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A-CDM Lite: Situation Awareness and Decision-making for Small Airports based on ADS-B Data

Michael Schultz*, Judith Rosenow*, Xavier Olive†

*Institute of Logistics and Aviation
Technische Universität Dresden
Dresden, Germany

†ONERA – DTIS
Université de Toulouse
Toulouse, France

Abstract—The data-driven analysis of aircraft movement data from public available sources provides further insights into the complex airport operations, beyond the capabilities of analytical and model-based methods. In the context of airport collaborative decision making, these data-driven approaches will allow cost efficient implementations, which are a key enabler for an appropriate integration of small/medium sized airports into the air transportation network. We propose an operational milestone concept based on Automatic Dependent Surveillance – Broadcast messages emitted by approaching and departing aircraft. Since aircraft have to be equipped with a compliant transponder from 2020, airports only need cheap receivers to observe operations at the runway/taxiway system and at the apron (including parking positions). These observations will allow for a systematic monitoring (using operational milestones) and predictive analytics to provide estimated values for future system states. This contribution aims at providing a reliable basis to develop innovative approaches for small/medium airports, which are both beneficiary for the air transportation network and cost efficient for local operators. In this contribution, we process aircraft movements in the vicinity and on the ground of Gatwick airport and address our approach to provide an enhanced situational awareness. The reasons for using Gatwick airport are threefold: (a) good data coverage, (b) simple runway layout, and (c) basis for upcoming validation studies, since Gatwick already runs a full airport collaborative decision making implementation.

Keywords—aircraft trajectory, operational milestones, ADS-B data, A-CDM concept, airport management

I. INTRODUCTION

The airport collaborative decision making (A-CDM) is a process of sharing information between stakeholders of the complex airport system to provide a common situational awareness and to enable joined strategies to solve operational challenges [1]. A-CDM was developed to improve the efficiency of airports and the air traffic network. 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]. Naturally, the air transportation system is both a competitive and collaborative environment, where stakeholders have to optimize their economic benefits considering various restrictions. The operational challenges could be located at levels with different look ahead times with an actual or (pre)-tactical time horizon. In Europe, A-CDM will be implemented

as part of the European Air Traffic Management Master Plan within the Single European Sky (SES) initiative [3]. The master plan serves as an ongoing roadmap for achieving the goals of the SES air traffic management (ATM) research program (SESAR) and as such contains important building blocks for the future European air traffic system.

A performance-based airport environment needed in order to get full A-CDM benefits (e.g. enhanced use of airport resources or reliable scheduling). In this context, the Total Airport Management (TAM) approach enables airport stakeholders to jointly work on dynamically agreed performance targets during the day of operations [4]. TAM focuses on entire airport operations, landside and airside, taking into account information available through SWIM (System Wide Information Management) [5]. By giving airport stakeholders access to data from different sources, airports will be able to make more accurate predictions about their operational progress in the next time frame, provided that stakeholders share their resulting priorities and intentions. This integrated airport management is embodied in an Airport Operations Centre (APOC), where all stakeholders coordinate tasks to monitor and maintain the agreed performance targets in their respective area of responsibility [4], [6], [7]. In this context, processes in SESAR Airport Operations Centers (APOCs [8]) could be significantly enhanced by data-driven predictions and machine learning techniques [9], since these techniques are able to show hidden interdependencies in the complex airport system. Airport Council International (ACI) Europe emphasizes the need for the digitization of aerodromes to provide a seamless transport and a resilient air transportation system [10]. According to current forecasts by Eurocontrol, which are listed in the "Challenges of Growth" report of 2018, transport demand is expected to increase by 53% by 2040 [11]. The speed and extent, with which data is shared, have massively increased over the last years as well as the need for implementation of new methods to evaluate this data. In the course of increasing digitization in almost all areas, airports are trying to implement innovative approaches in their current operations. In this context, the cooperation between the airport stakeholders is a prerequisite in order to achieve a high airport performance.

Local stakeholders (such as airports, ground handler, or airlines) differ in terms of size, strategy, status, constraints, and business models. A reliable implementation has to address

these distinctions appropriately, which involves various levels of collaboration and information sharing, considering the individual benefits of each stakeholder. Furthermore, imbalances between different stakeholders by means of costs and benefits have to be compensated (airlines often benefit most with small contribution efforts) [12]. A list of stakeholders and the corresponding information provided is given as follows [13].

- Air Navigation Service Provider: estimated arrival/ departure times, times based on planning, data provided by handling agent, runway in use and runway capacity
- Apron Control: landing times, in-/off –block times, start-up approval, take-off times
- Airport Operator: stand and gate allocation, environmental information, reduction in airport capacity and in runway availability, aircraft movement data
- Ground Handler: changes in turnaround times, target off-block time updates, planning data, possible deicing
- Airline: flight priority, flight plans, aircraft registration and type

A. Focus

We consequently follow a research agenda of a data-driven airport management. In a first step, an extension of the initial TAM concept was proposed, aiming at a performance-based, more integrated management concept was developed [6], [7] and tested with traffic/weather scenario using Hamburg airport as an example [14]. This step was followed by systematic analysis of the impact of severe weather conditions at European airports [15] and by the development of data-driven models to forecast operational delays using neural networks [16], [17]. Finally an initial concept of a data-driven airport management was introduced [18] and will be developed further with this contribution. In this context, a reduced amount of the defined A-CDM milestones (lite version) is used and associated time stamps are derived from ADS-B messages from arriving and departing aircraft. With this contribution we address the potential of data-driven performance monitoring, which will be extend by prediction capabilities in a future research step. Furthermore, we could easily import data from other airports in our generalized approach without major drawbacks in the preprocessing. Unfortunately, the data coverage at small/medium sized airport is poor (too few ADS-B receivers within line of sight to ground operations). Therefore we use the appropriately covered Gatwick airport (one runway layout) as an example, to show the general concept of data preparation and milestone calculation. Since this airport is also an A-CDM airport, subsequent research activities could focus on the validation of our tailored, ADS-B-based milestone concept.

B. Structure of the document

After the introduction of the collaborative decision making in the airport environment, Section II provides a deeper insight into the fundamentals of the A-CDM concept and potential roadblocks for the implementation at small/medium sized airports. An A-CDM-lite concept is proposed with a reduced number of milestones and based on ADS-B data. Section III

provides our methodology to derived an operational representation of the underlying airport environment. In Section IV we use 10 days of operational data for analysing the actual airport performance. Our contribution closes with discussion and conclusion.

II. A-CDM CONCEPT

The A-CDM concept consists of 16 milestones along the aircraft trajectory at the airport, focusing on an air-to-air view (airport-centric). These have to be monitored by the corresponding stakeholders for each flight, in order to provide reliable target off-block time (TOBT), which is the most important aircraft-related control parameter. Highly recommended milestones [1] are (1) ATC Flight Plan activation, (2) estimated off block time (EOBT)– 2 hours before arrival, (3) take off from outstation, (4) local radar update, (5) final approach, (6) landing, (7) in-block, (10) target start-up approval issue, (15) off-block, and (16) take off. Since our A-CDM-lite concept focuses on local airport operations, the local radar update will be the first milestone available. In an extended version of this concept, data from all connected airport will be used as sources as well, which allows to cover some milestones before the local radar update.

The only issue left will be the target start-up approval time (TSAT, see Fig. 1), and its connection to the TOBT (provided by ground handling). Our approach is about finding a proxy for the TSAT with an assumed time for aircraft ready (ARDT, take first ADS-B timestamp of departing flight). A forecast of (subsequently) following milestones events can be dynamically adapted to actual situations. Important connections exist between TOBT, TSAT and target take-off time (TTOT), as tactical decision of the air traffic flow and capacity management takes effect (cf. Fig. 1).

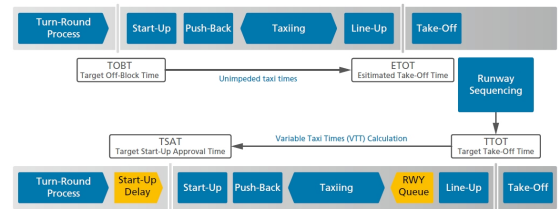


Figure 1. Calculation of Target Start-up Approval Time (TSAT) [19].

At this stage, only airside operations are discussed, but the essential TOBT is mainly driven by aircraft ground operations (turnaround) [20]–[22]. In particular, the progress of passenger boarding (landside operation) could mainly effect the overall operational performance [23], [24]. Unfortunately, for the A-CDM-lite approach this milestone could not be derived from the data input, because ADS-B messages only cover airside operations.

However, the establishment of A-CDM is characterized by extensive negotiations between the companies involved and the establishment of new procedures. In particular, the exchange of information is a challenge for all stakeholders, as both technical and procedural infrastructure must be developed.

At the same time, concerns are raised that shared data (information) will not only be used for A-CDM, but also for the evaluation of competitor's business structure. Beside the complex data/information sharing tasks, the estimated costs for a full A-CDM implementation is about 2.5 M€, with annual maintenance costs of 150 k€ [2].

A cost-benefit view emphasizes that A-CDM process may results in network benefits, which mainly arise by improved take-off predictability, and in local airport benefits come from reduced taxi times. Thus, A-CDM seems to be reasonable for major airports [25], operating close to its capacities, but not a suitable solution for small-/medium-sized airports. These airports often do not have any problems with extended taxi times or may significantly influence the air transportation network performance. However, sharing data and information to better reach joint performance targets is an essential key enabler for a seamless and efficient transportation. To significantly reduce costs for implementation and annual maintenance, we suggest establishing an A-CDM-lite approach.

One key aspect of our solutions is to use publicly available data for which no access rights need to be negotiated and the equipment and maintenance cost are low, such as ADS-B (automatic dependent surveillance broadcast). The obligation to equip aircraft with a transponder will begin in Europe in June 2020 [26], [27] and in the US almost all airspaces will be reserved only for appropriately equipped aircraft from January 2020 [28]. It is expected, that current surveillance systems will be extended by ADS-B and future ground stations will be fully based on this technology, which is significantly cheaper to install and to operate. Due to the simple requirements on the receivers, ADS-B has contributed to the development of online services that display the current air traffic in real time with worldwide receiver networks (depending on the local coverage), such as OpenSky Network (opensky-network.org) or Flightradar24 (flightradar24.com). This technology also offers a solution for monitoring remote areas and flights over the oceans with space-based ADS-B [29]. Furthermore, the equipment of ground vehicles at aerodromes should enable a more comprehensive monitoring of the traffic situation on the corresponding movement areas at the apron [30].

A. Tailored approach: A-CDM-lite

As already stated, a full implementation of A-CDM is not favorable for small/medium sized airports. However, in order to provide benefits for the entire air transportation system, local implementations must be both cost-effective and tailored to the corresponding airport environment. The processing of ADS-B data and a simplified performance monitoring in combination with intelligent data-driven methods will provide a reliable foundation for this. Beside the common concept of data sharing (1) and the introduced milestone approach (2), A-CDM consists of further elements: (3) variable taxi times, (4) pre-departure sequencing, (5) handling of adverse conditions, and (6) collaborative management of flight updates. Instead of using pre-defined values for aircraft taxiing, the calculation of variable taxi times (VTT) and provision of taxi time forecasts

will enable an optimize use of the apron/taxi capacities in times of high dense operations. Flight data (e.g. aircraft type, location), current situation (e.g. runway configuration, traffic demand) and historical data are input values for VTT calculation. Once the TOBT is provided, VTT enables to derive the actual demand on the taxi/runway system and to optimize the corresponding start-up approvals to be given.

In this context, airline priorities should be taken into account during the calculation of the pre-departure sequence. In the case of adverse operational conditions, the collaborative approach is aiming on mitigation and/or recovering procedures to return quickly to normal operations. Furthermore, the mutual exchange of flight updates messages (FUM) and departure planning information (DPI) between the network manager and airports supports local and network-wide (re-) planning processes. The DPI informs the network manager about changes to flights, whereas FUM provides the airport with more detailed information about approaching aircraft, which can be used to support tactical planning. Finally, the developed concept of operations of the A-CDM-lite focus on the following objectives: (1) reduce the number of milestones, (2) find appropriate proxies for missing data, (3) provide equivalent degrees of accuracy and precision, (4) predict single flight events and airport performance.

B. Milestones of A-CDM-lite

The milestones for the A-CDM-lite concepts are based on data provided within the ADS-B messages, which contains the following relevant information:

- timestamps (from the receiver, enabling multi-lateration);
- transponder unique identifiers (to be related to tail number and aircraft type) and callsigns;
- positional information: latitude and longitude ($^{\circ}$, 4 digits), altitude (ft, with steps of 25ft);
- velocity information: ground speed (kts), track angle ($^{\circ}$) and vertical speed (ft/min);
- specific positional messages are sent when the aircraft is on ground (the switch being a sensor located in the landing gear, with related uncertainties)

We assign unique flight identifiers for convenience based on heuristics combining transponder identifier, callsigns and timestamps labelling collected data. In the future, we plan to use identifiers assigned to flight plan information with related in- and off-block times.

In accordance with the common A-CDM milestone approach, an operational (time-based) aircraft trajectory will be described in A-CDM-lite by the following eight timestamps: (1) first radar contact, (2) starting final approach, (3) landing, (4) in block, (5) aircraft ready, (6) off-block, (7) take-off, and (8) last radar contact (see Fig. 2). Each milestone is extracted from the ADS-B messages, while first/last contact depends on the observation area and for aircraft ready the first signal on ground is taken. A flight is initialized on ground and can be connected via the aircraft tail number to determine the duration of the ground operations. The landing and take-off times are defined as the change of altitude to/from 0 m

(on ground indicator changes). If necessary, this definition could be extended by specific descent/climb rates or speed restrictions. The off-block milestone is calculated by distance threshold to the position, where the aircraft achieves the "ready" status. The in-block value is calculated in a similar manner: after the aircraft stops transmitting the ADS-B messages, the in-block time is defined as the time, when the aircraft approaches its final position (distance threshold). In both cases, the threshold is set to 40 m. Starting the final approach will be defined by the first position update, after the aircraft passes the altitude of 2500 ft [18].

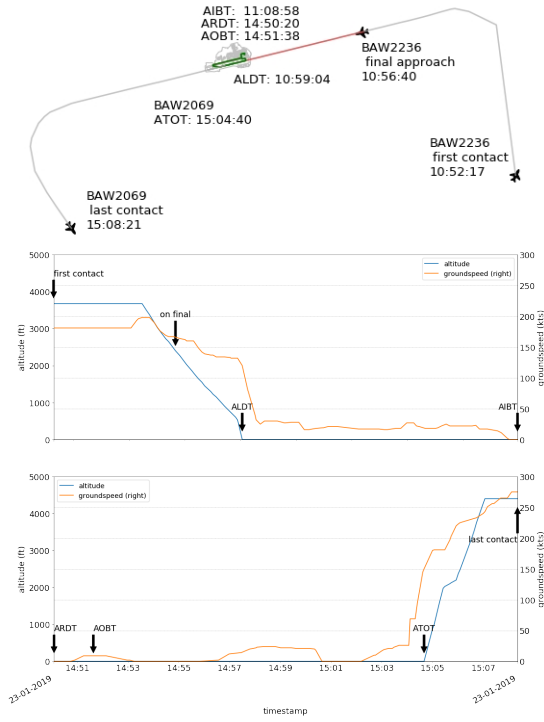


Figure 2. A-CDM-lite milestones using lateral (top) and vertical profile (below) of a sample flight with actual landing time (ALDT), actual in/off-block time (AIBT, AOBT), aircraft ready time (ARDT), actual take off time (ATOT).

C. ADS-B data

ADS-B is a cooperative surveillance technology, which provides situational awareness in the air traffic management system. Aircraft determine their position via satellite, inertial and radio navigation and periodically emit it (roughly one sample per second) with other relevant parameters to ground stations and other equipped aircraft. Signals are broadcast at 1090 MHz: a decent ADS-B receiver antenna can receive messages from cruising aircraft located up to 400 km far away, while the range is much lower for aircraft flying in low altitude or on ground. The collected data used for this study contains one year of ADS-B data of aircraft flying in a bounding box around London–Gatwick airport and below 10,000 ft, between 1.10.2018 and 6.9.2019. Relevant features include timestamps, transponder 24-bit identifiers, callsigns, latitude, longitude, altitude, groundspeed, track angle and vertical speed.

Inherent data uncertainties are not provided decoded in the OpenSky Network [31] database but could be processed [32] from the raw messages on an as-need basis. However, we kept the uncertainty analysis out of the scope of this paper and chose to manually filter irrelevant data (see Section III-A) as part of the preprocessing step. As a matter of fact, there are a limitations inherent to the quality of data received: (1) reception of trajectories on ground is only possible when active receiving antennas are in line of sight with all taxiing aircraft. This can be made possible with antennas conveniently installed at airports; (2) positions of aircraft are computed with embedded inertial systems if satellites are out of sight. This can lead to trajectories not matching the apron structure until the GPS signal is properly caught. Cross-validation with other sources of information (ground radars, signals from other antennas processed for multilateration) is a way to mitigate this issue.

III. METHODOLOGY

A. Preprocessing of data and exploratory analysis

a) *Preprocessing of data:* Trajectories collected in the original dataset require specific preprocessing to address several commonly known issues stated above in order to select only trajectories with enough quality in terms of accuracy (the tracks should fit the apron) and precision (a trajectory should consist of enough samples during taxi). Invalid trajectories in our original dataset include:

- ground trajectories computed only from the inertial systems before catching GPS signal (Fig. 3.a)). We chose to discard these trajectories for this analysis;
- ground trajectories with not enough samples to fully represent the aircraft position at all times (Fig. 3.b)). We chose to discard these trajectories;
- ground trajectories recorded early from the parking position to the gate, broadcasting their positions during the whole boarding (resp. disembarking) process before starting taxiing (Fig. 3.c)). We chose in this contribution to select the gate-to-runway part of the trajectory.

We use the declarative preprocessing grammar of the Python traffic [33] library to describe the preprocessing steps applied to our dataset of trajectories. For instance, the following preprocessing was used for all trajectories 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]
# 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()
```

a) trajectory computed by inertial systems (no GPS signal)



b) missing data points in ground trajectory



c) trajectory from parking to gate then from gate to runway



Figure 3. Invalid trajectories detected in the dataset

b) *Exploratory data analysis:* A first exploratory data analysis of the ground trajectories may yield hints about the structure of traffic at London–Gatwick airport. Fig. 4 plots all reported positions associated to landing aircraft and respecting the two following constraints: (1) aircraft are not moving and; (2) aircraft are not located at a gate.



Figure 4. Density map of aircraft positions with ground speed = 0

This density map reveals the *hot spots* on the airport's apron. These are mostly located before intersections of taxiways: some intersections are more problematic than others with a

lot of aircraft having to be requested to wait and let another aircraft go. Other *hot spots* are mostly located not far from parking positions, when aircraft wait for clearance before following the instructions of the marshaller to the parking position.

A second natural blind analysis we may conduct would be a clustering of ground trajectories. Clustering is a challenging task to conduct on trajectories because of the difficulty to find a proper distance function between them. Moreover, after resampling trajectories to enough samples to grasp the structure of the traffic, vectors of very high dimensions will be passed to the clustering algorithm and the curse of dimensionality will hit. A common workaround is to project highly dimensional samples into a lower dimensional space and to perform clustering in this new space. A wide variety of techniques are available to compute relevant projections: Principal Component Analysis, Autoencoders, t-SNE [34]. Fig. 5 plots a small subset of the clusters resulting from a DBSCAN [35] clustering on the two dimensional space where t-SNE projected the trajectories, consisting of 50 samples of latitudes, longitudes and ground speeds.

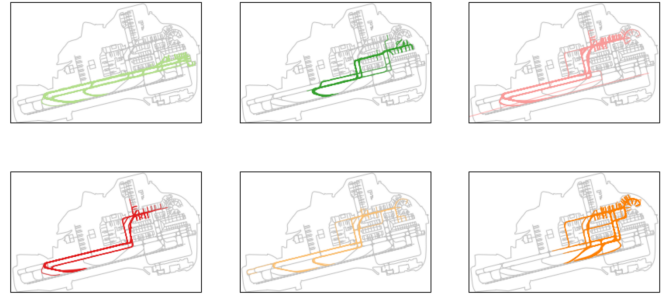


Figure 5. A subset of the clusters detected using latitude, longitude and ground speed as features: the top right (pink) and bottom left (red) correspond to similar flows, but the difference lies in the ground speed profile (see Fig. 6)

Clusters reflect various typical ground trajectories followed by aircraft after landing. In the subset displayed on Fig. 5, the top right (pink) cluster has a very similar structure than the bottom left (red) cluster. Fig. 6 focuses on one trajectory representative of each cluster: the clustering algorithms was here able to separate trajectories taxiing directly to the gate from trajectories being requested to yield the way to neighbouring aircraft. Here clustering gives insights about the nature of ATC ground control's actions.

B. Creation of operational network

The recorded ADS-B data contains data points with no additional information. Thus, the number of positions will be reduced by applying the Ramer–Douglas–Peucker algorithm [36], using aircraft location (latitude and longitude) with a maximum distance between compressed and original trajectory of $d = 25$ m. In addition, the compressed trajectory always contains the A-CDM-lite milestones as mandatory points. As Fig. 7 exhibits, setting the distance to 100 m and 50 m reduces the initial number of positions from 67 to 5

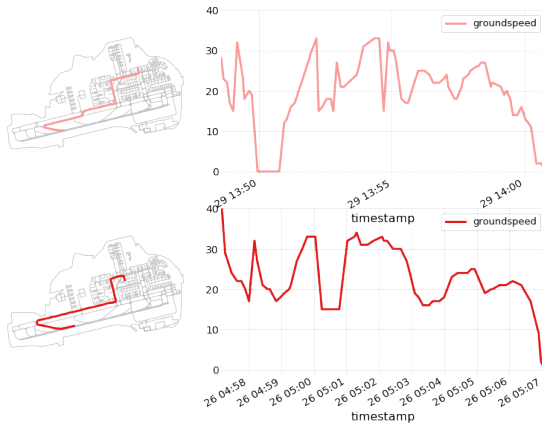


Figure 6. The two trajectories fall in different clusters because of their ground speed profiles: the top trajectory stops to avoid a conflict on ground.

and 8, respectively. Finally, a distance of 25 m was finally implemented [18], [37], which results in 9 remaining positions for the aircraft ground trajectory (reduction of 83%).

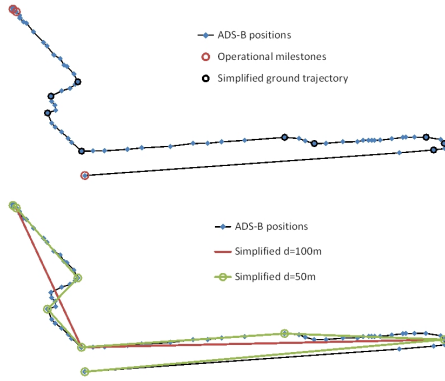


Figure 7. Compression of exemplary ground trajectory of departing aircraft: (top) operational milestones and distance of 25 m, (below) compression with 100 m and 50 m distance.

The compressed trajectories are further processed by using kernel density estimation and hill climbing strategy [38]. The clustered points results in a representation of operational hot spots (Fig. 8), which will be the basis for a graph representation of the airport (landside). This graph representation will not fully represent the airport surface but only relevant intersections.

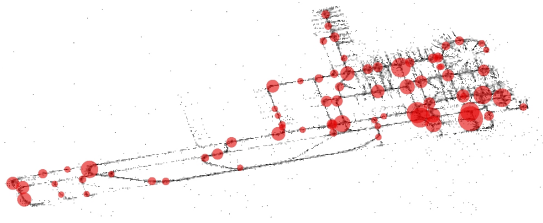


Figure 8. Creation of operational hot spots as basis for graph representation of airport apron and taxi system of Gatwick airport.

Finally, this directed graph should be used for prediction of variable taxi times, which will be the focus of our next research activities. Our approach could be easily adapted to other airport environment, since we did not implement specific airport features (Fig. 9). This scalable and modular approach allows to provide operational information about both current and connected airports.

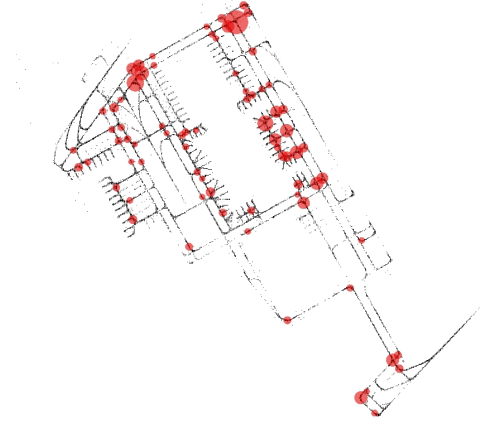


Figure 9. Creation of operational hot spots for Tokyo Haneda airport.

IV. ANALYSIS OF MILESTONES

The introduced A-CDM-lite milestones enable a first analysis of the airport environment. Therefore the dataset is reduced to the 10 highly frequented days of operations. The dataset contains 8,827 flights with 831,597 position updates (139,740 simplified positions). This dataset is used to analyse the duration of the landing approach (time between the milestones 'starting final approach' and 'landing'), the time between 'aircraft ready' and 'off block', and the taxi times.

A. Approach duration

The duration of the final approach is shown in Fig. 10: 55% of the flights possess a duration shorter than 250 s, 90% are landed 310 s after passing the defined entry point at an altitude of 2500ft.

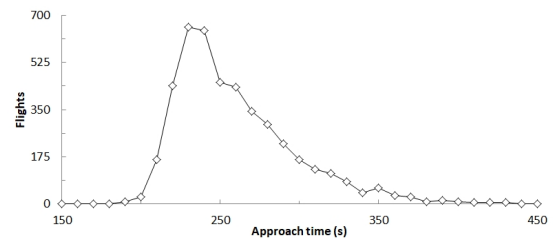


Figure 10. Time on the final approach (starting an altitude of 2500ft).

B. Aircraft ready time

Since ADS-B messages only contain position updates of aircraft, information from airport landside or pilot requests are

not available in this approach: the aircraft ready timestamp is introduced as proxy for the start-up request. In this context, we assume starting ADS-B as a process parallel to requesting for start-up. The analysis depicted in Fig. 11, points out a time difference between 'aircraft ready' and 'off block' of less than 2 min for 67% of the flights (90% with less than 5 min). According to this analysis, we see our assumption confirmed and will use the aircraft ready time to predict the subsequently following milestones.

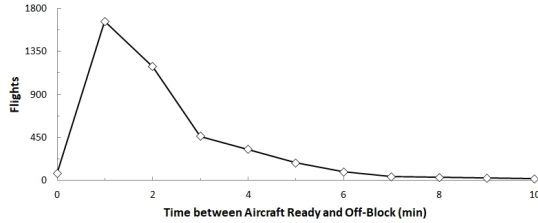


Figure 11. 'Aircraft ready' milestone active before aircraft goes off block.

C. Taxi times

Taxi time is a major contributor to airport performance. The whole taxi system needs to be efficiently managed to drive aircraft seamlessly to and from the runway (Fig. 12). Gatwick airport operates one of the most busiest single runway, which is accompanied with long waiting times in the runway lineup. Fig. 12 emphasizes the correlation between amount of aircraft movements and taxi times. While outbound taxi times show a higher taxi time with increasing aircraft movements at the airport, the inbound taxi time is nearly constant.

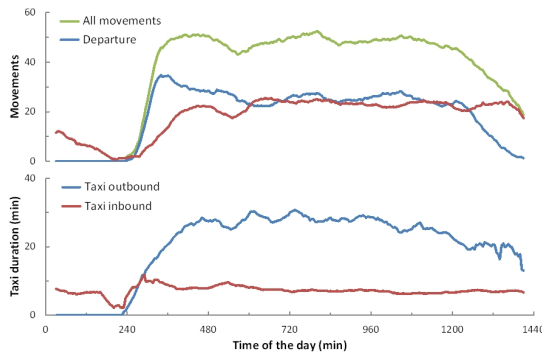


Figure 12. Correlation of aircraft movements (top) and taxi times (below).

A deeper analysis considering starts in easterly (08) or westerly (25) direction, depicts additional differences of the outbound taxi times. The probability density of the taxi times, show a shift of 2-3 minutes between these directions (see Fig. 13). At easterly operations 50% of the flights need less than 22 min for taxi and 90% less than 31 min (for westerly operations 19 min and 29 min, respectively).

A direct comparison of the number of aircraft movements and the taxi times yields interesting results. As already indicated in Fig. 12, the outbound taxi times increases with higher

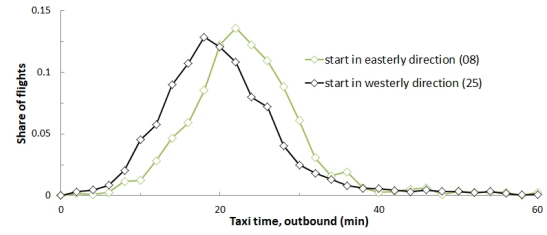


Figure 13. Probability density of taxi outbound times during easterly (08) and westerly (25) operations.

numbers of active aircraft movements. Assuming a linear correlation, each additional movement increase the taxi time (outbound) by nearly 0.5 minutes (starting with approx. 4 min taxi time, see Fig. 14 (top)). By only taking into account active arrival movements, outbound taxi times exhibit a logarithmic shape (see Fig. 14 (below)). The inbound taxi time is nearly unaffected by an increasing amount of traffic.

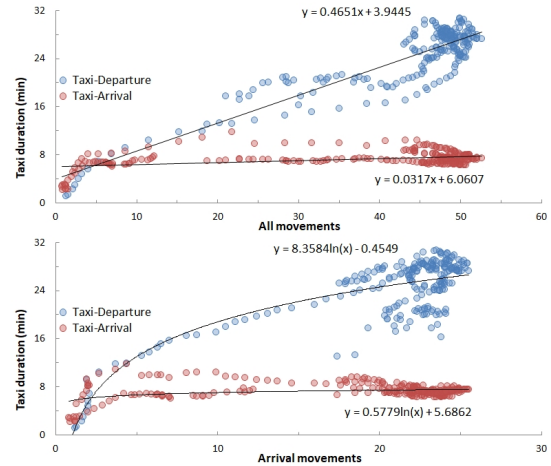


Figure 14. Impact of aircraft movements to the inbound and outbound taxi time.

V. DISCUSSION

The analysis of available ADS-B data at Gatwick airport which currently offers a decent coverage on ground shows interesting patterns in taxiing and correlations found with traffic density that are consistent with what we would expect from the way airports are usually operated. Our proof of concept shows promising results for a full implementation when ADS-B becomes mandatory in 2020, although delays are to be expected. The use of ADS-B is convenient as it is very cost-effective: the installation of a decent decoding installation nearby airports costs less than 1,000€ (with most basic receivers going down to 20€), making replication and validation of positions by multilateration an option to address spoofing attacks. This study only analyses the airside trajectory part with open sources of data, which validates part of the concept. Future works will include the incorporation of flight plan and operational history data accessible through Euro-control B2B services, for a further validation of the concept

and for improving the predictive power of our approach. The inclusion of more sources of data [15]–[17] to address possible causes of disruptions (such as weather, see Fig. 15) and predict operational behaviors at the airport is also considered.

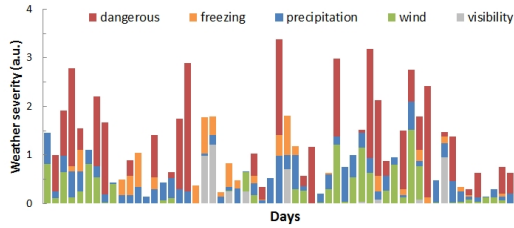


Figure 15. Classified METAR data to assess severity of weather effects using as input for performance forecasts.

Today, small/medium sized airports are not well covered by ADS-B receivers, why we choose Gatwick airport, as an airport with an appropriate data coverage for the ground movements and a single runway layout. Gatwick airport also opens the opportunity to validate our approach against the current A-CDM environment, when the prediction capabilities of our tailored milestone approach are implemented. As our approach points out, no interaction with the actual airport systems is needed to derive a situational awareness from ADS-B data. Thus, we are not expecting additional challenges when applying our approach to small/medium airports. Furthermore, we hope to encourage airports installing more cost-effective ADS-B receivers to enable the implementation of ACD-M-lite.

VI. CONCLUSION

We introduced a lite version of the A-CDM milestone approach, which only contains eight milestones. These milestones can be fully derived from public available ADS-B messages emitted by arriving and departing aircraft. To take the first received message during departure as 'aircraft ready' milestone, seems to be a promising approach to predict the aircraft off block time. First test with trajectory clustering and the creation of operational hot spots, without any additional infrastructural data from the airport environment, indicate a high potential to scale our approach to arbitrary airport environments. The benefits for A-CDM-lite implementations are threefold: (1) local airport awareness, (2) awareness about the performance of connected airports, and (3) provide milestone data from A-CDM-lite to the network manager for network-wide improvements. Currently, we improve our concept of operations in close cooperation with Cologne-Bonn airport.

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