

PROVIDING SENSOR INFORMATION FOR BOARDING TIME PREDICTION

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Abstract

Reliable prediction of aircraft boarding time is essential for meeting negotiated target off-block times within airport collaborative decision making. A major limitation of current operations is the lack of measurable information about the actual boarding state inside the aircraft cabin and along the boarding path. Passenger positions, aisle occupation, and carry-on baggage directly affect boarding progress, yet they are not continuously observable in turnaround management systems. We develop and evaluate sensor-based perception approaches to monitor passenger states and carry-on baggage during boarding. The experimental environment combines video- and LiDAR-based sensing, personalized localization, and mixed reality visualization in a modular aircraft cabin setup under realistic boarding scenarios. The results demonstrate the feasibility of sensor-based boarding state estimation, quantify the performance and limitations of both sensing modalities, and show that aggregated baggage information can be extracted as a practical process indicator. The work establishes a foundation for sensor-supported boarding sequence assessment, data-driven boarding time prediction, and future dynamic boarding monitoring and management.

Keywords: passenger handling, aircraft boarding, carry-on baggage detection, LiDAR sensing, mixed reality

1. Introduction

In air transport, boarding is the final and critical ground handling process. It is strongly influenced by passenger behavior [1]. Boarding duration depends largely on passengers' travel experience and on their willingness and ability to support the boarding process. Passengers expect a comfortable and fast boarding experience [2]. Airline and airport management, in contrast, aim to meet agreed target times for punctual and reliable ground operations. These target times account for the current operational state, experience, and expectations of the involved stakeholders regarding turnaround progress. For ground handling, reaching the target off-block time (TOBT), the time at which the aircraft is ready for operation after boarding, is a key milestone within airport collaborative decision making (ACDM) [3]. Based on the TOBT, air traffic control determines the target start-up approval time (TSAT) for flight operations, including apron use, taxiing, and runway access. The TSAT defines the time at which an aircraft is cleared to leave its parking position to ensure efficient runway sequencing. If the predicted TOBT exceeds the TSAT during ground handling, ongoing processes must be rescheduled. The TOBT is therefore a critical milestone and a central element of efficient airport and airspace management.

At present, this prediction remains uncertain because passenger boarding inside the cabin is only weakly observable during operations. The aircraft cabin therefore acts as an operational black box for turnaround management. Passenger states, aisle occupation, baggage handling, and seat row access are not continuously available, although these variables directly determine boarding progress. Our laboratory approach addresses this limitation by providing a sensor-based environment in which these hidden process states can be observed, evaluated, and linked to operational decision support.

It enables boarding-related practices to be tested and helps to make the hidden process observable (see Figure 1).
While cabin-based sensing is required to observe the process after passengers enter the aircraft, useful indicators can also be obtained before cabin entry. In this paper, we therefore use carry-on baggage as a first operationally relevant example. The quantity and characteristics of baggage brought into the cabin influence aisle interference and seat row access, while gate scans provide information on the passenger sequence. Together, these external observations offer early indications of the expected boarding burden and complement cabin-based sensing for data-driven boarding time prediction.

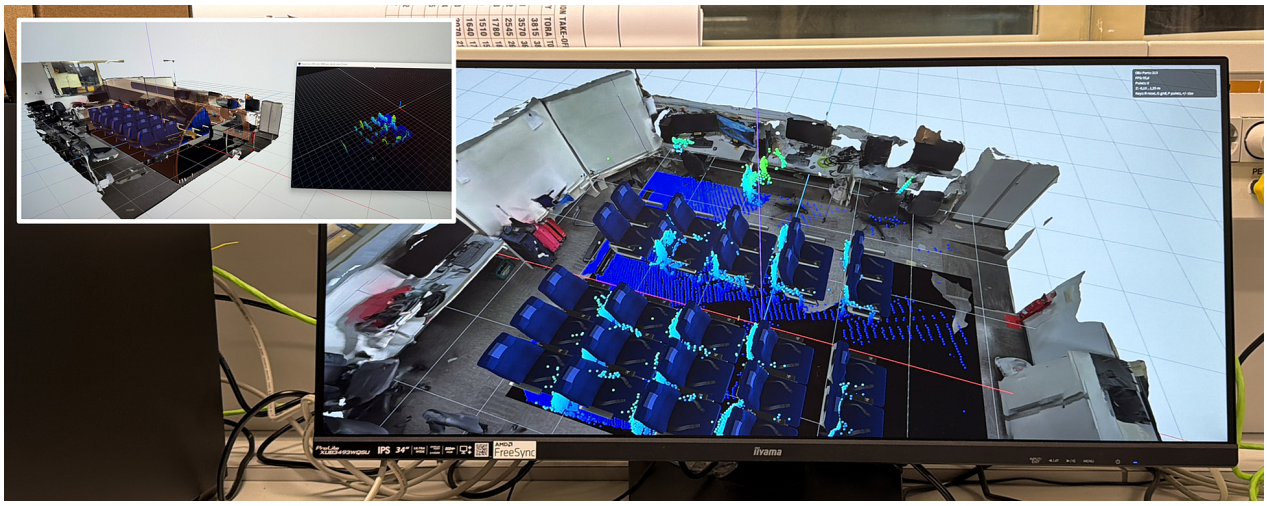


Figure 1 – Development of a mixed reality aircraft cabin setup including an integrated sensor environment.

1.1 Literature overview

Previous work has established initial approaches to improve the understanding and prediction of boarding processes. These include boarding time prediction using trained Long Short-Term Memory (LSTM) models [4] and evaluation of sensor measurement accuracy within the aircraft cabin [5]. The COVID-19 pandemic, which imposed minimum distance requirements between passengers, highlighted the absence of operational monitoring capabilities inside the cabin. At the same time, it demonstrated the substantial potential of such monitoring for process optimization [6]. Cabin monitoring does not necessarily require fixed sensor installations. Sensors embedded in seats or mounted above seat rows are not the only option. Passenger-owned mobile devices can also be used for position estimation and may become integral components of a digitally connected aircraft cabin [7]. These monitoring concepts are particularly relevant because improved observability can connect theoretical boarding models with the actual state of an ongoing boarding process. This connection is important for boarding sequence optimization. Optimizing boarding sequences is a complex combinatorial problem, and existing solutions are mostly based on evolutionary and genetic algorithms. However, such optimization approaches are often far removed from operational reality, where strict requirements, limited flexibility, and heterogeneous passenger behavior prevail. In practice, the greater challenge is therefore not to derive theoretically optimal boarding sequences, but to reliably predict boarding progress and completion time under real operating conditions. Machine learning can support boarding time prediction in real operational processes. This requires sensor data to be available and usable. Such data could then be complemented by synthetic data generated within the existing simulation environment (see Figure 2).
Against this background, the central research gap lies in the transition from model-based boarding time prediction to operationally available sensor input. Existing prediction approaches can process passenger sequence information and synthetic process data, but their operational value depends on measurable state variables during boarding. The present work therefore focuses on the provision of

such input variables. Passenger positions and carry-on baggage information are considered observable process indicators that can be generated by a sensor-based cabin and gate environment and then used to support boarding time prediction.

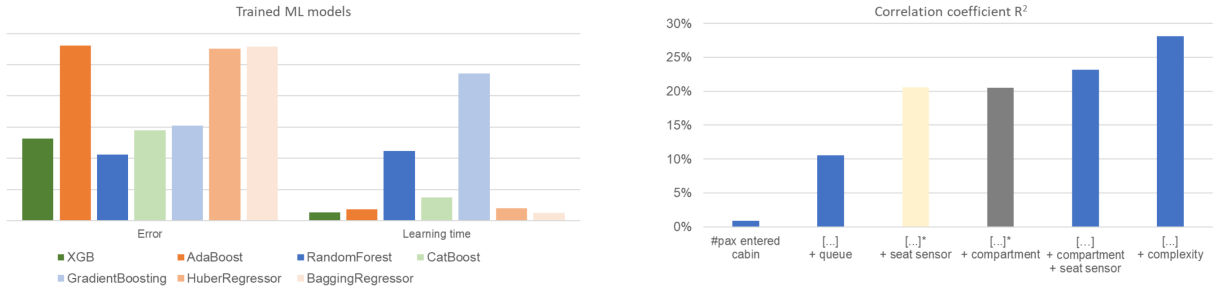


Figure 2 – In a synthetic environment, virtual sensor feedback is used to predict boarding time using multiple machine learning approaches (left). The prediction accuracy increases with both the quantity and quality of the available sensor input (right).

1.2 Scope and contribution

The paper addresses the impact of passenger boarding order and carry-on baggage on overall boarding duration. Both factors are closely linked to typical sources of delay, including aisle interference, seat re-access, and hand baggage stowage. The focus is placed on sensor information as a prerequisite for future concepts of dynamic boarding control and boarding time prediction. The analysis therefore evaluates whether relevant passenger and baggage states can be captured in a realistic laboratory environment and whether this information can support the assessment of boarding progress.

The specific focus on hand luggage is motivated by previous simulation studies. These studies indicated that knowledge about the number of hand luggage items can support the design and evaluation of boarding sequences. In the investigated simulation setting, considering hand luggage information provided an improvement potential of approximately 10% compared with configurations that did not account for this information. This finding provides the operational motivation for the present work and defines the subsequent measurement problem. The central question addressed in this paper is whether the required baggage information can be detected and quantified with sufficient reliability using camera-based and LiDAR-based sensing.

The contribution of the paper is threefold. First, it presents a mixed reality laboratory environment that links a physical cabin mock-up with a sensor-based data acquisition and visualization architecture. Second, it evaluates video-based and LiDAR-based perception approaches for detecting passengers and carry-on baggage under structured boarding scenarios. Third, it discusses how sensor-derived baggage information can provide a practical input for future boarding management and prediction concepts.

2. Experimental cabin environment

To evaluate sensor-derived boarding information under controlled but operationally meaningful conditions, a modular laboratory cabin environment was established. The setup reproduces relevant spatial constraints of a single-aisle aircraft cabin using a seating arrangement based on an Airbus A220 configuration. It includes seat rows, aisle structures, and a defined passenger movement area. This configuration allows passenger flow, carry-on baggage handling, and sensor visibility to be investigated within a reproducible experimental environment.

The laboratory setup provides a compromise between operational representativeness and repeatability. It does not reproduce a complete aircraft cabin, but focuses on those spatial constraints that are most relevant for boarding. These include aisle width, seat row access, and the interaction between passengers and baggage items. As a result, individual scenarios can be repeated with controlled variations in passenger density, baggage quantity, distances between persons and objects, and partial occlusions.

This controlled structure also enables the systematic comparison of different sensing modalities. The same physical scenarios can be recorded with camera-based and LiDAR-based systems, while additional localization sensors provide independent positional references. The experimental environment therefore serves not only to demonstrate perception algorithms, but also to evaluate whether the resulting information is sufficiently robust for boarding-related process analysis.

2.1 Sensor architecture and mixed reality integration

The sensor environment combines LiDAR, camera-based reference data, and personalized localization sensors. The LiDAR system provides the primary geometry-based data source for detecting and tracking passengers and carry-on baggage. It captures three-dimensional point clouds and allows the analysis of object positions, spatial distances, and movement patterns. The camera system is used as a secondary reference source for plausibility checks and for visual cross-validation of the LiDAR point clouds. In this configuration, the core detection pipeline remains based on geometric sensor data, while image data supports experimental validation of the perception results.

Additional localization information is provided by a HTC Vive and SteamVR Lighthouse tracking system with personalized wearable sensors. These sensors increase tracking stability in multi-participant scenarios and provide an independent positional reference for validating the laboratory experiments. A middleware layer aligns the heterogeneous data streams and buffers the sensor information for subsequent analysis. This architecture enables stable data logging, repeated experimental runs, and consistent spatial calibration between the physical laboratory setup and the digital processing chain.

The laboratory cabin is further linked to a mixed reality environment. A parameterizable three-dimensional aircraft cabin model was implemented using a Blender-to-Unity workflow. The virtual cabin can represent the seating configuration and spatial dimensions of the experimental setup. Real-time position data from the sensor environment is streamed into Unity and rendered as dynamic entities within the virtual cabin. The environment was deployed on a Meta Quest 3 headset, enabling immersive inspection of passenger positions and sensor-based state estimates.

The mixed reality integration connects the physical experiment with its digital representation and thereby supports both validation and demonstrator applications. By combining the cabin mock-up, LiDAR point cloud processing, personalized localization, and immersive visualization, the architecture provides a sensor-based test environment for boarding-related data acquisition. Sensor outputs can therefore be evaluated with respect to detection metrics and their operational usefulness for boarding process analysis.

2.2 Perception and data processing methods

The proposed perception approach addresses the automated detection and association of passengers and their carry-on baggage to support the aircraft boarding process. The objective is to capture passenger states reliably in the boarding area and to provide sensor-based input for subsequent process analysis. Two sensing modalities are considered and evaluated under comparable laboratory conditions, representing the boarding area at gate 31/32 of Munich Airport and the modular cabin-related laboratory setup.

For the video-based approach, a perception pipeline is implemented using YOLOv5 [8] for object detection and DeepSORT [9] for multi-object tracking. The system detects passengers and baggage items and maintains consistent identities over time. The camera-based approach provides high information density and visual interpretability. It is therefore well-suited as a reference modality for validation. At the same time, it raises data protection concerns in public terminal and cabin environments, because image data may contain identifiable persons.

To address data protection requirements, a LiDAR-based perception pipeline is implemented as an alternative. A solid-state LiDAR sensor (Blickfeld Qb2) provides three-dimensional point cloud data of the boarding area. Four detection strategies are implemented and evaluated, ranging from density-based clustering using DBSCAN to sensor-internal tracking and hybrid approaches. The processing focuses on geometric features, point cloud segmentation, object clustering, and the association of detected baggage items with nearby passengers.

LiDAR-based perception provides a privacy-preserving and light-independent alternative to image-based sensing. Its main methodological challenge lies in the separation of closely spaced objects.

Passengers and baggage items may merge into a single point cloud cluster when they move close together or when the baggage item is partly occluded by the passenger's body. The resulting perception task is therefore not limited to object detection, but also includes robust association and aggregation of imperfect observations.

2.3 Experimental scenarios and evaluation metrics

The video-based system is evaluated using 38 boarding scenarios. These scenarios include different passenger and baggage constellations and allow the assessment of detection and tracking performance under repeated laboratory conditions. The LiDAR-based system is evaluated using 32 scenarios. Key influence factors include sensor positioning, lighting conditions, obstacles such as glass surfaces, varying passenger density, differences in baggage quantity, spatial distances between persons and baggage items, and partial occlusions.

The experimental design reflects the intended operational use of the sensor information. The goal is not to reproduce all possible passenger behaviors, but to test whether the sensing approaches can provide stable process indicators under conditions that are relevant for boarding. This includes the presence of multiple passengers, changes in object proximity, temporary occlusions, and varying visibility of hand luggage items.

The evaluation uses standard detection metrics. Precision measures the share of detected objects that correspond to correct detections. Recall measures the share of relevant objects that are successfully detected. The F1 score combines precision and recall into a single performance indicator. These metrics are applied to quantify the detection performance of the sensing approaches and to compare their suitability for boarding state estimation.

In addition to object-level metrics, the analysis considers aggregated baggage information. This distinction is important because future boarding management systems may not require a stable identity for each baggage item over the full boarding process. Aggregated variables, such as the number of baggage items per passenger group or the estimated baggage load entering the cabin, may already provide useful information for operational decision support.

3. Results

The evaluation follows the distinction between sensor performance and operational usefulness. At the sensor level, the question is how reliably persons and baggage-related objects can be detected. At the process level, the question is whether these observations can be transformed into aggregated baggage indicators for subsequent boarding process analysis. This distinction is essential because object-level detection and operational process information represent different requirements. Figure 3 illustrates the corresponding point cloud-based detection of hand luggage and shows the geometric nature of the available sensor information.

3.1 Detection Scores

Table 1 summarizes the object-level detection performance of the investigated sensing modalities. The camera-based implementation achieves higher detection performance and demonstrates real-time capability in live operation. The LiDAR-based implementation reaches lower values for precision, recall, and F1 score. The main reasons are close object proximity, temporary occlusion, and the merging of passengers and baggage items into common point cloud structures. The lower LiDAR-based detection score must be interpreted with respect to the intended operational use case. LiDAR does not provide visual identity information and is largely independent of ambient light. It therefore remains relevant for privacy-preserving boarding monitoring, especially in public terminal, boarding bridge, or cabin environments.

Table 1 – Summary of detection performance for the investigated sensing modalities.

Sensing modality	Precision	Recall	F1 score
Camera-based perception	0.70	0.83	0.76
LiDAR-based perception	0.52	0.48	0.50

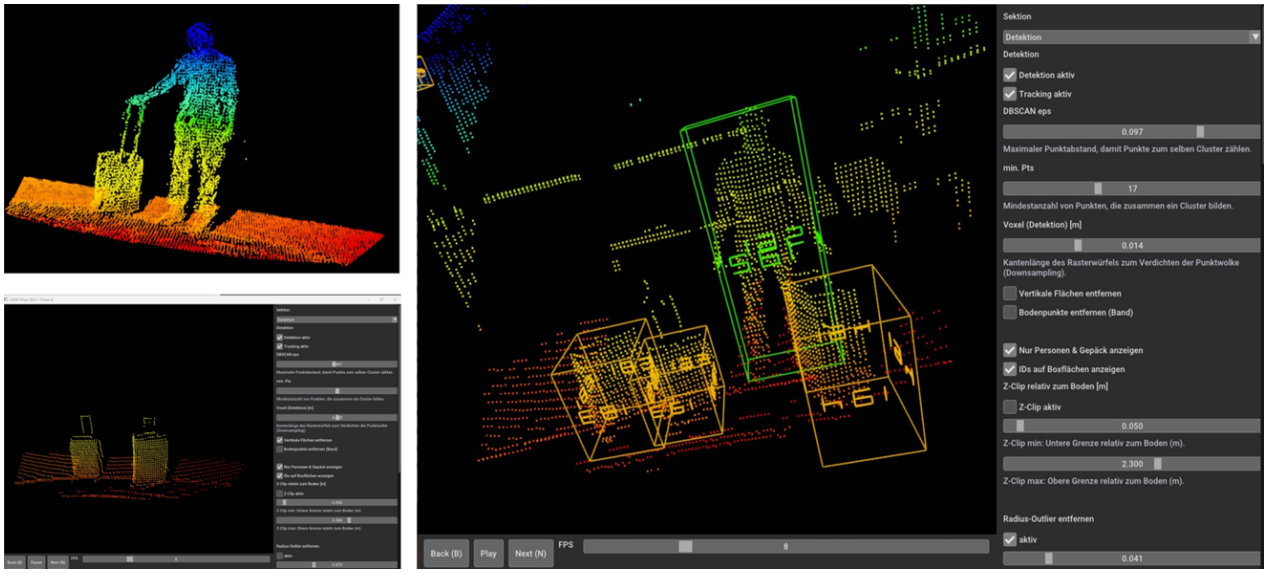


Figure 3 – Detection of hand luggage using LiDAR sensor and point cloud segmentation.

The comparison shows that the two sensing modalities provide complementary information. Camera-based perception is more accurate under the investigated laboratory conditions and can support reference annotation and validation. LiDAR-based perception is less accurate at the object level, but provides a privacy-preserving geometric representation of passenger and baggage states. Its main limitation is the separation of closely spaced objects, rather than the general ability to observe boarding-related movement.

For boarding process analysis, this limitation has to be interpreted in relation to the intended use of the information. A future prediction or control system may not require a stable identity for each baggage item over the complete boarding process. Aggregated variables, such as the estimated number of carry-on baggage items entering the cabin, the average baggage count per passenger, or the distribution of baggage load along the boarding sequence, may already provide useful information for operational decision support. These variables are less sensitive to short-term detection errors and still represent the operational burden caused by baggage handling.

3.2 Operational interpretation for boarding sequence support

The operational relevance of hand luggage information was identified before the sensor experiments. Prior simulation studies indicated that knowledge about the number of hand luggage items can support the design and assessment of boarding sequences. In these simulations, considering baggage-related information led to an improvement potential of approximately 10 percent compared with configurations that did not account for this information. This result is a simulation-based motivation for the sensor work. It is not an experimental improvement of a boarding time prediction model.

The present experiments, therefore, address the subsequent and more practical question. If knowledge about hand luggage items is valuable for boarding sequence design and process assessment, can this information be detected and quantified by sensors under realistic laboratory conditions? The results show that both camera-based and LiDAR-based sensing can contribute to this task. The camera-based approach provides higher detection performance, while the LiDAR-based approach offers a privacy-preserving alternative that is suitable for further development.

This interpretation changes the role of the sensor system. The sensing architecture is not intended to replace boarding models. It provides missing operational input variables that can be used by such models. Hand luggage count is particularly relevant because it links passenger behavior with physical cabin constraints. It affects aisle interference, local waiting times, and the duration of seat row access, because passengers have to stop, search for available overhead bin space, and stow their items before taking their seats.

The results also support a realistic interpretation of sensor requirements. For operational decision support, the decisive criterion is not necessarily perfect object-level perception. The more relevant

question is whether stable process indicators can be extracted from imperfect sensor observations. In this context, baggage count represents a compact and interpretable input variable. It can serve as a practical bridge between sensor-based state estimation, boarding sequence assessment, and future concepts for dynamic boarding monitoring and management.

4. Conclusions and future work

Sensor information becomes operationally useful when it can be condensed into process indicators for boarding time prediction. In this study, hand luggage count provides such an indicator because baggage handling translates passenger heterogeneity into measurable constraints on aisle movement, seat row access, and local waiting times.

The experiments show that camera-based and LiDAR-based sensing can generate baggage-related observations that support this abstraction. Camera-based perception provides a strong reference for detection and annotation, whereas LiDAR-based sensing provides a privacy-preserving and light-independent geometric representation of the boarding situation. The relevant outcome is the derivation of aggregated baggage indicators from these observations, rather than the continuous tracking of individual objects throughout the complete boarding process. This result connects sensor-based perception with boarding sequence assessment and data-driven time prediction. It defines hand luggage information as an input variable that can be measured before or during boarding and then used to characterize the expected process burden. The presented approach, therefore, supports the transition from simulation-based boarding assessment toward observation-based model input.

Future work should transfer the approach to larger and more variable boarding scenarios. This includes higher passenger density, more heterogeneous passenger behavior, and a systematic comparison of sensor positions at the gate, in the boarding bridge, and inside the cabin. A further step is the integration of aggregated baggage indicators into prediction models to quantify their contribution to operational boarding time estimation.

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