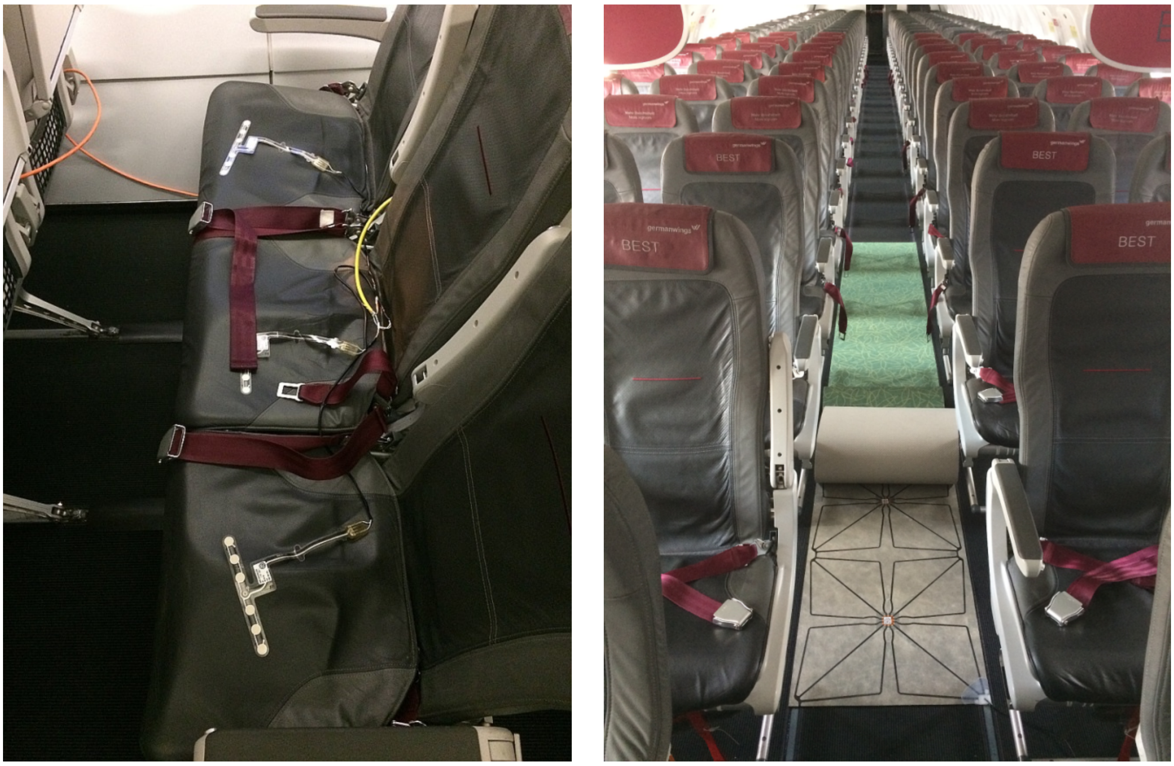

Fig. 5 Installation of sensor network in the aircraft cabin to detect passenger positions and cabin status (e.g. passengers seated, congested areas in the aisle).

7 Outlook

This paper provides a brief overview of the status quo of aircraft turnaround, with a specific focus on aircraft boarding. A stochastic boarding model is introduced that considers both individual passenger behavior and operational constraints. The input parameters of the boarding model are calibrated with data from field trials and the model finally shows deviations smaller than 5% between measured and simulated boarding times. The stochastic boarding model is implemented in a simulation environment to evaluate specific boarding scenarios using different boarding strategies and technologies. In particular, infrastructural changes, such as the innovative Side-Slip Seat, show additional potential to shorten the boarding time.

It is assumed that future aircraft cabins will be designed as a sensor network (cyber physical system, connected cabin) to provide information on passenger convenience, communication devices, or maintenance planning. In the context of aircraft boarding, this information could be used to assess the current and future status of boarding progress. In combination with an integrated airline information management (e.g. sequence of boarding passengers), the boarding process could be transformed from a black box to a transparent process with the operator's real-time ability to react to significant deviations from the planned process.

References

[1] Bronsvoort, J., G. McDonald, R. Porteous, and E. Gutt. 2009. Study of Aircraft Derived Temporal Prediction Accuracy using FANS. 13th ATRS, Abu Dhabi.

[2] Mueller, E.R. and G. B. Chatterji. 2002. Analysis of Aircraft Arrival and Departure Delay. AIAA Conference, Los Angeles.

[3] Eurocontrol. 2016. CODA Digest All-Causes Delay and Cancellations to Air Transport in Europe – 2016.

[4] Tielrooij, M., C. Borst, M.M. van Paassen, M. Mulder. 2015. Predicting Arrival Time Uncertainty from Actual Flight Information. 11th USA/Europe ATM Seminar, Lisbon.

[5] Rosenow, J., M. Lindner, and H. Fricke. 2017. Impact of climate costs on airline network and trajectory optimization: a parametric study, CEAS Aeronautical Journal 8(2), 371–384

[6] Rosenow, J., H. Fricke, and M. Schultz. 2017. Air traffic simulation with 4d multi-criteria optimized trajectories, Winter Simulation Conference, 2589-2600.

[7] Niklaß, M. et al. 2017. Potential to reduce the climate impact of aviation by climate restricted airspaces. Transport Policy.

[8] Rosenow, J. et al. 2018. Minimizing contrail formation by rerouting around dynamic ice-supersaturated regions. AAOAJ 2(3): 105-111.

[9] Rosenow, J., S. Förster, and H. Fricke. 2016. Continuous climb operations with minimum fuel burn. 6th SESAR Innovation Days.

[10] Kaiser, M., M. Schultz, and H. Fricke. 2012. Automated 4D descent path optimization using the enhanced trajectory prediction model. 5th ICRAT, Berkeley.

[11] Kaiser et al. 2012. Tradeoff between optimum altitude and contrail layer to ensure maximum ecological en-route performance using the Enhanced Trajectory Prediction Model. 2nd ATACCS, London.

[12] Luchkova, T. et al. 2015. Analysis of Impacts an Eruption of Volcano Stromboli could have on European Air Traffic, 11th USA/Europe ATM Seminar, Lisbon.

[13] Kreuz, M., T. Luchkova, and M. Schultz, 2016. Effect Of Restricted Airspace On The ATM System. WCTR Conference 2016, Shanghai.

[14] Gerdes, I., A. Temme, and M. Schultz. 2018. Dynamic airspace sectorisation for flight-centric operations. J. of Trans. Res. Part C: Emerg. Techn. (under review).

[15] Standfuß, T. et al. 2018. Dynamic Airspace Optimisation. CEAS Aeronaut. J.

[16] Gerdes, I., A. Temme, and M. Schultz. 2016. Dynamic airspace sectorization using controller task load. 6th SESAR Innovation Days, Delft.

[17] Cook, A.J. and G. Tanner. 2015. European airline delay cost reference values. Technical Report. EUROCONTROL Performance Review Unit.

[18] Airbus. 2017. Airbus A320 Aircraft Characteristics - Airport and Maintenance Planning.

[19] Fricke, H. and M. Schultz. 2008. Improving Aircraft Turn Around Reliability, 3rd ICRAT, 335–343.

[20] Fricke, H. and M. Schultz. 2009. Delay Impacts Onto Turnaround Performance. 8th USA/Europe ATM Seminar, Napa.

[21] Schmidt, M. 2017. A Review of Aircraft Turnaround Operations and Simulations. Progress in Aerospace Sciences 92: 25–38.

[22] Jaehn, F., and S. Neumann. 2015. Airplane Boarding. European Journal of Operational Research 244(2):339–359.

[23] Nyquist, D.C. and K.L. McFadden. 2008. A study of the airline boarding problem. J. Air Transp. Manage. 14: 197–204.
[24] Mirza, M. 2008. Economic impact of airplane turn-times. AERO Quart. 4, 14–19.
[25] Montlaur, A. and L. Delgado. 2017. Flight and passenger delay assignment optimization strategies, J. of Trans. Res. Part C: Emerg. Techn. 81, 99–117.
[26] Oreschko, B., M. Schultz, and H. Fricke. 2011. Skill Analysis of Ground Handling Staff and Delay Impacts for Turnaround Modeling. Air Transport and Operations, 310-318.
[27] Oreschko, B. et al. 2012. Turnaround prediction with stochastic process times and airport specific delay pattern. ICRAT, Berkeley.
[28] Ivanov, N., F. Netjasov, R. Jovanovic, S. Starita, and A. Strauss. 2017. Air Traffic Flow Management slot allocation to minimize propagated delay and improve airport slot adherence, J. Transp. Res. Part A 95, 183–197.
[29] Du, J.Y., J.O. Brunner, and R. Kolisch. 2014. Planning towing processes at airports more efficiently. J. of Trans. Res. Part E 70, 293–304.
[30] Schultz, M. et al. 2013. Microscopic Process Modelling for Efficient Aircraft Turnaround Management. International Air Transport and Operations Symposium, Delft, The Netherlands.
[31] Kafle, N., and B. Zou. 2016. Modeling flight delay propagation: A new analytical-econometric approach. J. Transp. Res. Part B 93, 520–542.
[32] Grunewald, E. 2016. Incentive-based slot allocation for airports, Transportation Research Procedia 14, 3761 – 3770.
[33] Schmidt, M., A. Paul, M. Cole, and K.O. Ploetner. 2016. Challenges for ground operations arising from aircraft concepts using alternative energy. J. Air Transp. Manage. 56, 107-117.
[34] Milne, R.J., and A.R. Kelly. 2014. A New Method for Boarding Passengers onto an Airplane. J. Air Transp. Manage. 34:93–100.
[35] Qiang, S.-J., B. Jia, D.-F. Xie, and Z.-Y. Gao. 2014. Reducing Airplane Boarding Time by Accounting for Passengers' Individual Properties: A Simulation Based on Cellular Automaton. J. of Air Transp. Manage. 40:42–47.
[36] Milne, R.J. and M. Salari. 2016. Optimization of Assigning Passengers to Seats on Airplanes Based on Their Carry-on Luggage. J. of Air Transp. Manage. 54, 104-110.
[37] Zeineddine, H. 2017. A Dynamically Optimized Aircraft Boarding Strategy. J. of Air Transp. Manage. 58, 144–151.
[38] Fuchte, J. 2014. Enhancement of Aircraft Cabin Design Guidelines with Special Consideration of Aircraft Turnaround and Short Range Operations. Ph.D. Thesis, TU Hamburg-Harburg.
[39] Schmidt, M., P. Nguyen, and M. Hornung. 2015. Novel Aircraft Ground Operation Concepts Based on Clustering of Interfaces. SAE Technical Paper 2015-01-2401.
[40] Schmidt, M., P. Heinemann, and M. Hornung. 2017. Boarding and Turnaround Process Assessment of Single- and Twin-Aisle Aircraft. AIAA 2017-1856.
[41] Schultz, M. 2017. Dynamic Change of Aircraft Seat Condition for Fast Boarding. J. of Trans. Res. Part C: Emerg. Techn. 85, 131-147.
[42] Gwynne, S.M.V. et al. 2018. Small-scale trials on passenger microbehaviours during aircraft boarding and deplaning procedures. J. Air Transp. Manage. 67, 115–133.
[43] Schultz, M. 2017. Aircraft Boarding - Data, Validation, Analysis. 12th USA/Europe ATM Seminar, Seattle.
[44] Schultz, M. 2018. Field Trial Measurements to Validate a Stochastic Aircraft Boarding Model. Aerospace 5(1), 27.
[45] Schultz, M., T. Kretz, and H. Fricke. 2010. Solving the Direction Field for Discrete Agent Motion. 9th ACRI, 489–495, Ascoli Piceno.
[46] Schultz, M. 2014. Stochastic Transition Model for Pedestrian Dynamics, In Pedestrian and Evacuation Dynamics 2012, 971–986. Springer.
[47] Schultz, M. 2010. Entwicklung eines individuenbasierten Modells zur Abbildung des Bewegungsverhaltens von Passagieren im Flughafenterminal. PhD thesis. TU Dresden. http://nbn-resolving.de/urn:nbn:de:bsz:14-qucosa-85592
[48] Schultz, M., C. Schulz, and H. Fricke. 2008. Passenger dynamics at airport terminal environment. Pedestrian and Evacuation Dynamics 2008, 381-396
[49] Schultz, M. and H. Fricke. 2011. Managing passenger handling at airport terminals. 9th USA/Europe ATM Seminar, Berlin.
[50] Schultz, M., C. Schulz, and H. Fricke. 2008. Efficiency of Aircraft Boarding Procedures. 3rd ICRAT, 371–377.
[51] Schultz, M., T. Kunze, and H. Fricke. 2013. Boarding on the Critical Path of the Turnaround. 10th USA/Europe ATM Seminar, Chicago.
[52] Schultz, M. 2018. Implementation and Application of a Stochastic Aircraft Boarding Model. J. of Trans. Res. Part C: Emerg. Techn. 90, 334–349.
[53] Schultz, M. 2018. Fast Aircraft Turnaround Enabled by Reliable Passenger Boarding. Aerospace 5(1), 8.
[54] Schultz, M. and M. Schmidt. 2018. Advancements in passenger processes at airports - An aircraft perspective. 7th Transportation Research Arena, Vienna.
[55] Schultz, M. 2017. Faster aircraft boarding enabled by infrastructural changes. 50th Winter Simulation Conference, 2530–2541, Las Vegas.

[56] Schultz, M. 2017. The seat interference potential as an indicator for the aircraft boarding progress. SAE Technical Paper 2017-01-2113.

[57] Schultz, M. 2018. A metric for the real-time evaluation of the aircraft boarding progress. J. of Trans. Res. Part C: Emerg. Techn. 86, 467-487.

[58] Schultz, M. and S. Reitmann. 2017. Prediction of passenger boarding progress using neural network approach. 8th ICRAT, Barcelona.

[59] Schultz, M. and S. Reitmann. 2018. Machine learning approach to predict aircraft boarding. J. of Trans. Res. Part C: Emerg. Techn.(under review)

[60] Steffen, J.H., and J. Hotchkiss. 2012. Experimental Test of Aircraft Boarding Methods. Journal of Air Transport Management 18(1):64-67.

[61] Steiner, A. and Philipp, M. (2009). Speeding up the airplane boarding process by using pre-boarding areas. 9th Swiss Transport Research Conference, Monte Verità/Ascona.

[62] Kierzkowski, A. and T. Kisiel. 2017. The Human Factor in the Passenger Boarding Process at the Airport. Procedia Engineering 187:348-355.

[63] Miura, A. and K. Nishinari. 2017. A passenger distribution analysis model for the perceived time of airplane boarding/deboarding, utilizing an ex-Gaussian distribution. J. Air Transp. Manag. 59, 44-49.

[64] Schultz, M. Reliable Aircraft Boarding for Fast Turnarounds. 5th International Workshop on ATM/CNS, Tokyo.

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