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FASTER AIRCRAFT BOARDING ENABLED BY INFRASTRUCTURAL CHANGES

Michael Schultz

German Aerospace Center (DLR)
Institute of Flight Guidance
Lilienthalplatz 7
Braunschweig, GERMANY

ABSTRACT

Aircraft boarding is a process mainly impacted by the boarding sequence, passenger behaviour and the amount of hand luggage. Whereas these aspects are already addressed in scientific research and operational improvements, the influence of infrastructural changes are only focused upon in the context of future aircraft design. The innovative Side-Slip Seat technology holds the potential for sustainably improving the boarding time by providing a wide aisle during the boarding progress. A comprehensive, validated simulation environment is used to analyse the benefits of this technology and an adapted boarding strategy is identified using evolutionary algorithms. Considering the operational reality of the air transportation domain (e.g. seat load), the individual passenger behaviour (e.g. conformance to procedures), and operational deviations (e.g. delay), the Side-Slip Seat could fasten aircraft boarding by both 20% shorter average boarding time and a more stable boarding progress (smaller standard deviation).

1 INTRODUCTION

Aircraft boarding always influences the entire aircraft trajectory over the day of operations since it is the last process of the aircraft turnaround (deboarding, cleaning, catering, fueling, (un-) loading, boarding) and determines the actual time of aircraft departure. Extension or reductions of the boarding may directly result in additional outbound delays or compensation of inbound delays. In particular, short range flights require a reliable turnaround progress to avoid negative impacts on the following flight legs. The paper provides an assessment of an innovative infrastructural change and an associated boarding concept, which will significantly improve the aircraft boarding.

1.1 Status Quo

In the following section, a short overview concerning scientific research on aircraft boarding is given (see also Schultz 2013). A common goal of 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 (2002) 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 (2005) 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 (2008) support the classical *back-to-front* policy in comparison to *random* boarding strategy. In this context, *random* means that each passenger has a seat assigned but the sequence of arriving passengers follows no rules. An approach to cover both a stochastic behaviour model and operational constraints was developed by Schultz and Fricke (2008). This aircraft boarding model considers the amount of hand luggage, inter-arrival times, seat load factors, and passenger conformance to the provided boarding strategies.

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On the basis of the individual boarding strategy proposed by Steffen (2008), which considers the time a passenger needs to store baggage, the model developed by Milne and Kelly (2014) assigns passengers to seats so that the hand luggage is distributed evenly throughout the plane. Chung (2012) 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. (2009). 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 et al. (2014).

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. (2005) shows a significantly improved boarding time by group boarding policies over the traditional method from the back to the front of the aircraft. Based on a mathematical model that is related to the 1+1 polynuclear growth model with concave boundary conditions, Bachmat et al. (2013) 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. (2012). Based on a linear integer 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 (2006). The interactions of passengers during the boarding process (e.g. occupied aisle) are also in the focus of a study by Frette and Hemmer (2012) and Tang et al. (2012). 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 (2012). They tested different boarding methods and described the potential savings for airline companies through reduced boarding times. Fuchte (2014) focusses on the aircraft design and, in particular, the cabin modifications with regard to the efficiency of the resulting boarding process. Schmidt et al. (2017) 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 or conformance to the boarding strategy) or the non-deterministic nature of the underlying processes (e.g. amount of hand luggage). Furthermore, there is clear lack of reliable data from the aircraft operations and the passenger handling. Assumptions regarding the individual passenger processes are often derived from simplified research environments or gathered in less realistic test setups. In this paper, a validated stochastic simulation environment is used to ensure a reliable evaluation of the proposed infrastructural changes (Schultz 2013, 2017).

2 BOARDING MODEL

The proposed dynamic passenger movement model for the boarding simulation is based on the asymmetric simple exclusion process (ASEP). The ASEP was successfully adapted to model the dynamic passenger behaviour in the airport terminal (Schultz and Fricke 2011, Schultz 2013). 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 free or contain exactly one passenger.

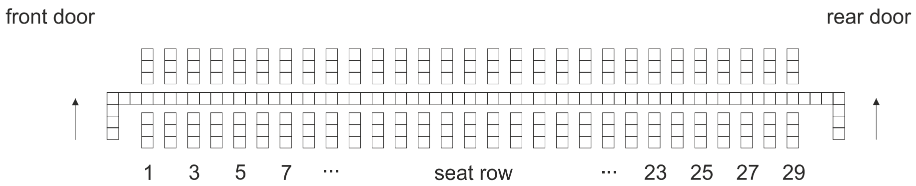

Figure 1: The Grid-based simulation environment uses an Airbus A320 as reference layout.

The boarding progress consists of a simple set of rules for the passenger movement: a) enter the aircraft at the assigned door (based on the current scenario), b) move forward from cell to cell along the aisle until reaching the assigned seat row, and c) store the baggage (aisle is blocked for other passengers) and take the seat. The movement process only depends on the state of the next cell (free or occupied). The storage of the baggage is also a stochastic process and depends on the individual amount of hand luggage and the amount of time to store the hand luggage in the overhead compartment (or under the seat). 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 (e.g. average boarding time or standard deviation of boarding time). 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, the number of available doors (default one front door), the specific boarding strategy (default: *random* boarding) and the conformance of passengers in following the current strategy (default: 85%). The conformance rate describes several operational deviations from the intended boarding strategy caused by boarding services provided by airlines (e.g. priority boarding, 1st class seats) or late arrival of passengers. Further details regarding the stochastic boarding model and the simulation environment are available at Schultz (2013). The default values are used to derive a reference boarding time, which is defined by a value of 100%. To model different boarding strategies, the grid-based approach enables both the individual assessment of seats and classification/aggregation according to the intended boarding strategy of the airline. In Fig. 2, the seats are colour-coded (grey-scale) and aggregated to a superior block structure. The boarding takes place in the order of the grey-scale value (darker seats are boarded first).

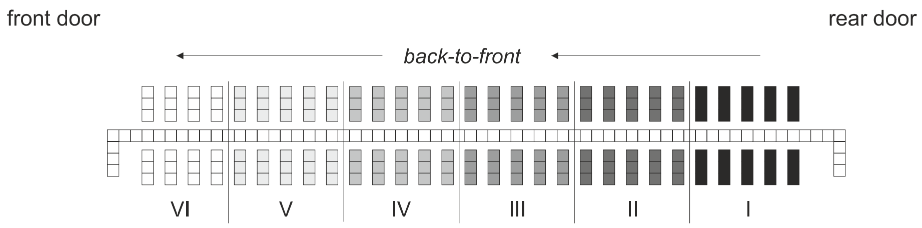

Figure 2: An example for *block* boarding strategy modelled in the simulation environment (darker seats are boarded first, this case results in a *back-to-front* regime).

During several validation trials in cooperation with a German airline, all model parameters are measured and used to calibrate the simulation environment, which finally results in ± 5% difference between simulation results and measured boarding times (Schultz 2017). Using the calibrated boarding model, several boarding strategies could be evaluated against their average boarding times and the accompanying standard deviation of the boarding times. To ensure significant results from the boarding model, each scenario is simulated 100,000 times. Due to the stochastic nature of the developed aircraft boarding model, the result of the simulation is not only a boarding time but also a set of output values:

average boarding time, standard deviation (SD) and quantiles of the boarding time. A fast boarding strategy has to efficiently manage two relevant processes: storing of hand luggage in the overhead compartment and seating process. Both processes result in a blocked aisle situation which directly affects other passengers.

There are different ways to significantly improve the boarding process: implementation of higher complex boarding procedures (from *random* boarding to *individual* seat assignments (Steffen 2008), luggage constellations (Milne and Kelly 2014) or dynamic approaches (Zeineddine 2017)), use of the second aircraft door, the reduction of the amount of hand luggage, and the introduction of infrastructural changes (e.g. Fuchte 2014). Individual seating results in a 35% faster boarding time regarding to the *random* boarding of the A320 reference aircraft (Schultz 2017) The use of the second aircraft door, which is more or less standard procedure for apron positions, holds the potential of being 30% faster but will eliminate a boarding sequence due to the bus shuttle or walk boarding. To ensure a nearly unimpaired boarding sequence for A320/B737 types, a gate position with an additional aircraft entry is necessary, such as the over-the-wing bridge (FMT 2017). Depending on the specific airline boarding procedure, the reduction to strictly one piece of hand luggage per passenger could fasten the boarding time by 5%-15% and the consequent avoidance of cabin suitcases/bags (e.g. only allow few shoulder bags) could reduce the boarding time by 20%-25% in comparison to the calibrated A320 reference scenario with the *random* boarding strategy (Schultz 2017). A highly promising infrastructural approach to further improve the aircraft boarding is the Side-Slip Seat (Molon Labe Seating 2017), which will be analysed in detail in the following sections.

3 INFRASTRUCTURAL CHANGES – SIDE-SLIP SEAT

Standard approaches to accelerating the boarding process mainly address the management of passenger behaviour 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, 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. 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.

Figure 3: The Side-Slip Seat technology provides a wider aisle for boarding (Molon Labe Seating, 2017).

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. If both sides of the seat row are in initial folded condition, a second passenger can pass without reducing the walking speed. If only one side is folded, the individual passenger walking speed is reduced by 50%. If both sides are used by passengers (unfolded), only one passenger is allowed to move in the aisle. To cover the individual passenger behaviour, two usage scenarios are taken into consideration to operate the Side-Slip Seat: if a passenger wants to sit on the middle/aisle seat, he/she stores the hand luggage first and then unfolds the seat or the other way around.

As expected, the effect of passing passengers in the aircraft aisle due to the use of the Side-Slip Seat results in significant savings in the average boarding time. With the default input parameter in the A320 reference scenario the boarding time could be reduced by 14% for a *random* boarding (random sequence of already assigned seats) without changes in the standard deviation. More complex boarding strategies (e.g. *block* or *outside-in* boarding (cf. Schultz 2013)) will also benefit from the implementation of the Side-Slip Seat. The simulation results are very promising as regards achieving significant improvement of the aircraft boarding time. But neither the *outside-in* (window seats first, aisle seats last) nor an *individual* boarding sequence is operationally considerable since the pre-sorting effort at the gate is too high (e.g. specific sorting areas, or call-in of too many groups) and inconvenient from the passenger perspective. Since new infrastructure often demands adjusted procedures, it is expected that a customized boarding strategy may additionally generate benefits out of the Side-Slip Seat. In this paper evolutionary algorithms will be used to identify an appropriate boarding strategy, instead of the systematic testing of conceived boarding strategies.

4 EVOLUTIONARY ALGORITHM

Since the prior analysis focuses on specific boarding sequences, the question arises as to whether there is an optimal solution for achieving a minimum boarding time. It has already been shown that specific strategies such as *outside-in* or *individual sequences* hold the potential of further improvements of the commonly used *block* strategy. The results of the three and six block examples demonstrate that the alternation of seat rows reduces the boarding time (Schultz 2013). If one passenger stores his hand luggage, passengers with a smaller seat row number are able to start their storing and seating process in parallel. A gap between these passengers ensures a minimum of potential interferences in the aisle. If these effects are used in one approach - board from outside to aisle, from back to front and use alternating sequence - it is expected that the accompanied passenger sequence will result in a minimal boarding time. From a combinatorics point of view, three different blocks (1, 2, 3) can be arranged in six different sequences (123, 132, 213, 231, 312, 321), six blocks in 720 sequences and 174 individual passengers result in $174! = 6.42 \times 10^{315}$ different sequences. Obviously, it is not possible to check all sequences in an appropriate amount of time.

4.1 Fitness Function

One approach towards finding the optimal boarding sequence is to apply evolutionary algorithms to explore the problem space efficiently. The idea behind this approach is to start with a set of possible solutions (population) and allow them to evolve over time using biologically-inspired processes of selection, heredity (cross-over and mutation) and replacement of least-fit populations. In a first step, a set of valid sequences have to be provided: in the case of boarding of the reference A320, each sequence has to contain all aircraft seats (no double entries). Then, the sequence has to be simulated to define the average boarding time (μ_{bt}) and standard deviation (σ_{bt}). In the case of an efficient boarding strategy, these two values are summed up to a value of fitness F, because a boarding strategy with a smaller standard deviation is preferable to a sequence with a same average boarding time but higher standard deviation: $F = \mu_{bt} + \sigma_{bt}$. Hence, the fundamental approach for passenger behaviour is based on a stochastic movement model, hand luggage amount and storage time as well as seat interactions; a minimum of simulation runs is needed to calculate the average boarding time and standard deviation. In Fig. 4 (left), the effect of a higher number of calculation runs is shown. If only a small number of simulation runs are aggregated to one exercise (one scenario), the result for the expected value of the boarding time $\mu_{exercise,bt}$ and accompanied standard deviation $\sigma_{exercise,bt}$ (see Eq. (1)) exhibit significant differences.

$$\mu_{exercise,bt} = \frac{1}{\text{runs}} \sum_{n=0}^{\text{runs}} \mu_{bt} \quad , \qquad \sigma_{exercise,bt} = \sqrt{\frac{1}{\text{runs}} \sum_{n=0}^{\text{runs}} \left(\mu_{bt} - \mu_{exercise,bt}\right)^2} \tag{1}$$

In Fig. 4 (left), the distribution of the calculated average boarding time per exercise is shown using 400 and 10000 simulation runs per exercise. Even at 10,000 simulation runs per exercise, the results for the average boarding time differ by ± 0.1% from the reference boarding time. That implies a poorer boarding sequence could still perform better than a superior sequence and could be rated as a least-fit sequence according to *F*. It is assumed that a sufficient amount of simulation runs should lead to $\sigma_{excercise,bt} = 0$, so that $\mu_{excercise,bt} = \mu_{bt}$ and each exercise with the same input parameters shows the same result. To find an appropriate number of calculations needed, both the necessary precision and the calculation time have to be taken into consideration.

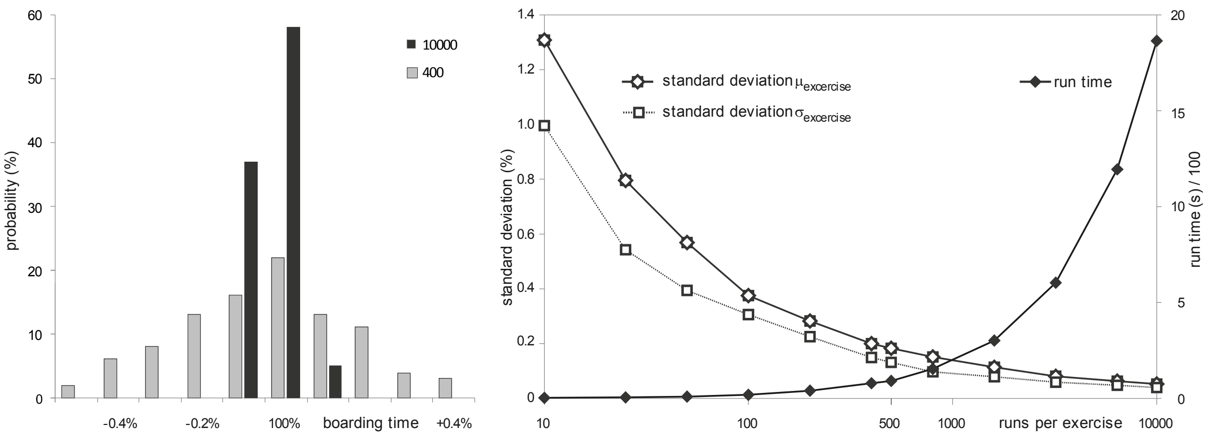

Figure 4: Distribution of boarding time (left) and precision of boarding time and standard deviation (right) considering different numbers of simulation runs for calculation.

At 10,000 simulation runs per exercise, the calculation time reaches a level of 18 s per exercise to determine an average value for only one boarding sequence (Fig. 4, right). Using the value of 500 runs per exercise, a fair trade-off between precision (also measured in standard deviation, see Eq. (1)) and simulation time is reached: standard deviation of $\mu_{excercise,bt}$ and $\sigma_{excercise,bt}$ are < 0.2%, calculation time per exercise is 0.9 s.

4.2 Recombination of Sequences

The fitness value *F* of each sequence of the population can now be evaluated and ranked according to its fitness in an ascending order (smaller values represent a higher fitness regarding the task of searching for minimum boarding time). The sequences with the best fitness are now used for replication. The underlying idea of biological replication uses specific sequences of each parental gene and recombines them to form new gene sequences. Finally, the new generation of children contains partial sequences of the involved parents. In the context of aircraft boarding sequences with individual seats, this simple approach of recombination will fail using the uniform crossover principle. The uniform order-based crossover (Davis 1991) uses the same initial approach of the stochastic recombination but introduces a bitmask to assign elements of the parents to the two children (Fig. 5). If the bitmask value is zero, the element from the first parent is transferred to the first child; if the value is one, the element from the second parent is transferred to the second child. In the following intermediate step (see Fig. 5, top right *), the missing elements are filled up in the order in which they appear at the other parent. As an example, the elements 2-3-5 are missing at the first child and appear at the second parent in the order 5-3-2, which results in the final sequence of 1-5-3-4-2-6.

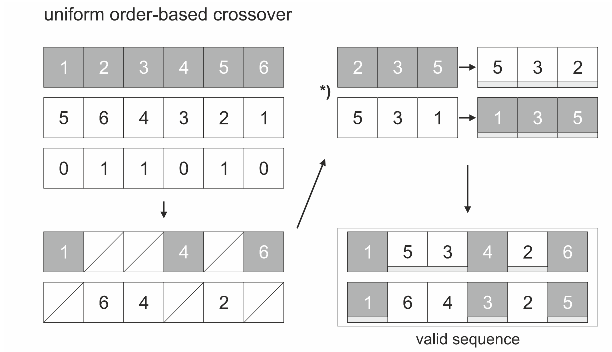

Figure 5: A crossover algorithm for the recombination of sequences.

In the context of the travelling salesman problem, the edge recombination (Whitley 1989) is another approach towards solving the identified combinatorial task. Both approaches are implemented, but in the following analyses the uniform order-based crossover approach is used, since it requires a smaller calculation effort. After building up a population, defining the fitness function and modelling the replication process, the final step will be to set up an algorithm to allow for a mutation (minor changes in the sequence caused by random processes) to continuously influence the evolution of the population. Two typically used approaches for mutation are the swapping and the insert approach. The swapping algorithm exchanges the position of two elements of the sequence and the insert algorithm removes one element of the sequence and inserts this element in a different position.

4.3 Adaptation of the Boarding Model Approach

The basic principles of the evolutionary algorithm are now described and implemented in the simulation environment. First tests with the simulation environment demonstrate that after 6.5 hours of calculation time with more than 12.5 million simulation runs, the evolutionary algorithm starts to converge but still identifies fitter sequences. Since the simulation environment was initially developed as a comprehensive tool to cover all operational aspects (e.g. data analysis, visualization, testing), efforts to increase the calculation speed are expected to result only in one order of magnitude. To benefit from the evolutionary algorithm, a faster implementation of the boarding process is mandatory. Therefore, some assumptions of the comprehensive model have to be ignored, if these assumptions will not affect the boarding sequence. The following elements will not be included, since they are randomly distributed and result in average values at high numbers of calculations: baggage distribution (amount and time to store), walking speed, arrival rate, conformance rate, and seat load factor. Primary elements of the fast implementation are the seat shuffle and the influence of the blocked aisle due to the seating process. The aircraft is parted into a left and a right side; for each side, a status array consisting of all rows is implemented. Each row status S_{row} aggregates the status of three seats $S_{seat,\,n}$ (window, middle, aisle), with 0 if seat is free and 1 if seat is occupied, to an integer value (see Eq. (2)).

$$S_{\text{row}} = 2^2\, S_{\text{seat, window}} + 2^1\, S_{\text{seat, middle}} + 2^0\, S_{\text{seat, aisle}} \quad (2)$$

The status demands a specific amount of movement of the involved passengers in order to solve the seating process (see Schultz 2013). Each status directly results in an amount of movements; only the case of an occupied middle seat additionally depends on the arriving passengers. If the passenger takes the aisle seat, one movement is necessary; if the window seat is used, five movements are necessary to unblock the aisle. If all seats are occupied, the seat row status reaches a value of seven (2^2 x **1** + 2^1 x **1** + 2^0 x **1** = 7); if only the middle seat is free, the status value is five (2^2 x **1** + 2^1 x **0** + 2^0 x **1** = 5).

To cover the effect of the blocked aisle, the number of influenced passengers has to be defined. In the boarding sequence, a passenger is marked as influenced if he/she is positioned later in the sequence and has a higher seat row number. This influence is expected to have a decreasing behaviour (decreasing with a higher distance dx in the sequence) and will be modelled with an exponential function $f(dx) = A\, e^{-B\,dx}$. The factor A is defined as a switch with the value of one if the passenger is influenced and zero if not. Factor B is a scaling factor and set to the value of 0.4, which results in a suitable decreasing behaviour (influence on the next passenger in the sequence is 33% lower). The seat row status and the influence calculation are summarized to a new fitness function (see Eq. (3)).

$$F = \sum_{i=0}^{n} \sum_{j=0}^{i} S_i A_j e^{-B(i-j)} \quad (3)$$

4.4 Implementation of Evolutionary Algorithm

To start the algorithm, additional parameters (e.g. mutation rate) and the specific progress of the evolutionary algorithm have to be defined. The following eight steps are implemented in the simplified simulation environment and defined as a tournament.

1. The start population consists of 100 randomly chosen boarding sequences.
2. The fitness F of all sequences is calculated.
3. The best 25 sequences are mutated with a probability of p_m and stored (mutation insert).
4. These 25 sequences are used to create the child population (50), where the second parent is randomly chosen out of the least fittest sequences.
5. Each of the 50 child sequences is mutated with a probability of 0.1% (mutation insert).
6. 15 of the fittest sequences are copied and mutated (one random mutation insert process).
7. 10 random sequences are added to the new population.
8. Double entries in the list of sequences are deleted and replaced with random sequences as appropriate to ensure that always 100 sequences are in the tournament.

Finally, the new population should usually consist of the 25 fittest survivors, 50 children, 15 mutants, and 10 new sequences. The fitness of the tournament is defined by the best fitness value of the 100 sequences (in the case of the fitness function (see Eq. (3)): smaller values demonstrate a better fitness). The mutation probability p_m starts with a value of 0.2% and decreases with every tournament by 0.01% if the fitness of the current tournament is better than the average fitness over the last 100 tournaments (stabilizing the calculation). If the average fitness over the last 100 tournaments is equal to the fitness of the current tournament, p_m increases by 0.02% ('heating' to create disorders). This behaviour is comparable to the simulated annealing approach to overcome local minima in the problem space. The simplified evaluation model for the boarding approach reaches a calculation speed of 325 s for 12.5 million boarding sequences, which is approx. 72 times faster than the comprehensive stochastic boarding model. In Fig. 6, the progress of the evolutionary algorithm is shown with clear local minima.

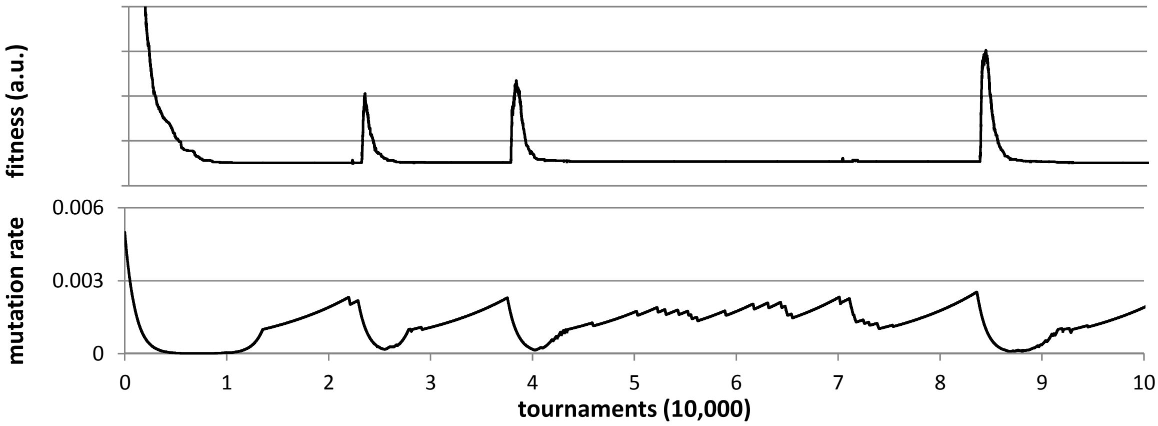

Figure 6: Progress of the evolutionary algorithm (100,000 tournaments) with fitness function (above) and dynamic mutation rate (below).

4.5 Refinement of Initial Assumptions

Several minor modifications of the algorithm were developed during the course of the development of the evolutionary approach. The first adaptation was to distinguish between different levels of the mutation rate. If the mutation rate is higher than 0.1%, the change rate is set to one order higher. Further on, a different change rate for increasing/decreasing the mutation rate exhibits no beneficial behaviour (e.g. faster convergence or higher stability). If the fitness values start to converge, the value of 15 mutated parents is increased stepwise to 25 and the insertion of random sequences is finally only needed if double entries occur (see steps 6, 7 and 8 of the algorithm). In Fig. 7, the progress of the evolutionary algorithm is shown using the arisen sequences for visualization. The disorder at the beginning changes to a regular sequence. After 200,000 tournaments, the pattern of the local minima obviously indicates a sequence which prefers the window seats first (followed by middle and aisle seats) and inner ‘back to front’ behaviour order.

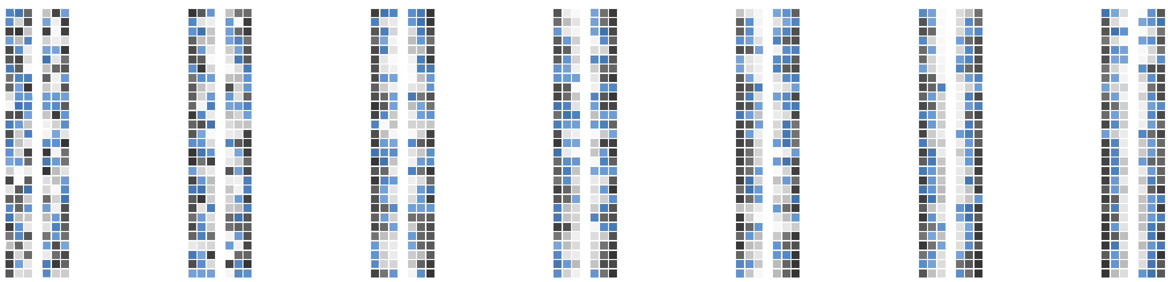

Figure 7: Progress of the evolutionary algorithm: increasing fitness from left to right sequence (order of boarding: dark grey followed by blue followed by light grey).

If this optimized sequence is used as input in the comprehensive simulation environment, it results in an faster boarding time (41% faster than reference boarding), which is significantly better than the prior evaluated boarding sequences (Schultz 2013) and faster than the individual boarding sequence proposed by Steffen (2008) which is 35% faster. As a result, the simplified simulation model is able to solve the boarding sequence problem. The evolutionary algorithm is now applied to the Side-Slip Seat technology to identify an appropriate boarding sequence. The fitness function is therefore adjusted by adding a value

C_i which considers the condition of the aisle (see Fig. 3): $C_i = 0$ if both sides of the row are folded after the passenger takes the seat (passing the row without interactions), $C_i = 1$ if the seats at one side of the row are unfolded (minor interaction) and $C_i = 2$ if the seats of both sides are unfolded (major/standard interactions, waiting). This straightforward implementation of the expected Side-Slip Seat benefits results in a left/right pattern inside the boarding sequence. To underline this effect, C_i is modified to differentiate between left/right, so $C_i = 1.1$ and $C_i = 0.9$ if left side is unfolded/right side is folded and vice versa. In Fig. 8, the sequence evolution is shown; the last sequence shows the slightly modified left/right solution to emphasize the existing pattern. After boarding, the window seats, middle and aisle seats of the right side are occupied before the middle/aisle seats on the left side.

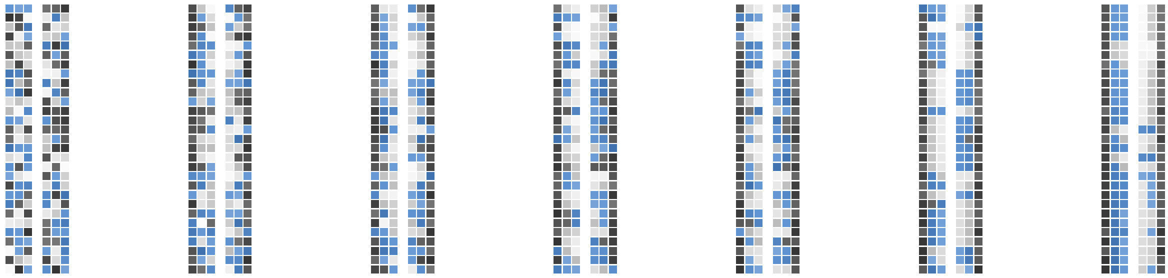

Figure 8: Side-Slip Seat, evolution of boarding sequences with increasing fitness from left to right (order of boarding: dark grey followed by blue followed by light grey).

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 Side-Slip Seat technology. Using the reference A320 layout, the default input values and the Side-Slip Seat, a *random* boarding strategy with this left/right approach results in a 19% faster boarding accompanied with a 10% smaller value for SD.

5 SUMMARY AND OUTLOOK

The paper provides a comprehensive analysis of the innovative approach of using Side-Slip Seats in the aircraft to significantly improve the boarding time. Current approaches only address the passenger boarding sequence, but the presented research indicates that infrastructural changes will also sustainable contribute to the improvement of the aircraft boarding process. The implementation of the new dynamic aircraft seats demand for an appropriate adapted boarding strategy. To identify optimal boarding sequences, a validated comprehensive simulation model (Schultz 2013, 2017) was used as a reliable basis to derive a simplified, fast simulation environment. This fast environment uses an evolutionary algorithm to continuously improve an initial set of boarding sequences. Finally, the identified optimal sequence is evaluated with the comprehensive model.

In the case of the Side-Slip Seat, the optimal boarding sequence differentiates between the boarding of the passenger seats from the left and the right side of the aisle, where current operational boarding approaches prefer a boarding from the back to the front. Even under realistic, operational boundary conditions (e.g. seat load, passenger conformance regarding to the boarding sequence), the average boarding time and standard deviation exhibit significant savings, by means of faster boarding and smaller deviations of the boarding times (*random-left/right* strategy: 19% faster, SD 10 % smaller). The savings are comparable with the use of a second door (rear door) for the passenger boarding of 20-30% (Schultz 2013).

After introducing a stochastic approach for passenger boarding (Schultz 2013), a measurement and validation campaign (Schultz 2017) and this investigation in infrastructural changes, two new topics in the context of boarding will be focused upon: the online prediction of the boarding time using sensor information from the connected aircraft cabin (e.g. seat occupation and queueing in the aisle) and the

SeatNow concept, which addresses operational improvements by efficiently replace the current standard call-in boarding procedure.

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AUTHOR BIOGRAPHY

MICHAEL SCHULTZ is Head of the Air Transportation Department of the Institute of Flight Guidance at the German Aerospace Center (DLR), Braunschweig, Germany. He holds a diploma degree in business and engineering and a Ph.D. in aviation technologies and logistics from the Technische Universität Dresden, Germany. His research interests include stochastic, agent-based simulations and their applications in the transportation sector, particularly in air traffic and airport management. His e-mail address is: michael.schultz@dlr.de.