Emerging from the dark cabin age: sensor-based prediction of passenger boarding times

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A high degree of standardization in operational processes is required to ensure efficient and effective air traffic management during the flight phases and ground-handling stages. Deviations and disruptions in the complex and closely interlinked handling processes often lead to delays, which as the day progresses can have an increasingly negative effect on airline operations - and indeed of the entire air traffic network. Ground-handling processes are considered aircraft turnaround and consist of the unloading and loading of freight and baggage, refueling, cleaning, catering, and the boarding and disembarking of passengers (cf. [1]). Aircraft boarding is always a critical process and mostly driven by the behavior of the passengers [2]. The duration of boarding is influenced by their air travel experience and their willingness or ability to follow boarding procedures. In fact, there is no feedback from the cabin about the current situation or indications of future conditions. It is reasonable to describe the cabin as a black box in today's digital age. This is more surprising given that most passengers carry their own transceivers (mobile devices) and thus technological solutions for feedback from the cabin do exist.

In previous studies, we have already developed initial approaches by predicting boarding times with trained Long Short-Term Memory (LSTM) models [3] or by assessing the precision of sensor readings in the cabin [4]. The Corona pandemic, with the required minimum distances between passengers, showed that there is no operational monitoring capability in the cabin, but that this could have contributed significantly to process optimization [5]. The sensors do not necessarily have to be installed in the aircraft cabin, such as sensors in the seats or above a seat row. Mobile devices belonging to passengers could be used to determine positions and become part of a digitally connected aircraft cabin [6]. To solve the complex problem of optimizing boarding sequences, evolutionary/genetic algorithms are commonly applied. There are no approaches to solve this problem with machine learning (ML), which is also a consequence of the insufficient data availability. The previously implemented LSTM model [3] is based on a complexity metric to evaluate the current seating situation in the cabin [7] and a comprehensive set of input data is provided by a validated boarding simulation environment [1]. In the absence of sensors, boarding progress cannot be predicted at this time, and estimates for boarding times are based on the experience of on-site operators. The aircraft cabin is a challenging environment for a sensor network due to its design and confined space. Location-aware radio-based communication networks provide a technical solution for passenger state monitoring and handling (see Fig. 1).

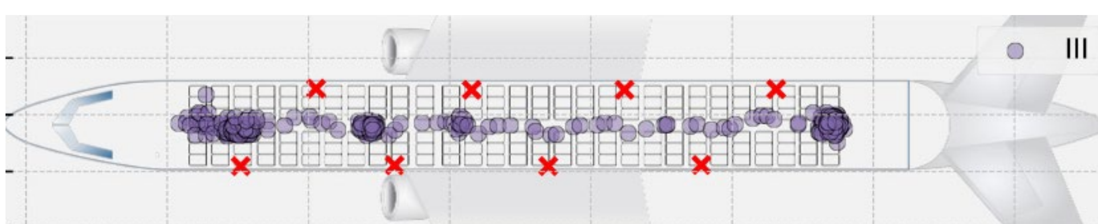

Figure 1: Trajectory of a single passenger including positional errors using radio propagation simulation [6]

From a research perspective, we want to answer three questions. (1) What sensor information needs to be provided at what quality? (2) How to cover domain knowledge in the ML models using complexity metrics? (3) How accurately could aircraft boarding times be predicted?

Approach

In the original research approach, the progress of boarding was predicted using 100% accurate feedback from an operational simulation environment. This approach was subsequently refined in two key areas. Firstly, different sensor configurations and their potential feedback were analysed. Initially, the focus was solely on improving the prediction. However, as the project progressed, the quality of the sensor feedback, the signal processing and the complexity of the sensor network were also considered.

Fig. 2 (left) shows different regression models to predict passenger boarding time. The AdaBoost, Hubert Regressor, and Bagging Regressor algorithms are unable to learn the model effectively, resulting in high error rates. Random Forest and Cat Boost algorithms require significant training times. In our further experiments, we used XGB and added different sensor information to improve the prediction (Fig. 2, right), starting with the number of passengers already entered the cabin, added the size of the queue in front of the aircraft door, using a seat and compartment sensors to indicate used seats and utilization of capacities, and finally add a complexity metric (consider passenger and bag constellations in the cabin – domain knowledge). As Fig. 2 (right) illustrates, the predictive capabilities of the algorithm are reinforced by the incorporation of each additional sensor. Regarding the compartment and seat sensors, it appears that both provide comparable levels of information for the regression model; therefore, from an operational view, operators are encouraged to implement the more convenient sensor environment.

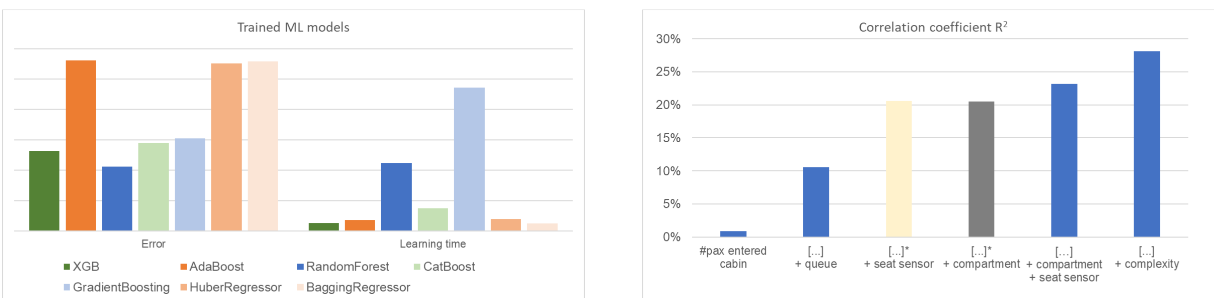

*Figure 2: (**left**) ability of ML models to learn the boarding process (error) and time needed for learning, (**right**) increase of model accuracy when adding additional sensor information and complexity metrics (covering domain knowledge)*

The preliminary outcomes are encouraging and indicate that further enhancements to the prediction model are feasible.

References

[1] M. Schultz et al. Future aircraft turnaround operations considering post-pandemic requirements. J Air. Transp. Manag. 89 (2020), 101886.
[2] M. Schultz. Implementation and application of a stochastic aircraft boarding model. Transp. Res. Part C Emerg. 90 (2018), 334–349
[3] M. Schultz and S. Reitmann. Machine learning approach to predict aircraft boarding. Transp. Res. Part C Emerg. 98 (2019), 391–408.
[4] P. Schwarzbach et al. Evaluation of Technology-Supported Distance Measuring to Ensure Safe Aircraft Boarding during COVID-19 Pandemic. Sustainability 12 (20) (2020).

[5] M. Schultz and M. Soolaki. Analytical approach to solve the problem of aircraft passenger boarding during the coronavirus pandemic. Transp. Res. Part C Emerg. 124 (2021), 102931
[6] P Schwarzbach et al. Simulation-based evaluation of indoor positioning systems in connected aircraft cabins. Transportmetrica B: Transp. Dyn. 12 (1) (2024), 2321454
[7] M. Schultz. A metric for the real-time evaluation of the aircraft boarding progress. Transp. Res. Part C Emerg. 86 (2018), 467–487