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# Data-driven airport management enabled by operational milestones derived from ADS-B messages

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***Abstract*—Standardized, collaborative decision-making processes have already been implemented at some network-relevant airports, and these can be further enhanced through data-driven approaches (e.g., data analytics, predictions). New cost-effective implementations will also enable the appropriate integration of small and medium-sized airports into the aviation network. The required data can increasingly be gathered and processed by the airports themselves. For example, Automatic Dependent Surveillance – Broadcast (ADS-B) messages are sent by arriving and departing aircraft and enable a data-driven analysis of aircraft movements, taking into account local constraints (e.g., weather or capacity). Analytical and model-based approaches that leverage these data also offer deeper insights into the complex and interdependent airport operations. This includes systematic monitoring of relevant operational milestones as well as a corresponding predictive analysis to estimate future system states. In fact, local ADS-B receivers can be purchased, installed, and maintained at low cost, providing both very good coverage of the airport apron operations (runway, taxi system, parking positions) and communication of current airport performance to the network management. To prevent every small and medium-sized airport from having to develop its own monitoring system, we present a basic concept with our approach. We demonstrate that appropriate processing of ADS-B messages leads to improved situational awareness. Our concept is aligned with the operational milestones of Eurocontrol's Airport Collaborative Decision Making (A-CDM) framework. Therefore, we analyze the A-CDM airport London–Gatwick Airport as it allows us to validate our concept against the data from the A-CDM implementation at a later stage. Finally, with our research, we also make a decisive contribution to the open-data and scientific community.**

***Keywords*—airport operations, aircraft movements, data-driven management, aircraft ADS-B messages, A-CDM milestone concept**

## I. Introduction

Shared situational awareness at airports enables operational challenges to be successfully addressed. In this context, performance-based collaboration among airport stakeholders enabled by the concept of airport collaborative decision making (A-CDM) [1] could improve the efficiency of both the aviation network and the local airport [2]. A-CDM is an information-sharing process focused on defined operational milestones along aircraft trajectories and is part of the European Air Traffic Management Master Plan under the Single European Sky initiative [3]. Within the Airport Operations Center [4], stakeholders monitor the agreed performance targets in their respective responsibility areas and implement appropriate control measures in the event of (expected) deviations at both land and airside [5–7].

The digitalization of operational processes at and around airports will facilitate further optimization of operations and the development of new processes soon [8]. New technological improvements will take place at the local and aviation network level to provide seamless passenger and freight transport. The amount of data exchanged in the airport environment has increased significantly and with it the need for methods to analyze this data and turn it into knowledge. Using data from a variety of sources (including publicly available data), airports can make better predictions about future system states and the efficacy of mitigation strategies. Data analytics and machine learning approaches can reveal hidden correlations in the complex airport system.

In our work, we investigate the capabilities of data-driven performance monitoring for small and medium-sized airports, which could be extended to include predictive capabilities in a future research step. Thus, we introduce a concept of data-driven airport management where operational milestones are derived from aircraft ADS-B messages (A-CDM-lite). We use London–Gatwick Airport as a demonstration environment to show our approach to data preparation and milestone calculation. Although it is not one of the small and medium-sized airports, we chose it for the following reasons. First, the airport is well covered with ADS-B receivers so that not only flying aircraft around the airport but also their ground movements on the entire apron can be captured and processed. Second, the airport has a simple runway layout, so extensive differentiation of complex runway or apron procedures is not required. Third, Gatwick is already an A-CDM airport, and the next step in our research is to compare the results of our approach with the actual A-CDM milestones.

After this introduction of the performance management in the airport environment and a brief literature review is given in Section II. Section III provides a deeper insight into the fundamentals of the A-CDM concept and potential roadblocks for the implementation at small/medium-sized airports. Herein, the A-CDM-lite concept for small and

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medium-sized airports is proposed considering a tailored set of milestones derived from locally received ADS-B messages. Section V provides our methodology to derive an operational representation of the underlying airport environment. In Section VI we use 10 days of operational data for analyzing the actual airport performance. Our contribution closes with a discussion and conclusion.

## II. Literature review

Various data analytics and machine learning approaches are already being used to gain deeper insights into the following research topics of the air traffic domain.

- Clustering of aircraft trajectories [9–12],
- Detection of anomalies [13–16],
- Prediction of aircraft trajectories [17–19],
- Development of dynamic airspace designs [20, 21],
- Analyses of runway and apron operations [15, 22–24], or
- Airport performance evaluation considering local weather events [25, 26].

Further initiatives to use open surveillance data (ADS-B) to improve the state of the art are already commonplace, especially in the field of aircraft modeling [27, 28].

With the current contribution, we consequently follow a research agenda for data-driven management of airport operations starting with the concept of performance-based, integrated airport management [6]. A first general application aims at the analysis of operational scenarios to mitigate impacts of local capacity restrictions [29]. A systematic analysis of correlations between airport performance and (severe) weather conditions at European airports [30] contributes to a reliable model of local airport delays in the European air traffic network. This comprehensive analysis was improved by data-driven approaches to forecasting operational delays using neural networks [25, 26]. With a focus on specific airport operations, a next step was taken by looking into the airport system to forecast particular operations at the airport ground, such as runway occupancy times [22]. We continue this research by processing ADS-B messages and adopting the concept of operational milestones. This will provide a reliable basis for follow-up data-based research activities.

## III. Data-driven airport management

Reliable implementation of data-driven approaches needs to address diverse airport environments and consider the participation and benefits of local stakeholders [31]. Each stakeholder has their view of the airport system and could provide a different set of data (Tab. I). The data provided by various parties are consolidated and processed into a reliable basis for decision-making.

### A. Airport Collaborative Decision Making

A-CDM supports communication between stakeholders and the exchange of information in aircraft handling at airports. This leads to improved process compliance, management of deviations from agreed performance targets, and optimization of operational processes. This requires appropriate processes and facilities for efficient information exchange between all stakeholders, as well as effective implementation of A-CDM procedures and the necessary technical architectures. The estimated cost for the full implementation of an A-CDM system is about 2.5 M€, and the annual maintenance cost is about 150 k€ [2]. The introduction of A-CDM contributes, for example, to delay reduction in traffic flow management ($-10.3\%$), shorter taxi times ($-7\%$), or lower fuel consumption ($-7.7\%$) [2] and thus seems to be a reasonable solution for large airports operating close to capacity [33]. With a focus on airports, A-CDM will provide solutions, which are generating cost reductions, environmental benefits, capacity optimization, and efficiency improvements. This is achieved, for example, by shortening taxi times ($-7\%$), decreasing fuel burn ($-7.7\%$), and reducing ATFM (Air Traffic Flow Management) delay ($-10.3\%$) [2]. For a complete implementation of A-CDM, several aspects have to be considered [1], such as:

1) a common concept of data sharing,
2) measurements for the introduced milestones,
3) determination of variable taxi times,
4) implementation of a pre-departure sequencing,
5) concept to manage adverse conditions,
6) collaborative management of flight updates.

From a cost/benefit perspective, full implementation of A-CDM is not favorable for small and medium-sized airports. However, to provide benefits for the entire air transportation system, local implementations must be both tailored to the corresponding airport environment and cost-effective. The use of ADS-B data and the development of a data-driven management system aligned with this database will provide a reliable foundation for this.

The effort required to operate an ADS-B receiver network at the airport (data acquisition, processing, storage) is several

| Stakeholder | Information provided |
|---|---|
| Air Navigation Service Provider | estimated arrival/departure times<br>times based on planning<br>data provided by handling agent<br>runway in use and runway capacity |
| Apron Control | landing times<br>in-/off –block times<br>start-up approval<br>take-off times |
| Airport Operator | stand and gate allocation<br>environmental information<br>reduction in airport capacity<br>reduction in runway availability<br>aircraft movement data<br>special events (such as air shows, etc.) |
| Ground Handling | changes in turnaround times<br>target off-block time updates<br>planning data<br>information concerning deicing |
| Airlines | priority of flights<br>flight plans<br>aircraft registration and type |

TABLE I
PROVISION OF INFORMATION FROM AIRPORT STAKEHOLDERS (CF. [32]).

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orders of magnitude smaller. For example, a dedicated receiver with an efficient antenna costs less than 1,000 €. With this significantly reduced effort, the question arises for which airport a comprehensive A-CDM implementation should be considered and what (local) benefits can be expected. However, A-CDM does still not appear to be a reasonable solution for small and medium-sized airports, which generally do not have capacity problems and have only a minor impact on the performance of the air transport system. This gap can be closed, if already broadcast data can be cost-efficiently processed and used for local, integrated airport management and made available to the network management.

### *B. A-CDM Milestones*

The A-CDM concept consists of 16 milestones along the aircraft trajectory, focusing on an airport-centric perspective. These milestones are monitored by the corresponding stakeholders. In the context of airport operations, Target Off-Block Time (TOBT) is the primary aircraft-related control parameter. The entire A-CDM process is based on estimating TOBT as precisely and reliably as possible so that all stakeholders can align their processes accordingly.

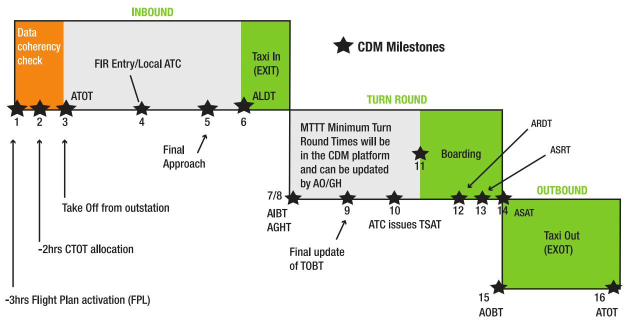


Figure 1. Defined milestones along aircraft trajectory according to the A-CDM concept with: calculated cake off time (CTOT), actual take-off time (ATOT), actual landing time (ALDT), actual in/off-block time (AIBT, AOBT), target off-block time (TOBT), target start-up approval time (TSAT), aircraft ready time (ARDT), actual start-up request time (ASRT), actual start-up approval time (ASAT), actual take off time (ATOT) [1].

The [1] defines the following milestones as highly recommended for the efficient implementation of an integrated airport management. The numbering is consistent with Fig. 1.

1) Flight plan activation by air traffic control (3 hours before estimated off block time)
2) Calculated take off time (2 hours before estimated off block time)
3) Take off from outstation
4) Local radar update (flight enters corresponding flight information region)
5) Flight begins with the final approach phase to the destination airport
6) Aircraft touchdown on runway (actual landing time)
7) Arrival time of an aircraft in-blocks
10) Time at which air traffic control issues the target start-up approval time
15) Time the aircraft pushes back/vacates the parking off-block
16) Time of aircraft takeoff from the runway

At the current stage of development of the A-CDM-lite concept, we assume that only data from the vicinity of the airport can be processed. Therefore, milestone (4), the local radar update, is the first milestone we consider. In the future, when multiple A-CDM (lite) implementations are active in network management, information from and to connected airports can also be taken into account. Concerning the highly recommended milestones, only the determination of the target start-up approval time (TSAT) provided by Air Traffic Control (ATC) seems to be problematic when only aircraft position information is available. Given the close relationship to TOBT (provided by ground handling) and Target Take-off Time (TTOT) in the overall control loop for the flow and capacity management (see Fig. 2), a substitute for this milestone must be found.

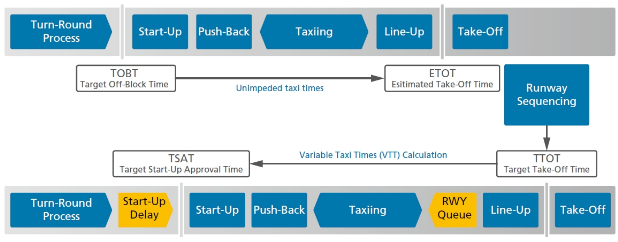


Figure 2. Calculation of Target Start-up Approval Time [34].

Besides the milestone approach, the introduction of variable taxi times (VTT) is currently under consideration at A-CDM airports. Today, static values are still used for taxi times. Given the dynamic changes on the apron, these are not suitable to enable optimal use of apron/taxi capacities. Especially in times of high traffic demand, the associated loss of capacity leads to delays caused by operational inefficiencies at the airport. Thus, the use of VTT could lead to a sustainable improvement in airport performance. As Fig. 2 shows, when the (TOBT) is announced, the expected traffic demand and active movements on the taxiway/runway system could be determined and be available as input to the VTT calculation. Other input variables that could be used in the VTT calculation include current status information and historical performance data.

For a complete ACDM implementation, the following steps still need to be implemented. In order to enable an user-oriented pre-departure sequencing, individual airline priorities should also be taken into account in the future. To handle significant disruptions in airport operations, collaborative approaches for mitigation and/or recovery strategies must be implemented. Finally, the timely exchange of flight update messages (network manager) and departure planning information (airport) ensures that local and network-related information is efficiently integrated at the respective planning level.

### *C. Automatic Dependent Surveillance Broadcast*

To test our concept, we use publicly available data for which no access rights need to be negotiated and the equipment and maintenance costs are low (ADS-B networks).

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Airports should not only record their data, but also share it in these networks. Many stakeholders can benefit from this open-data approach. For example, an airport could immediately receive all departure information from its connected airports (in addition to the first three A-CDM milestones) or the research community could improve operational predictions using the latest developments in machine learning.

Automatic Dependent Surveillance Broadcast consists of the following elements.

- *automatic*: aircraft transmits data periodically, without interrogation
- *dependent*: position data comes from on-board global positioning system (GPS) signal or flight management system (FMS)
- *broadcast*: data transmitted to any listeners (including air traffic control ground stations, satellites, other aircraft)

For safe flight operations, aircraft position is currently determined using ground-based radar systems, primary surveillance radar (PSR) and secondary surveillance radar (SSR). With the introduction of Mode–S protocol [35], controllers' situational awareness was further improved by assigning a fixed 24-bit address per flight and allowing only the directly addressed transponders to reply. The Mode–S transponders transmit aircraft position and status (e.g., speed over ground, rate of climb/descent, heading) on the 1090-MHz SSR Mode–S downlink frequency (ADS–B Out), and signals can be received up to a distance of 400 km. Since visibility is more limited near the ground and on the airport apron, receiver positioning is more important here. Aircraft determine their position via satellite, inertial, and radio navigation and transmit it at regular intervals (about one scan per second) along with other relevant parameters to ground stations and other equipped aircraft. According to the EU implementing regulation [36, 37], all flights must be equipped with Mode S transponders if they are operated under instrument flight rules (IFR) and the aircraft is flying faster than 250 knots and with more than 5700 kg. Similar regulations increasingly apply to other countries (cf. [38]).

In this context, ADS-B is a special format within the Mode-S protocol, and the signal can be received with simple 1090 MHz receivers (i.e., USB dongle and antenna $< 100$ €). This technology also offers a solution for monitoring remote areas and flights over the oceans with space-based ADS-B [39]. However, ADBS transmitters could be installed not only in aircraft but also in ground vehicles or equipment [40]. This would enable a completely new, perhaps even increasingly automated, traffic management at airports. The extent to which PSR and SSR systems can be supplemented or even replaced by simpler receiving systems in the future remains to be seen. However, it is already possible for airport operators to process aircraft data and incorporate it directly into their integrated management as a basis for collaborative decision-making. The ability to easily receive ADS-B messages has already contributed significantly to the development of online services that, for example, display air traffic in real-time with data from globally distributed receiver networks, such as OpenSky Network (opensky-network.org), Flightradar24 (flightradar24.com), or FlightAware (flightaware.com). In particular, the OpenSky Network consistently pursues the idea of open data and makes obtained datasets available to the scientific community.

The quality of the received data is subject to certain technical limitations, e.g. data reception on the ground is only possible if there is a line of sight between the antenna and the aircraft. Aircraft can also determine their position in different ways. If the number of satellites is not sufficient for a GPS-based determination, the aircraft position is calculated using the built-in inertial systems. However, the occurring integration drift of the sensors can lead to the fact that the recorded trajectories do not match the traffic infrastructure on the apron as long as the GPS signal is not acquired correctly. A similar problem exists in determining altitude, which can be provided as barometric altitude (standard atmosphere) or as satellite-based information. The uncertainties in the data that this inevitably creates are not provided in the decoded form in the OpenSky Network database [41], for example. However, these could be derived from the raw messages [42] if needed and taken into account during data processing. Since we want to focus on the A-CDM-lite milestone concept in this work, we do not perform uncertainty analysis but filter out irrelevant data manually during preprocessing.

## IV. Tailored approach: A-CDM-lite

We have derived a milestone approach using A-CDM-lite that considers the following four objectives. (1) The number of milestones must be reduced to a quantity that can be derived from publicly available aircraft movement observations (ADS-B). (2) Missing data must be appropriately supplemented or replaced with substitute data. (3) Our approach must achieve the same level of accuracy compared to the actual data acquired at the airport. (4) Our approach should be designed to analyze and predict both individual flights and overall airport performance.

If ADS-B messages are taken as the primary input for integrated, data-driven airport management, only aircraft movements (airside operations) could be analyzed. However, the essential TOBT milestone is mainly determined by aircraft ground operations (turnaround) and related landside operations (e.g. baggage or passenger handling). For example, passenger boarding is a process on the critical path with a significant impact on the operational performance [43, 44]. Also, we cannot determine the TSAT timestamp directly from the flight movement data, so we have to use an alternative timestamp. The data analysis shows that ADS-B messages are sent by aircraft even before the push-back. We, therefore, assume that the activation of the ADS-B transponder by the pilots is a signal that the aircraft is ready. With this in mind, we consider the time of receipt of the first ADS-B message during departure to be the Aircraft Ready Time (ARDT). In the absence of a better estimator for TSAT at this time, ARDT should be used as a substitute.

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The A-CDM-lite milestones are based on data extracted from ADS-B messages [42]. The following data are used for further analysis and processing.

- timestamps of received messages, set from the receiver (enables multi-lateration);
- transponder code and aircraft identification (call sign);
- information about aircraft location: latitude and longitude (°, 4 digits), calibrated altitude (ft, with steps of 25ft);
- information about aircraft speed: ground speed (kts), track angle (°) and vertical speed (ft/min);
- specific position messages, e.g. 'on-ground' when the aircraft is on the ground (corresponding signal is provided by a landing gear sensor)

Since the received data are not containing unique flight identifiers, we assign these identifiers by a heuristic combination of transponder code, call sign, and timestamps of data received. Later, we want to use the identifiers assigned to the flight plan information to add the corresponding scheduled times for arrival/departure and in/off block. However, the flight schedule information is not transmitted via ADS-B and would have to be provided from additional data sources.

As a region of interest, we consider London–Gatwick Airport (EGKK) in our contribution. The airport was already used to determine the weather impact on airport performance [30] and for weather-delay categorization with machine learning [26]. The airport has a dependent parallel runway system with a distance of 200 m between and operates one of the busiest single runway in the world. Since only 08R/26L possesses an instrument landing system (ILS), 08L/26R is mainly used as a taxiway or as a backup runway during maintenance (see Fig. 3).


Figure 3. Apron and terminal layout of London–Gatwick Airport.

Concerning the available data, an appropriate milestone approach should take into account the quality of the input data and the frequency with which this data is provided. Aircraft determine their position and periodically emit it (roughly one sample per second) with other relevant parameters to ground stations and other equipped aircraft. The quality significantly depends on the availability of active receiving antennas in line of sight and on a proper caught GPS signal. Fig. 4 depicts the interarrival time between two consecutive received messages containing a specific, aircraft-based update: 20% of the updates are received within 5 s, 66% within 10 s, and 92% within 20 s, respectively. A comparison of ADS-B messages with radar data showed that in 50% of the cases the positions were updated within 1.5 s (80% within 10 s) [45].

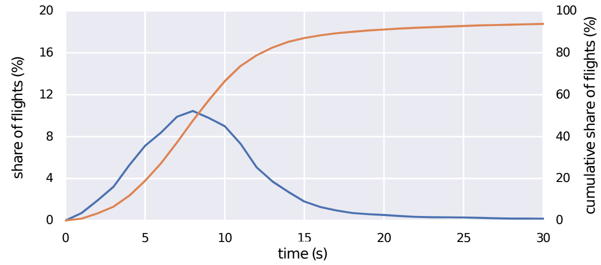


Figure 4. Distribution of time intervals between two consecutive updates of aircraft position obtained from ADS-B messages.

The aircraft position is given in degrees and has an accuracy of four decimal places. At the location of EGKK, with a latitude of 51.1481° and longitude of -0.1903°, one latitudinal step (0.0001°) has a distance of approx. 11 m and one longitudinal step have a distance of approx. 7 m. These values are smaller than the average position error of about 21 m obtained during radar verification [45]. The higher resolution in longitudinal direction could have an impact on subsequent analyses (such as clustering), but will not be further addressed in this contribution.

In the context of the A-CDM-lite concept, the resolution of the altitude with 25 ft is not expected to be a major quality issue during the calculation of the milestone. The final approach follows a constant vertical guidance path provided by the glideslope transmitter (between 2.5° and 3.5°, recommended 3° [31]). Thus, several position updates along the glide path will provide additional data for correction (position interpolation). If the aircraft is landed, the altitude will be set to 0 m in the received ADS-B dataset, regardless of the actual elevation above sea level. In the demonstration case of EGKK, the elevation is 62 m.

### A. A-CDM-lite Milestones

With A-CDM-lite, as in Eurocontrol's A-CDM concept, a time-based trajectory is described by the following 8 operationally relevant time stamps. While each milestone is directly processed using the ADS-B messages, the first and last contact only depends on the focus set for the observation area, such as the arrival sequence and metering area (ASMA) with a radius of 40NM around the airport (cf. [46]).

1) first contact with the local radar
2) starting the final approach
3) aircraft landing
4) in-block
5) **aircraft ready** (introduced as proxy for the target start-up approval time)
6) off-block
7) aircraft take-off

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8) last contact with the local radar

The in-block timestamp is defined when the aircraft reaches its final position (gate or apron) and ends the data transmission. Due to the proximity of buildings and other obstacles, the accuracy of the transmitted positions decreases. We assume that the aircraft is in-block when the position is within 40 m of the (average) last transmitted position [23]. The off-block milestone is determined in the same manner if the distance from the first transmitted position at the apron or gate is getting greater than 40 m. At this stage, we are also aware that speed information, additional infrastructure data from open data sources (e.g., OpenStreetMap), or clustering of aircraft positions can lead to a more advanced determination of aircraft parking positions (see Fig. 5).

Figure 5. Density-based clustering of transmitted aircraft positions to derive airport infrastructure, such as parking positions or operational network (e.g. taxi way connections) validated against information from OpenStreetMap.

The timestamp for the aircraft ready status is set, when the aircraft starts transmitting ADS-B messages on the ground. The landing and take-off times are defined as the change of the 'on-ground' indicator. If necessary, this definition could be extended by airport information (e.g., elevation), specific descent/climb rates, or speed restrictions.

The last milestone, which has not yet been sufficiently defined, relates to the start of the final approach. The procedures for air navigation services state that the final approach fix should be within a range of 18.5 km (10 NM) to the threshold and the final approach segment should have a recommended length of 9.3 km (5 NM) [47]. Furthermore, ICAO [47] refers to five different aircraft categories, where the indicated airspeed at the final approach range from 130-180 km/h (category A) to 285-425 km/h (category E). Airline jets can generally be assigned to category C and therefore have a speed range of 215-295 km/h. According to the A-CDM implementation manual [1], the milestone for the final approach should be set at a point, when the aircraft is usually between 2 and 5 minutes away from landing. Assuming the range of approach speeds of airline jets and the time left to land, a distance to the runway threshold between 7.2 km (2 min, 215 km/h) and 24.6 km (5 min, 295 km/h) could be chosen as a position for this milestone. Considering average values for both approach speed (255 km/h) and time to land (3.5 min) the distance is 14.9 km (8 NM). Using the recommended glide slope angle of 3° and airport elevation of 0 m, the milestone for the final approach will be defined by the (interpolated) timestamp when the aircraft passes the altitude of 2,500 ft. According to local airport conditions (such as elevation or arrival procedures), the position of this milestone could be changed appropriately. Tab. II exhibits the derived milestones from the ADS-B data.

| A-CDM Milestones | | Description | ADS-B data used |
|---|---|---|---|
| 4 | | Local radar update inbound | First signal |
| 5 | | Final approach | Altitude $<$ 2500 ft |
| 6 | ALDT | Actual landing time | 'on-ground' set |
| 7 | AIBT | Actual in-block time | Distance from final position $<$ 40 m |
| 12 | ARDT | Actual aircraft ready time | First signal on ground |
| 15 | AOBT | Actual off-block time | Distance from start position $>$ 40 m |
| 16 | ATOT | Actual take-off time | 'on-ground' unset |
| x | | Local radar update outbound | Last signal |

TABLE II
MILESTONES FOR THE A-CDM-LITE CONCEPTS CONSIDERING THE EUROCONTROL A-CDM APPROACH (MILESTONE NUMBER AND ABBREVIATION).

In Fig. 6 two connected flights are exemplary used to show the derived operational milestones according to Tab. II. Both flights are operated by one aircraft and are connected via the aircraft tail number, which could be further used to determine the duration of aircraft turnaround.

## V. METHODOLOGY

To demonstrate our approach, ADS-B data are available around London–Gatwick Airport from October 1, 2018 to September 6, 2019. In the following, we show how the data is preprocessed (Sec. V-A), demonstrate how aircraft positions can be used to derive information about airport infrastructure and apron operations (Sec. V-B), and provide results of an initial exploratory data analysis with a focus on aircraft taxi (Sec. V-C).

### A. Data Preprocessing

As mentioned in Sec. III-C on ADS-B data, the dataset contains inherent uncertainties and may have gaps in the recorded data. Therefore, the trajectories composed of the data points must be preprocessed to meet two essential criteria: quality/quantity (sufficient number of recorded positions with a small number of outliers) and accuracy (the trajectories must be located at the taxiways). We identified three major artifacts, caused by a) GPS signal not present, b) small sample size, and c) data recording contains data outside the target range.

a) The trajectories show a clear offset to the taxi system of the airport. This is the case, for example, if the position was calculated only by the aircraft inertial systems before a GPS signal could be received for correction (Fig. 7a). These trajectories were discarded.

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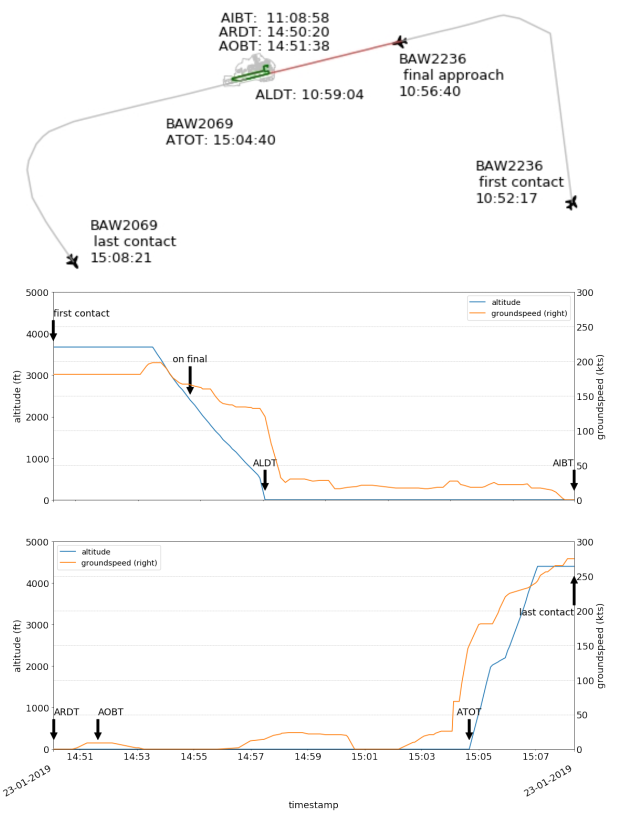


Figure 6. A-CDM-lite milestones using lateral (top) and vertical profile (below) of a sample aircraft operation (inbound and outbound flight) at London–Gatwick Airport with: actual landing time (ALDT), actual in/off-block time (AIBT, AOBT), aircraft ready time (ARDT), actual take off time (ATOT).

b) The ground trajectories do not consist of a sufficient number and regularly recorded positions and thus cannot correctly represent the aircraft movement profile (Fig. 7b). These trajectories are discarded.
c) The positions are already recorded since reaching the inbound parking position, so that not only the outbound trajectory, starting with aircraft ready milestone (or pushback) is available. Fig. 7c exhibits a gate change from the inbound to the outbound position. We reduced the corresponding trajectories to their outbound gate-to-runway section.

We use the Python library *traffic* [48] to preprocess the data. This library, with its declarative grammar, provides a lightweight definition of the steps necessary to ensure that only valid trajectories are provided for the next step of the exploratory analysis. This intuitive grammar is exemplified in the following Python sequence, which was used to filter out all taxi movements of landing aircraft.

```
raw_dataset
# each trajectory must cross the runways
.intersects(airports["EGKK"].runways)
# only keep trajectories with more than one minute of data
.longer_than("1 minute")
# only keep the successful attempt when go around
# i.e., the longest interval of consecutive data below 400ft
.query("altitude < 400").max_split()
# [custom function]
```

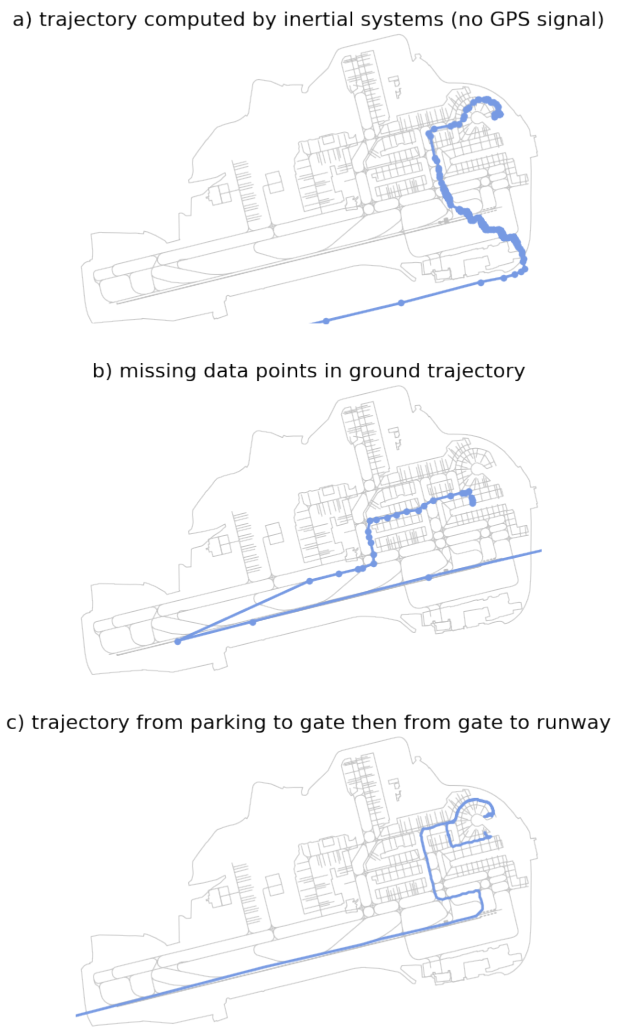


Figure 7. Invalid aircraft gournd trajectories detected in the dataset of London–Gatwick Airport.

```
# trim the trajectories after aircraft stop moving for a while
.pipe(trim_parking)
# only keep trajectories with more than one minute of data
.longer_than("1 minute")
# [custom function]
# keep trajectories with enough points during taxi
.pipe(enough_points_when_taxi)
# [end] evaluate the preprocessing
.eval()
```

### B. *Aircraft operations on airport infrastructure*

By observing movements, insights into immanent interactions have already been gained in many research areas. Thus, it is also a first, intuitive approach to look for these interactions also in the operational ground flows at the airport. The main point here is to investigate which infrastructures are used and how frequently, without considering detailed operational concepts. In our case, it is advantageous that aircraft movements take place on defined taxiways, and when a large number of movements are observed, the layout of the airport becomes apparent. At the same time, the identification of areas of operational interests should provide additional situational awareness. Typically, frequently used

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intersections in the taxiway system are important interaction points where the corresponding ground traffic needs to be efficiently managed by the ramp controllers. A first idea is to consider the taxiway system at the airport as a system of nodes and edges (resulting from aircraft ground movements). Here we propose the use of the Ramer–Douglas–Peucker (RDP) algorithm [49, 50], which is used for iterative simplification and smoothing of line segments (curves), considering a maximum distance threshold. From our point of view, this algorithm also works as a detector for nodes, allowing the recorded trajectories to be divided into edge segments.

The dataset contains position updates, which could be interpolated between preceding and succeeding positions (e.g. location and speed), these updates will not provide additional information and could be deleted. For a specific application, a trajectory may be resampled with the required sample rate. The number of positions will be significantly reduced by applying the RDP algorithm, using aircraft location (latitude and longitude). To ensure that no operational milestones are deleted by applying the RDP, trajectories are divided into segments (each beginning and ending with a milestone), and the RDP is then applied to those segments. As Fig. 8 exhibits, setting the distance thresholds for the trajectory simplification to 100 m and 50 m reduces the initial number of intermediate positions between the operational milestones from 64 to 2 and 5, respectively.

However, the use of these two distance thresholds for the RDP algorithm also demonstrates that the taxiways used are not adequately covered. A distance value of 25 m was finally implemented (cf. [23, 45]), which leads to sufficient coverage with 9 remaining intermediate positions for the aircraft ground trajectory between the operational milestones. Together with the 3 outbound operational milestones (ARDT, AOBT, and ATOT), the trajectory is now described by 12 data points, which indicates a data reduction of 82% compared to the original 67 data points.

All remaining positions of the simplified trajectories are clustered using kernel density estimation and hill-climbing strategy [51]. Areas of operational interests (Fig. 9) can now be derived from the clustered positions in a time-based manner and enrich the representation of the airport infrastructure already created (see Fig. 5). This graphical representation only shows the utilized section of the airport apron and, depending on the time period and the number of movements, is only partially representative of the entire airport system. Nevertheless, the frequently used intersections can be considered as additional input for ground safety and traffic management [52].

Finally, a directed graph could be derived from the (static) airport infrastructure, the observed movements, and the areas of operational interests. This graph could be used for the dynamic prediction of taxi time duration for inbound and outbound flights. Since our approach does not include any additional airport information but relies only on information from ADS-B messages, it can be used with no limitation to any other airport in the air traffic network. Fig. 10 shows for example the detected areas of operational interests at Tokyo Haneda Airport.

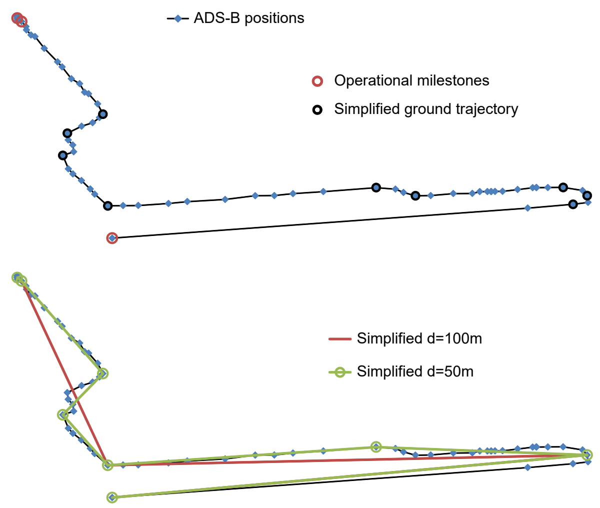


Figure 8. Compression of exemplary ground trajectory of departing aircraft: (top) operational milestones and distance of 25 m, (below) compression with 100 m and 50 m distance.

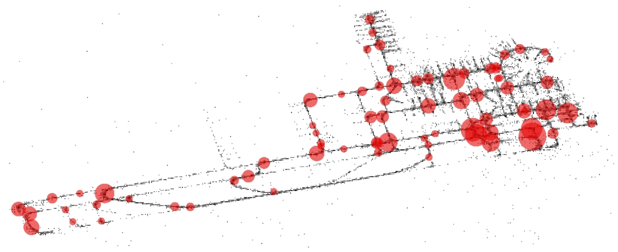

Figure 9. Areas of operational interests at the apron and taxi system of London–Gatwick Airport. The size of the circles corresponds to the number of aircraft movements per time counted at that location.

Figure 10. Areas of operational interests at Tokyo Haneda Airport.

This is a scalable approach that enables stakeholders to obtain operational information about their own and connected airports. Thus, in an airport network, hubs could

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run their analysis of the connected airports to anticipate observed deviations from planned operations and evaluate the expected impact on local airport performance.

### *C. Exploratory Data Analysis: Taxi Operations*

A more detailed, exploratory data analysis of taxi operations could provide additional insight into the procedure design and efficiency of ground traffic management at London–Gatwick Airport. In the previous analysis, we used only position data, but this does not appropriately describe aircraft ground trajectories. As traffic on the apron increases, so does the probability of interactions between aircraft, which generally results in aircraft having to wait at holding positions. The speed data can be used to determine at which apron locations aircraft have to wait and for how long. In Fig. 11 we have used the arriving traffic as an example to highlight all aircraft positions on the apron (no parking positions) for which zero ground speed was reported.

Figure 11. Density map of positions of aircraft with zero ground speed.

This density map allows distinguishing between two types of focal points: those on the taxi system and the apron. In the taxi system, as expected, the points are mostly located directly in front of the intersections, but also at a greater distance in front of them. At these particular intersections, high traffic demand leads to queues. The other type of focal point is mainly located near the parking positions (at the gate or on the apron). Here, pilots regularly wait for clearance to roll into parking positions or for clearance to leave positions after pushback toward the runway.

By using both locations and velocities we could derive additional information about the apron operations. In the next step, we will cluster the ground trajectories accordingly. The goal of clustering is to group similar trajectories, potentially providing further insight into the common structure of the trajectory clusters. However, the available data are not labeled (an unsupervised learning approach is required) and structure search requires determining the similarity of the trajectories using an appropriate objective function (e.g., close Euclidean distance). When clustering aircraft trajectories, it is a challenging task to find a suitable distance function, since not only location and time information, but also a multitude of other dimensions, e.g., aircraft speed, aircraft type, or environmental status data (e.g., apron utilization, weather) can be incorporated. To enable clustering even for high-dimensional spaces, the input data is usually projected into a low-dimensional space. The following approaches are commonly used for projection in the context of trajectories: Principal Component Analysis (PCA), Autoencoder, t-distributed Stochastic Neighbor Embedding (t-SNE) [53], or Uniform Manifold Approximation and Projection (UMAP) [54].

Fig. 12 shows six example clusters resulting from the application of the DBSCAN [55] algorithm to a two-dimensional space. For this purpose, ground trajectories were previously reduced to 50 data points each, with each data point containing position data (longitude and latitude) and ground speed. For the projection of the resulting 150 dimensions per trajectory onto the two-dimensional space, t-SNE was used.

Figure 12. Cluster subset based on three features (latitude, longitude and ground speed) and 50 samples per trajectory. The top right (pink) and bottom left (red) correspond to similar spatial flows but different ground speed profiles (see Fig. 13).

The exemplary landings in a westerly direction (25) for the first five clusters and in an easterly direction (08) for the last cluster (Fig. 12 bottom right, bold orange) already show typical aircraft taxi patterns. These mainly depend on the used runway exit and the assigned parking position, which can be derived very well from the given input features (location and ground speed). However, the plots in Fig. 12 focus only on the spatial characteristics of the aircraft ground trajectories. For example, the upper right (pink) and lower left (red) clusters appear to have a similar structure, but they differ significantly when comparing the velocity profiles of their respective representative trajectories.

As Fig. 13 shows, clustering with ground speed as an additional feature leads to different clusters for trajectories with waiting times at stops and without waiting times. In summary, this example demonstrates very well how a stepwise exploratory data analysis provides growing insights into airport operations and performance.

## VI. Analysis of Operational Milestones

To demonstrate that the A-CDM-lite milestones provide an appropriate analysis of the airport environment, we have initially used the 10 busiest operating days: 8,827 flights with 831,597 position updates (simplified to 139,740

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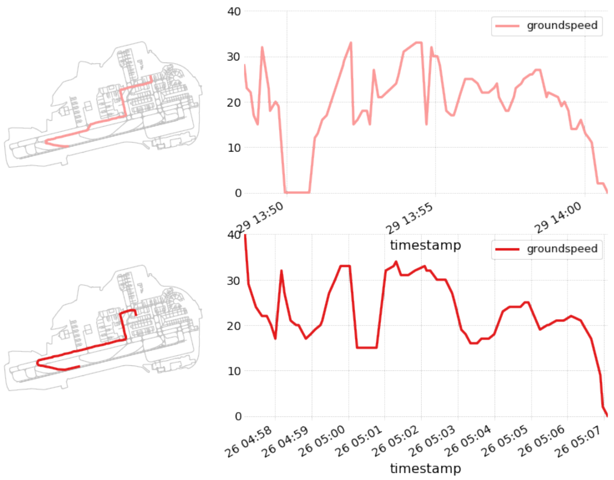


Figure 13. Reference trajectories fall in different clusters because of their ground speed profiles. The upper trajectory shows waiting times at intersections to enable prioritized traffic to pass first.

updates). This dataset is used to analyze the three following aspects: duration of the landing approach (time between the milestones 'starting final approach' and 'landing') (Sec. VI-A), the time between 'aircraft ready' and 'off-block' (Sec. VI-B), and the time for inbound and outbound taxi operations (Sec. VI-C).

### A. *Duration of Final Approach Phase*

About the expected final approach speed (feature aircraft type, cf. section IV-A), the duration of the final approach phase is an indicator for current the headwind/ tailwind component and thus also for the maximum arrival flow that can be achieved. This in turn has significant implications for airport capacity management. The distribution of the final approach phase duration is shown in Fig. 14. It can be seen that the final approach takes less than 250 s for 55% of flights and 90% of flights land 310 s after passing the defined final approach milestone.

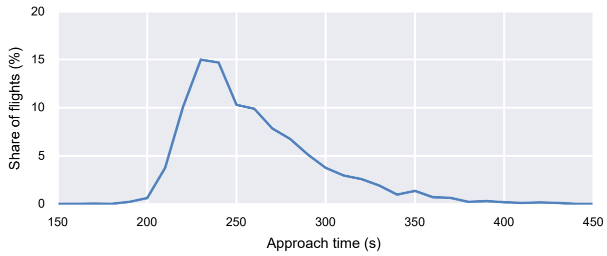


Figure 14. Distribution of final approach duration, starting at an altitude of 2,500 ft until landing.

### B. *Duration between ARDT and AOBT*

Leaving the parking position is defined by the AOBT milestone. By determining the time difference between AOBT and ARDT, the prediction of the variable taxi time can be improved in the future. In addition, the data from the A-CDM system can be used to test how effective the ARDT determined with A-CDM-lite is as a substitute for the TSAT (or TOBT). In Fig. 15, the distribution of the time difference is shown. After 2 min, 67% of all flights have already reached the AOBT milestone, 90% of flights have a duration of less than 5 min. We also expect this temporal order of magnitude when using the TSAT as a reference measurement, so that we can for the time being assume to have found a suitable substitute parameter with the ARDT.

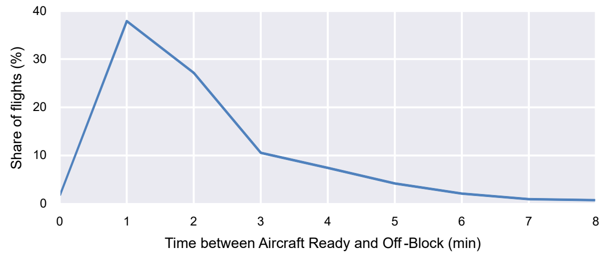


Figure 15. Distribution of duration between ARDT and AOBT.

### C. *Taxi times*

The taxi time, and even more so the additional taxi time caused by increased traffic volume, is an important factor in describing the performance of an airport. The design and most efficient use of the taxi/apron system have a critical impact on ensuring that the given capacity is fully used and that aircraft can reach the runways or assigned parking positions with minimal time delay.

London–Gatwick Airport has one of the busiest runways, but this is associated with long waiting times for take-off. To determine the effective taxi time (without runway movements), we also determined the time when aircraft leave/enter the runway. Thus, the taxi time is the difference from the AIBT/AOBT and also includes time spent at the queues before entering the runway for take-off. A closer look at Fig. 8 shows that the points for leave/enter the runway can already be easily determined by simplifying the trajectories. The relationship between the number of aircraft movements (arrival, departure, sum of movements) and the taxi times is shown in Fig. 16.

The taxiways depicted in Fig. 12 already indicate that the length of incoming taxi routes also varies depending on the operating direction of the runway. This is also true for outbound traffic. For example, taxi times for eastbound departures (08) are on average 2-3 minutes longer than for westbound departures (25). Fig. 17 shows the corresponding taxi time distributions. For westbound departures, taxi time is less than 19 min for 50% of flights (for 90% of flights less than 29 min), while for eastbound departures it is less than 22 min (31 min).

The relationship between taxi times and the number of aircraft movements (traffic demand) already indicated in Fig. 16 is examined in more detail below. In general, it can be assumed that with increasing traffic demand on the apron, aircraft interactions will also increase and that the

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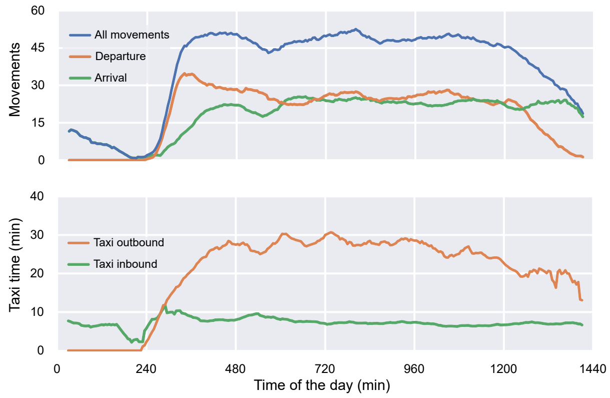


Figure 16. Characteristics of aircraft movements (top) and corresponding taxi times (below).

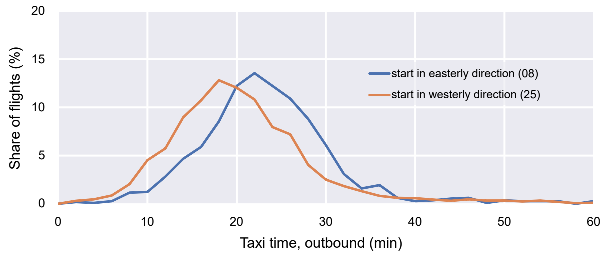


Figure 17. Probability density of taxi outbound times during easterly (08) and westerly (25) operations.

coordination effort required for this will lead to longer taxi times (and local congestion). Fig. 18 (above) shows the variation in taxi times for inbound and outbound traffic as traffic demand increases. Assuming a linear relationship, each additional movement on the apron leads to an increase in taxi time for outbound traffic of almost 0.5 min, with a minimum taxi time of about 4 min. In contrast, the analysis of inbound taxi time shows almost no dependence on the number of aircraft movements. Performing the same analysis, but this time only determining the dependence of taxi times on arrival movements, the outbound taxi times show a logarithmic progression (see Fig. 18 (below)). The inbound taxi times confirm the previously observed nearly independent behavior to increasing traffic demand.

## VII. Discussion and Outlook

Small and medium-sized airports are not yet sufficiently covered with ADS-B receivers today. Against this background, we had to choose another airport for our data-driven concept. We decided on London–Gatwick Airport: only one runway in operation, less complex apron layout, very good data reception on the entire apron, and, due to its status as an A-CDM airport, can also be used for later concept validations. The analysis of ADS-B messages in the context of a data-driven and performance-oriented airport management has shown that essential operational milestones along the aircraft trajectories can be derived if the airport is well covered by appropriate receivers. With a step-by-step exploratory data analysis, we were able to gain insights into

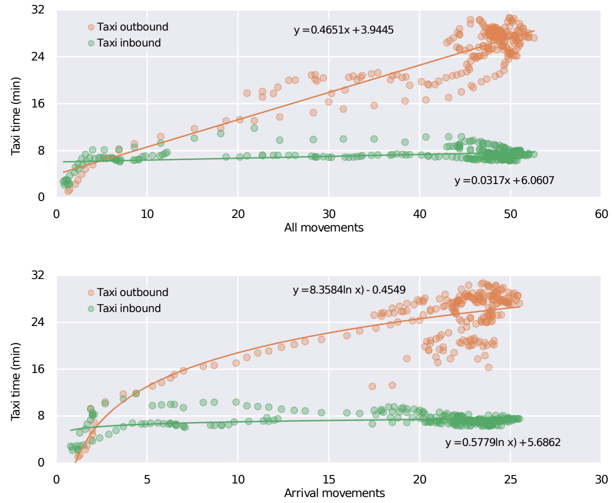


Figure 18. Impact of all aircraft movements (top) and particular arrival movements (below) on the inbound and outbound taxi times.

the apron infrastructure used and aircraft taxi operations. Furthermore, with in-depth performance analysis, we were able to show the correlations between traffic flow and taxi times that are expected for London–Gatwick Airport. For all of these analyses, we did not use airport-specific operational data, but only the freely receivable data broadcast by aircraft. We have not identified any issues with our tailored approach that would have required the use of third-party resources and hope that our contribution will motivate small and medium-sized airports to implement A-CDM-lite.

It was already apparent during the development of our initial concept ideas that the introduction of ADS-B in the field of civil aviation will be mandatory. Even if implementation delays are taken into account, it is possible soon to have access to received ADS-B messages worldwide, to make it available as open data, and to use it as a basis for data-driven airport operations (e.g., monitoring and predictions). From an economic point of view, there are no disadvantages to installing a local receiver network and sharing the recorded data. The information from connected airports can thus also be incorporated into the local decision-making process on time. We assume that the installation of a local receiver network will cost less than 1,000 € (most basic receivers cost less than 20 €). In this context, security-related intrusions, e.g. spoofing attacks, could also be detected and stopped by appropriate countermeasures (e.g. multilateration).

The use of our data-driven approach seems to be particularly beneficial for small and medium-sized airports. However, it should be noted that Open Data capabilities allow local decisions to be made at airports without the involvement of the network operator, which currently has a data monopoly. Also referring to the Braess paradox [56], the new amount of information and the associated local (self-interested) decisions can lead to situations in the aviation network that are not beneficial for many (all) stakeholders.

To validate the A-CDM-lite concept and to use it as a basis for the prediction of operational processes (states), we

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will examine in future work to what extent flight plan and operational history data are required for this purpose. These data could be integrated, for example, via Eurocontrol's B2B services. Our concept will also be gradually expanded by including other data sources to take into account significant causes of interference (e.g., weather, cf. Fig. 19) and to predict operational behavior at the airport (cf. [25, 26, 30]).

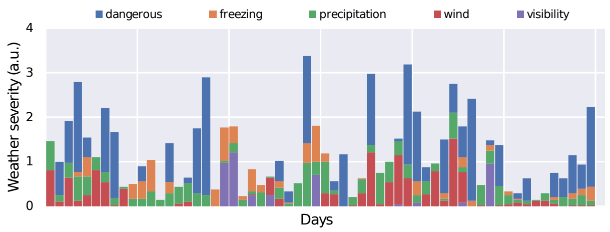


Figure 19. Classified weather data per day as input to assess the severity of weather impacts on local airport operations, as a basis for performance-based airport management.

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