33RD CONGRESS
OF THE INTERNATIONAL COUNCIL
OF THE AERONAUTICAL SCIENCES
STOCKHOLM, SWEDEN, 4-9 SEPTEMBER, 2022

ICAS 2022 SWEDEN

TRAJECTORY-BASED OPERATIONS TO IMPROVE LONG-RANGE AIR TRAFFIC FLOW MANAGEMENT*

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Abstract

Extending Air Traffic Flow Management techniques to longer distances across multiple countries is key to achieve efficient arrival schedules that incorporate regional and international flights. Trajectory-Based Operations (TBO) can help achieve this goal but international harmonization on this topic is key to maximize its benefits. This paper describes the main sources of uncertainty affecting Long-Range Air Traffic Flow Management (LR-ATFM) in the United States and Australia, and how TBO can help address some of them. Lastly, some next steps and opportunities identified through the data presented are discussed in the conclusions.

Keywords: Trajectory-Based Operations, TBO, Long Range Air Traffic Flow Management

1. Introduction

Trajectory-Based Operations (TBO) is a new paradigm for managing air traffic by using controlled times along flight routes [1] in order to create a schedule for orderly and efficient traffic flows. Currently used in the US, Europe and Australia to manage flights close to their arrival destination, in the future TBO is planned to be extended to control flights farther and farther away from their destination airport in order to increase the scope of potential benefits from this concept [2]. However, in order to extend the TBO concept to longer range flights where TBO can be most impactful, the challenges of extending Air Traffic Flow Management to larger geographical area and across different countries, defined as Long-Range Air Traffic Flow Management (LR-ATFM) in the literature [4], need to be understood and mitigated. Longer range flights can be impacted by multiple sources of uncertainty affecting the creation of an accurate schedule of flights, several hours in advance. The two main sources of uncertainty affecting LR-ATFM are:

1. Uncertainty in predicting the four-dimensional trajectory of long-range flights and the time they will enter the Air Navigation Service Provider (ANSP) controlled airspace, and
2. Uncertainty in predicting internal short-haul departures that are "pop-up" demand in the schedule which adversely impact the ability to integrate long range flights into an efficient arrival schedule.

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This material is based upon work supported under Air Force Contract No. FA8702-15-D-0001. Any opinions, findings, conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the U.S. Air Force.

The main cause of uncertainty in 1. is that long range flights can be significantly influenced by wind and weather forecast uncertainty. Over long flight times, the wind uncertainties can cause errors in the trajectory prediction and therefore of the time the long-range flights enter the ANSP-controlled airspace. Wind uncertainty also affects the ground systems that support Air Traffic Control (ATC) to create the arrival schedule, but also the flight deck guidance system (e.g., Flight Management System (FMS)) that has limited wind data capabilities. Weather along the arrival route can also affect the length of long-haul routes when deviations around weather are needed, thereby impacting the arrival time into airspace of interest as well.

The biggest challenge in accurately predicting 2. is the magnitude of the uncertainty in the take-off time for short-haul flights. This can be significant compared to the total duration of the entire flight. Therefore, for airports that accommodate both long and short range flights, accurately predicting the arrival schedule, multiple hours in advance, can be challenging.

This paper will quantify some of the uncertainties mentioned above, based on the example of two aerodromes: New York Newark Liberty International Airport (KEWR) and Melbourne Airport (YMML). Using these examples, the paper will set the scene for future work by these authors which aims to develop a generic model for ANSPs to determine the system performance and data accuracy required for successful LR-ATFM implementation for their respective operational scenarios.

2. Prior Work

The International Civil Aviation Organization (ICAO) Global TBO concept [3] lays out the requirements to implement TBO in a globally harmonized way. A foundational characteristic of Global TBO operations is the improved reliance on data sharing in a collaborative environment. This will be key to mitigate the innate sources of uncertainty affecting LR-ATFM. In [4], a concept of operations for LR-ATFM focused in the Asia-Pacific Region is presented. The concept suggests that using speed control in extended airspace around Singapore Airport, as far as seven hours from landing, could alleviate the demand/capacity imbalances caused by merging long and short-haul flights. To manage the same uncertainties, McDonald and Bronsvoort [5] propose to utilize multiple meter points. The concept can be supported by advanced FMS capabilities such as Required Time of Arrival (RTA) to meet the time constraints along the route. In [6] different extended metering ranges of 250 up to 650 nautical miles are proposed and tested to support Optimal Profile Descent (OPD) operations. The authors claim that, the farther the range, the more fuel savings can be achieved. Lastly, one of the key tools to manage demand/capacity imbalances in LR-ATFM is the use of Ground Delay Programs (GDPs). Jones and Lovell [7] propose an approach to manage the exemption that long range flights have to these programs. The authors present algorithms to improve the distribution of delays among short- and long-haul flights and eventually to increase the overall throughput. In [8] the authors study the effect of improved wind information to improve TBO systems performance, and describe some of the enhancements necessary to the automation to take advantage of the improved wind data.

3. LR-ATFM Uncertainty Sources Case Studies

In this section, the main challenges that affect LR-ATFM and how TBO can support in creating a robust schedule that includes both long- and short-haul flights will be described. To do so, a characterization of current uncertainties, both in demand and capacity (e.g., due to convective weather impacts) is necessary first. TBO and LR-ATFM integration with flight efficiency initiatives such as user-preferred routes and Continuous Climb and Descent Operations (CCO/CDO), and the use of flight deck capabilities (e.g., RTA), will be discussed next.

In order to provide focus to these assessments and to represent specific operational challenges and potential differences between international regions, operations at the following locations were considered:

- New York Newark Liberty International Airport (KEWR) with its mix of international, long range national and short-haul flights.
- Melbourne Airport (YMML), an Australian airport with a comparable traffic mix and similar

capacity and demand challenges to Newark.

ANSPs in different countries use different automation systems, data sources and traffic flow management techniques, such that international harmonization on this topic is key to maximize the benefits of TBO.

3.1 Newark Liberty Airport

Newark Airport (KEWR/EWR) is one of the busiest airports in the United States (US). Its high demand and limited runway capacity leads to it also being one of the most affected by delays, especially when wind and weather conditions are not favorable. In fact, in 2019 it was the airport generating the most amount of GDPs in the US. The arrival demand profile for a typical day in 2019 (Tuesday November 5) is presented in Figure 1. The demand is variable during the day, but after 18:00 Zulu time (13:00 local) it stays consistently close to the hourly arrival capacity, until it slows down after 02:00 Zulu time (21:00 local).

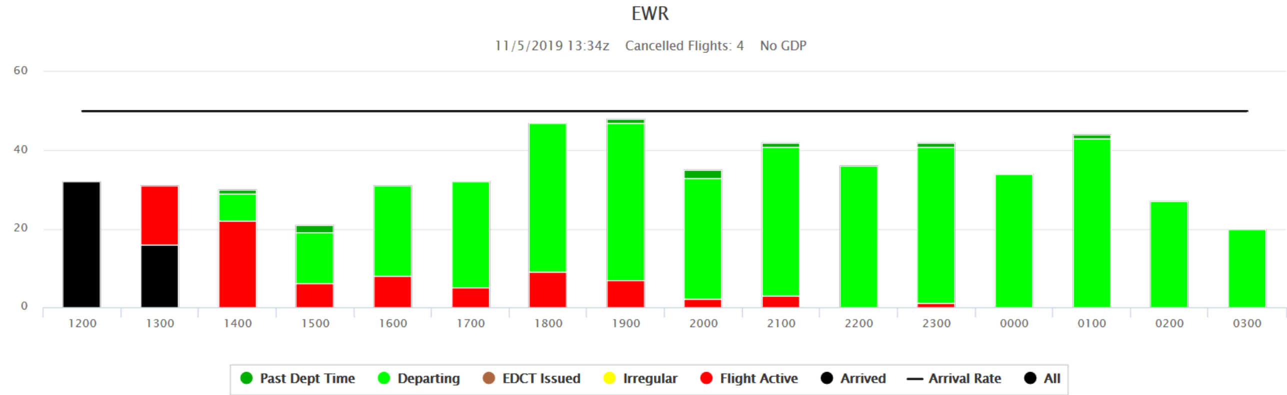

Figure 1 – EWR daily arrivals demand in 2019. Black represents flights already landed, red are taken off from origin, and green are scheduled. The black line is the airport arrival rate of 50 per hour on this day (https://www.fly.faa.gov/aadc/).

In terms of arrival demand, flights were classified by the flight time necessary to reach EWR. As can be seen in Figure 2 for the same day as Figure 1, EWR has a mix of long- and short-range demand of flights during the day. The shortest flight on the day was a repositioning flight from JFK Airport that took 24 minutes to land in EWR. The longest flight of the day arrived from Shanghai (China) flying for more than 13 hours. The majority of flights (46%) into EWR flew for more than two hours, 18% for less than one hour and 36% between one and two hours. This data shows the wide mix of flights that need to be managed into EWR's daily schedule, with a median flight time of 105 minutes with a large standard deviation of 131 minutes.

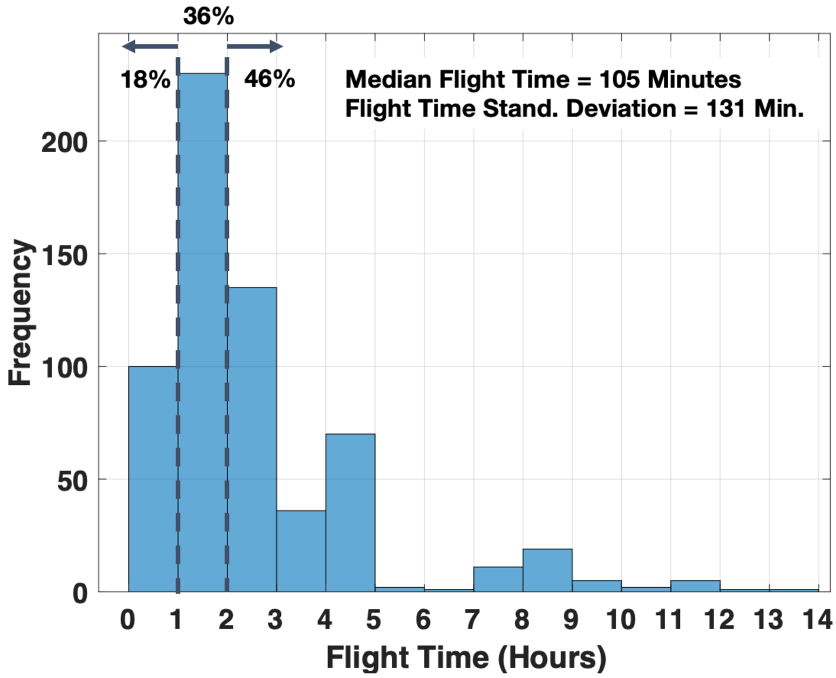

Figure 2 – EWR arrivals demand distribution of flight times on 5/11/2019.

Of the 109 flights in the day with less than one hour of flight time that could be defined as pop-ups, the majority came from Boston (22), 10 came from Pittsburgh, 8 from Washington Reagan (DCA) and Albany. 8 of these flights came from Canadian airports, 6 from Toronto and one each from Montreal and Quebec City. These flights pose an additional complexity because of both their short flight time, and some of that flight time is in Canadian airspace, where FAA ATC does not have control over them. The most frequent long-range origin airport is San Francisco (17 flights), then Fort Lauderdale (16) and Los Angeles (15). Roughly seven percent of the flights (45) that landed in EWR flew for more than six hours, the most frequent from London Heathrow (7) then from Tel Aviv (4). These are international flights that are excluded from any initiative to control demand such as GDP, AFP, etc.

3.2 Melbourne Airport

Melbourne Tullamarine Airport (YMML/MEL) is Australia's second busiest airport. Like Newark Airport, the capacity at Melbourne Airport can be severely impacted when wind and weather conditions are not favorable due to its crossing runway configuration. A maximum arrival capacity of 40 arrivals per hour can be reached in Visual Meteorological Conditions (VMC) when utilizing Landing And Hold Short Operations (LAHSO) on both runways. But strong northerly winds can reduce this capacity to just 20 arrivals per hour, even in VMC. Also, like Newark Airport, Melbourne Airport generated the highest number of GDPs in Australia in 2019. In fact, a GDP was in place nearly 80% of time the time between 6am and 11pm local time during 2019. This is due to high demand at Melbourne Airport in combination with challenging weather conditions due to Melbourne's geographic location as winds can change from warmer Australian continental northerlies to colder Southern Ocean southerlies.

Figure 3 provides the daily flight time distribution of all arrivals into Melbourne Airport averaged over 2019. The majority of the flights (44%) have a flight time of 1 to 2 hours, and includes departures from key domestic departure points such as Sydney (23% of 2019 arrivals), Adelaide (7% of 2019 arrivals) and Brisbane (10% of 2019 arrivals; flight time can be under 2 hours depending on prevailing winds), 15% of flights have a flight time less than 1 hour (e.g. Canberra (4% of 2019 arrivals) and Hobart (5% of 2019 arrivals), and 41% of flights have a flight time of more than 2 hours. Similar to Newark, the vast majority of flights (85%) have a flight timeout less than three hours. The longest flight into Melbourne in 2019 was from Vancouver, with a maximum flight time exceeding 17 hours.

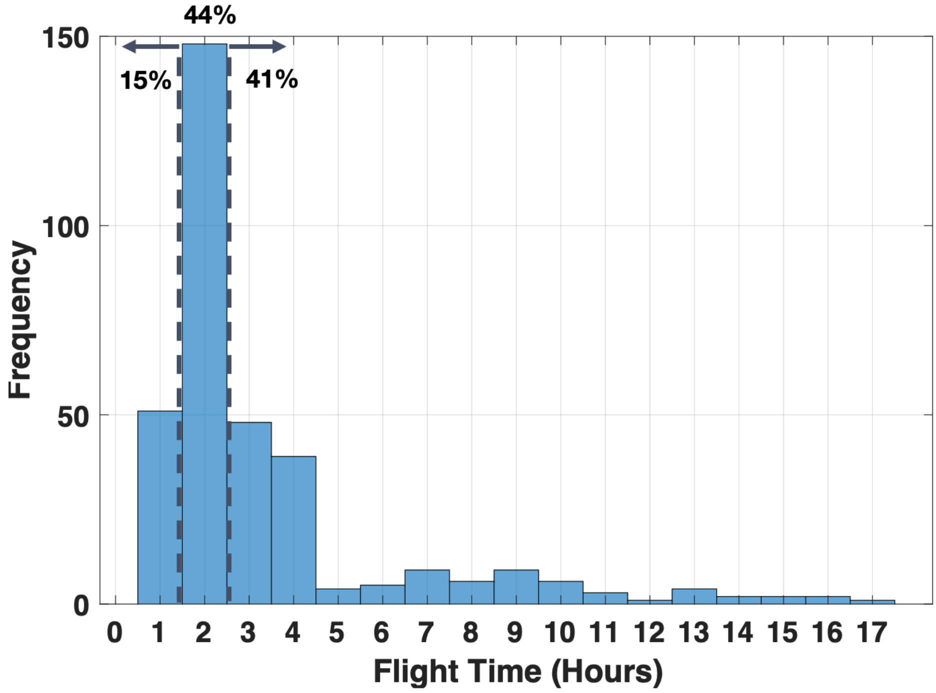

Figure 3 – MEL arrivals flight time distribution for 2019.

Figure 4 provides a distribution of flight time by local arrival hour at Melbourne (averaged over 2019). As can be seen, most long haul aircraft (over 5 hours flight time) arrive between 6am and 7am local time, with shorter haul domestic arrivals commencing from 7am. During the morning peak between 7am and 11am local time, approximately 40% of the arrivals has a flight time over 2 hours. The practical result of this is that GDPs implemented at Melbourne during those hours have limited effectiveness due to a high percentage of flights coming from departures more than 2 hours away. This, in combination with the typical capacity and demand imbalances at Melbourne Airport, make it a prime candidate for the implementation of LR-ATFM.

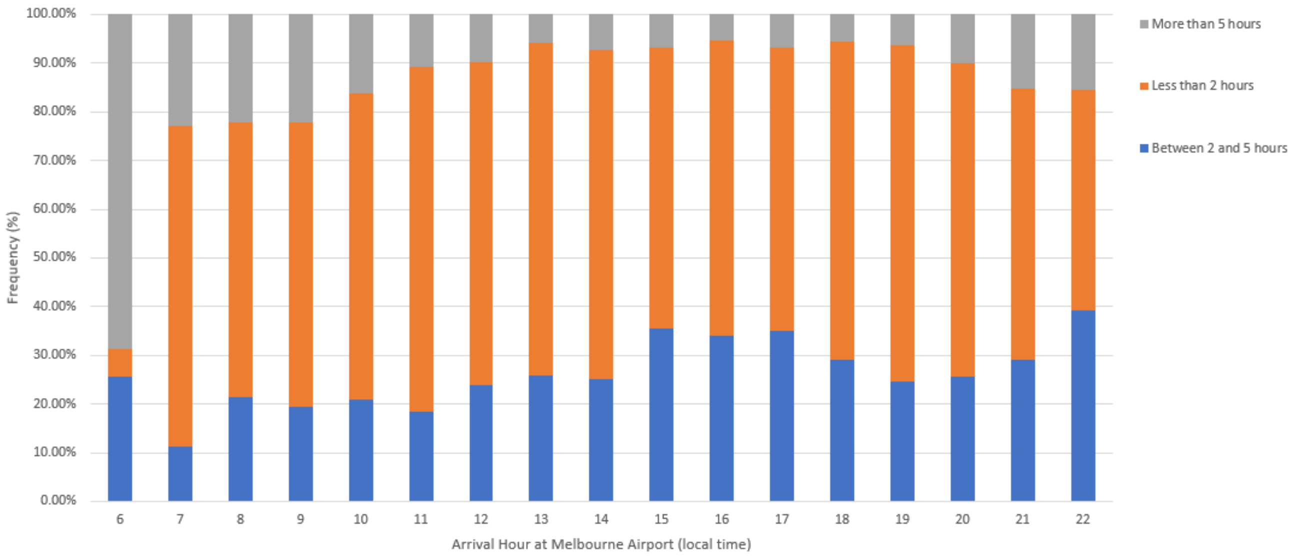

Figure 4 – Distribution of flight time groups by arrival hour at Melbourne (local time).

4. LR-ATFM Uncertainty Sources

This section describes some of the main uncertainties affecting LR-ATFM and the data to define them in each part of the world. These are summarized in Table 1 and additional details are then provided in the following sub-sections. The uncertainty in the FMS delivery is characterized using published data from the GE Aviation FMS and from the Honeywell Pegasus FMS. The Time-Based Flow Management (TBFM) tool is the arrival metering system used in the US. Its accuracy in predicting the crossing of the meter fix will be presented here. To characterize the uncertainty in the push-back time in the US, data from the FAA Aviation System Performance Metrics (ASPM) database that contains detailed information about delays in the major airports in the US, will be presented. The push-back uncertainty is of particular relevance to short-haul demand uncertainty.

Table 1 – Data available to calculate LR-ATFM error distributions.

	Flights Affected	**US/Canadian Data**	**Australian Data**
FMS trajectory delivery uncertainty	Long haul	GE FMS/Honeywell Pegasus	GE FMS/Honeywell Pegasus
Arrival Manager (AMAN) schedule uncertainty	Short & long haul	TBFM/AMAN	AMAN
Push back time uncertainty	Short haul	ASPM	AUS Database

4.1 FMS Trajectory Delivery Uncertainty

When metering to a constrained fix, air traffic controllers are responsible to direct flights, through re-routes and speed advisories, to meet the Scheduled Time of Arrival (STA) proposed by the ground arrival manager (AMAN in Australia, TBFM in United States). The main function of the FMS aboard an aircraft is to provide guidance and navigation, but through its Required Time of Arrival (RTA) functionality, the FMS can also be used to meet time targets at specific waypoints along the route currently flown by the aircraft as described in [9]. The RTA functionality has the advantage of being a closed loop solution to time-based metering, because the FMS actively controls the aircraft speed to meet the time at the constrained fix with a certain tolerance that varies across FMS types and pilot settings. Currently this approach to time-based metering is not applied either in Australia nor in the US, but in the future, it could be used given the high level of accuracy that can be achieved and studied in previous work.

Results from a Human-In-The-Loop (HITL) study [9] performed with a GE Aviation Boeing 737 NG simulator showed that flights that were metered using RTA had a smaller mean and standard deviation (STD) of crossing time errors than flights that were metering only using ATC speed advisories. The mean was reduced to 2 seconds from 3.1 and the STD from 11.1 to 8 seconds. This experiment was performed in a laboratory setting, therefore both results were operationally acceptable. In [10], data from a Boeing 757-200 Honeywell Pegasus FMS performing RTAs were evaluated. Multiple flights (276) across different wind conditions and with routes with speed constraints and without were simulated. Winds from two weather models, the High-Resolution Rapid Refresh (HRRR), and Global Forecast System (GFS) were used and true winds conditions with different number of Descent Forecast Levels (DFL) were tested. The distribution of the RTA time error calculated as the actual time of arrival when crossing the fix minus the assigned RTA time is presented in Figure 5. The distribution is skewed to the right (indicating aircraft arrived late at the meter fix more often than early), but the average error is around 5 seconds. The more DFLs that were provided to the Pegasus FMS representing better wind information, the tighter the distributions in Figure 5 are. It should be noted that the data presented in [9] were for flights in the cruise phase and therefore in level flight. The small deterioration of performance observed in [10] can be attributed to the increased uncertainty of meeting a time target in the descent phase of flight. The five seconds average performance is still very good operationally.

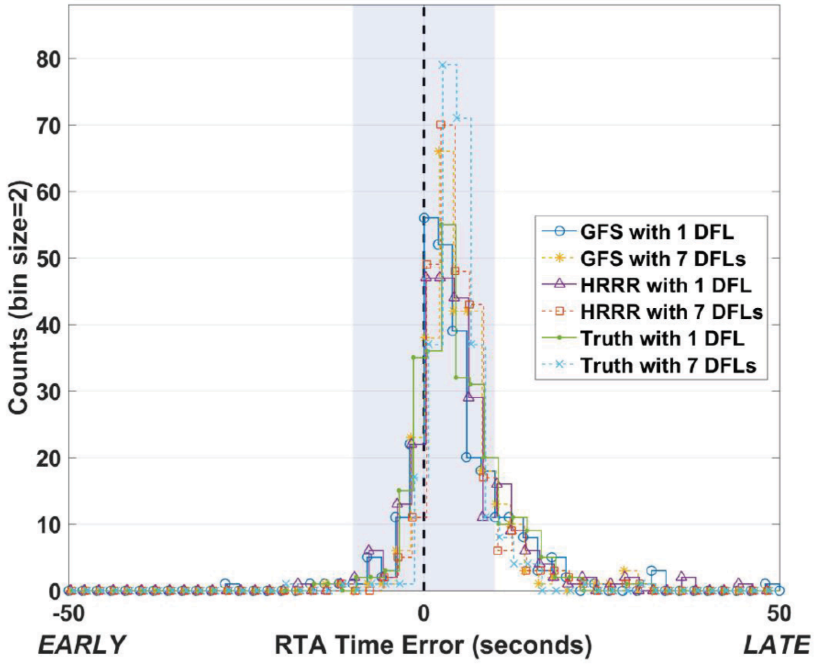

Figure 5 – RTA time error with GFS, HRRR and truth winds and different number of wind Descent Forecast Levels (DFLs) [10].

Lastly, results from a flight trial presented in [11] showed an average RTA time error of -5 seconds, which means that the flights arrived early. The flight trials were performed by Boeing 737-700 with GE FMSs. Even if the sign of the error is different, most flights arrived early instead of late, the magnitude of the average error is very similar to the one observed with simulated flights in [9] and [10], reinforcing the strong operational benefit of using RTAs to meet arrival manager scheduled times. Along current metering time horizons, FMSs are capable of very good delivery to very tight tolerance, therefore this capability should be considered as a strong candidate for supporting LR-ATFM.

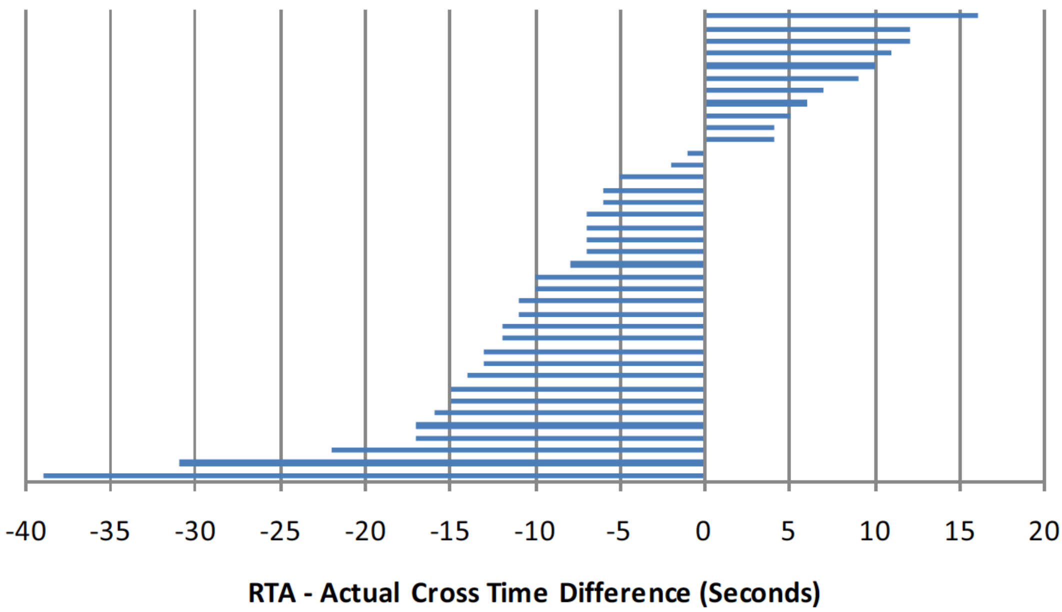

Figure 6 – RTA time error during the 2010 Seattle flight trials [11].

4.2 Arrival Manager Schedule Uncertainty

MIT Lincoln Laboratory is developing a TBO Weather Testbed [8] in collaboration with the FAA

William J. Hughes Technical Center (WJHTC) that includes TBFM, the system used in the US for time-based metering. A schematic representation of the TBO Weather Testbed is shown in Figure 7. The testbed includes TBFM with Terminal Sequencing And Spacing (TSAS) capabilities (the scheduling and separation extension of TBFM in terminal airspace), as well as the Dynamic Route for Arrivals in Weather (DRAW) capability developed by National Aeronautics and Space Administration (NASA) [12][13] that integrates convective weather avoidance actions into TBFM trajectory calculations. These systems can be provided multiple weather forecasts as input, such as the High-Resolution Rapid Refresh (HRRR), and, in the future, real-time wind observations obtained through Mode S Enhanced Surveillance (EHS) interrogations [14][15]. In creating the trajectories necessary for the TBO Systems, different levels of fidelity are available by leveraging Honeywell Pegasus FMSs, an MIT LL-developed simulation system called NASPlay and the Target Generation Facility (TGF) developed by the FAA WJHTC [16].

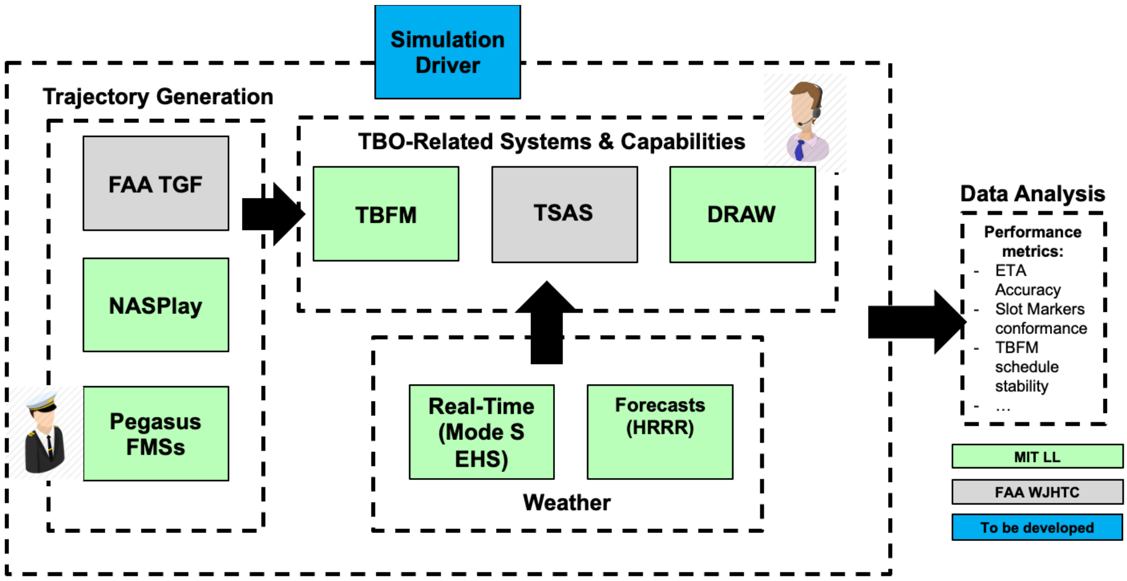

Figure 7 – MIT LL TBO Weather Testbed [8].

The Testbed output metrics in predicting Estimated Time of Arrivals (ETA) for TBFM schedule were collected to characterize the US arrival manager time error uncertainty. Five days of TBFM data of traffic into Philadelphia Airport were collected with high and nominal wind conditions. A sample set of results is presented in Figure 8 where each line in the plot represents a flight in the sample. Its ETA error is plotted from 20 minutes from the meter fix to the actual crossing time. The colored lines in Figure 8 represent the 50 best performing flights in terms of ETA error selected for the performance test. The lines greyed out represent the other flights in the sample, not selected for the performance test. TBFM runs were compared using the “cone test” that evaluates the evolution of the error of TBFM ETA predictions from the freeze horizon, approximately located 19 minutes from the meter fix (MFX) in the legacy NASA TBFM. This performance test was used in the field by the FAA to test TBFM performance requirements. The Root Mean Square Error (RMSE) at 19 minutes from the meter fix was used as the primary metric to characterize the ETA prediction error. Moreover, the cone (black) line represents an error of ± 60 seconds at 19 minutes from the MFX and linearly decreases up to 10 minutes from the MFX, where it is a constant ± 30 seconds thereafter. This was a performance requirement specified by the FAA that each new release of TBFM had to pass to be deployed in the field [17].

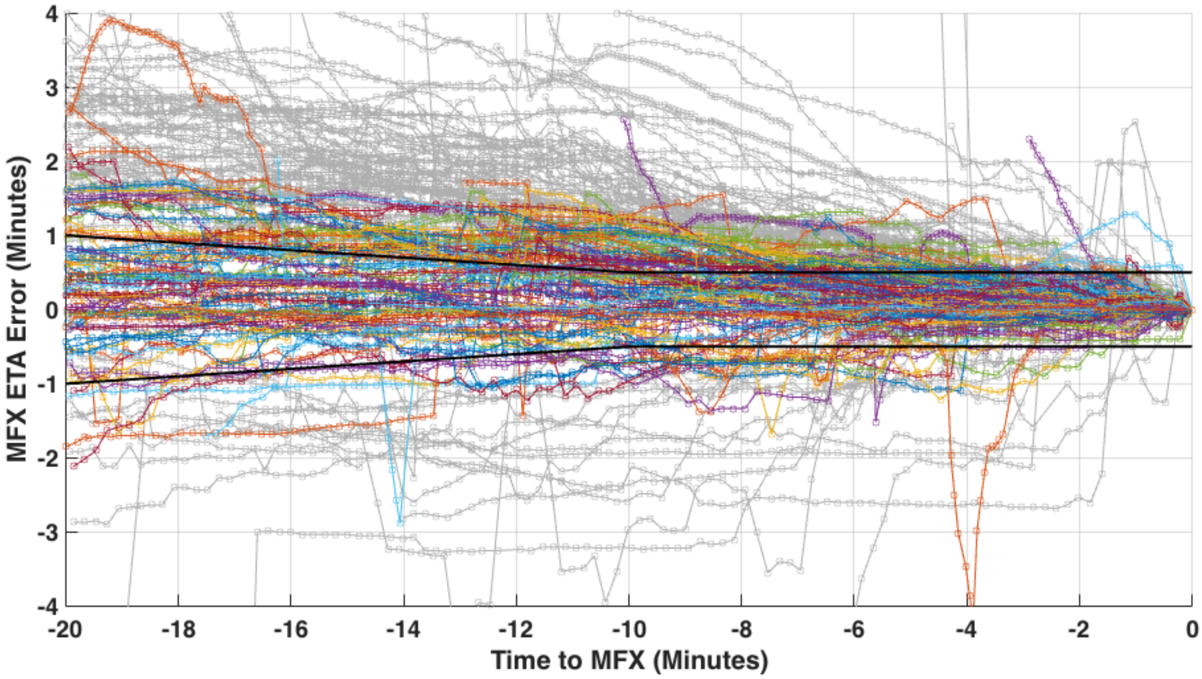

Figure 8 – TBFM ETA error at the meter fix vs time to cross [8].

There were more than 200 flights during the four-hour scenarios in each of the five days in the sample, thus more than 1,000 actual flights were analyzed. Some of the flights in the sample were either not descending to a meter fix or were impacted by ATC interventions after the freeze horizon. To filter them from the sample, flights were classified by their overall ETA performance (smallest ETA vs Actual Time of Arrival (ATA) error inside the Freeze Horizon). This metric was used as a proxy for ATC interventions (lateral route amendment or interim altitude during descent) on each flight. The smaller the ETA error, the more likely a flight was not impacted by ATC interventions, and hence the more likely a flight was good to test TBFM performance. To segregate the results by potential ATC impacts, the results for the overall sample, top fifty and top ten performing flights are presented in Table 2 for the high and low wind days. Therefore, the top ten group's results have the highest confidence of being a good representation of TBFM performance. Conversely, the overall results, potentially including multiple flights with ATC interventions, have the lowest confidence of being a good representation of TBFM performance. The top fifty results are somewhere in between.

Table 2 – TBFM ETA error results [8].

High Wind Days	
RMSE ETA Error @19 Min (all flights) [sec]	112.5
RMSE ETA Error @19 Min (top 50 flights) [sec]	39
RMSE ETA Error @19 Min (top 10 flights) [sec]	15.7
Low Wind Days	
RMSE ETA Error @19 Min (all flights) [sec]	133.4
RMSE ETA Error @19 Min (top 50 flights) [sec]	37.3
RMSE ETA Error @19 Min (top 10 flights) [sec]	18.4

Using the top 50 flights as a measure of TBFM ETA error uncertainty, Table 2 shows that 19 minutes from the meter fix, TBFM performs similarly in high and low wind days, both results are slightly under 40 seconds Root Mean Square Error. From Figure 8, it can also be seen that the ETA error uncertainty decreases as the aircraft approach the meter fix as expected. This result is representative of the fact that the closer the aircraft is to the meter point, the less uncertainty the arrival manager system has in predicting its crossing time. Nonetheless, it cannot be assumed that the same level of accuracy would be maintained for longer look-ahead times. For this reason, in the US, metering operations are extended through multi-tier systems. Basically, longer distances are broken into multiple metering points, therefore the arrival manager prediction horizon remains roughly the same for each metering tier. This environment, denominated extended metering (in US), helps managing the uncertainty of flights arriving from farther origin airports. On the flip side, each tier could be affected by pop-up flights that take off from airports inside the metering horizon. These flights are known to cause issues to the arrival manager system because of the uncertainty in their push back time. This will be discussed in the next section. Current ground-based metering systems can accurately predict the ETA at the meter fix, but to support LR-ATFM with extended metering horizons, improved wind information might be necessary.

4.3 Push Back Time Uncertainty

As mentioned in the previous section, aircraft taking off inside the metering horizon are denominated as pop-up flights, and notoriously create problems for time-based arrival manager systems [18][19]. The problem is that these flights need to be allocated in the arrival schedule before they have taken off. Push back time is subject to significant uncertainty, and therefore the arrival schedule is impacted by this uncertainty. In a simulated study [18] on the impact of pop-up flights on time-based metering operations, it was found that with an average push-back time uncertainty of 300 seconds, pop-ups account for 79% of metering timeline schedule position changes, compared to scenarios with no pop-ups and also cause an increased number of STA changes. STA changes also impact the pilots and controller workload, as they have to adjust to these revised time targets. In [19] three approaches for dealing with pop-up flights were proposed: 1) automatically reserve slots based on their proposed departure time, 2) reserve slots for them manually based on the most current information available, and 3) do not reserve slots for pop-ups and leave it to the sector controller to fit them into the stream after they take off. Each approach showed some pros and cons, but a combination of the three based on the departure airport, may provide the best results.

From these and other studies, it is apparent that the impact on the arrival schedule depends on the uncertainty in the push-back time. The bigger the uncertainty, the more the schedule and the workload are affected. Badrinath et al. have studied the accuracy of push-back times (defined as Early Off Block Time (EOBT) in the study) compared to scheduled time of departure and reported the results in [20]. The study found that the EOBT error varies across airports and with the lookahead time. In other words, the closer the estimation of the EOBT is to the actual push-back, the greater the accuracy (see Figure 9). This is expected and it is also similar to the ETA error uncertainty results presented in Figure 8. Both mean and standard deviation (STD) error at all the airports in the study increased with increased look-ahead time. It must be noted that the results in Figure 9 are for a single airline (denominated Airline A) which presented different accuracies in different airports. For example, EWR presented a STD in the EOBT time error around half of the one in DFW, 8.9 versus 18.4 minutes at 40 minutes lookahead, and of 3.1 vs 5.9 at 10 minutes lookahead. Results for two more airlines (B and C) were presented at EWR, with significant differences: Airline B STD at 40 minutes lookahead was 17 minutes versus 13.2 minutes for Airline C. Similar trends persisted for 10 minutes lookahead time, 11.4 minutes for Airline B versus 9.8 minutes for Airline C. Both Airline B and C performed worse than Airline A for all lookahead times analyzed. These results speak to the challenge of accurately estimating push back times even for a given airline at different airports, but also the variability in quality of pushback time prediction data between airlines.

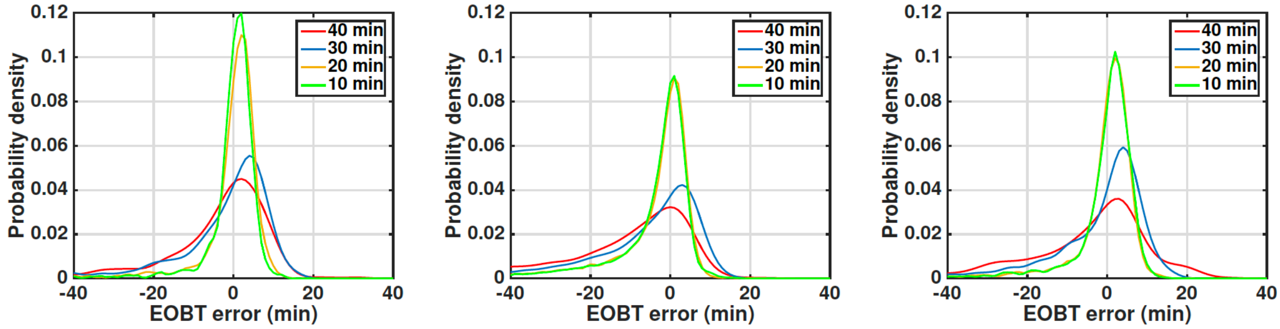

Figure 9 – Early Off-Block Time error as a function of prediction lookahead time for multiple airports in the US: Newark (left), Dallas-Fort Worth (middle) and Charlotte (left). All results for Airline A [20].

Figure 10 provides a distribution of the variation in actual take-off with the with GDP-assigned Calculated Take Off Time (CTOT) for Australian domestic departures to Melbourne in 2019. In Australia, airlines need to comply with the GDP-assigned push-back time at the gate, but actual off blocks time is often not available and hence GDP compliance is determined using the take-off time as a reference. This indicative compliance as shown in Figure 10 is therefore a combination of true GDP compliance at push back and any variation in taxi-out time, i.e. delay on taxi-out. In 2019, less than 3% of flights departed more than 5 minutes early of CTOT (early non-compliant), 82% of flights between 5 minutes early and 15 minutes late (compliant), and 15% of flights more than 15 minutes late (late non-compliant). Although the vast majority of flights departed compliant, this still means a window of 20 minutes in which a flight can depart, which can result in large tactical variation of the arrival sequence, especially if these flights depart from within the Melbourne metering horizon. As shown by the Newark and Melbourne Data, push-back time error is still a big issue for LR-ATFM.

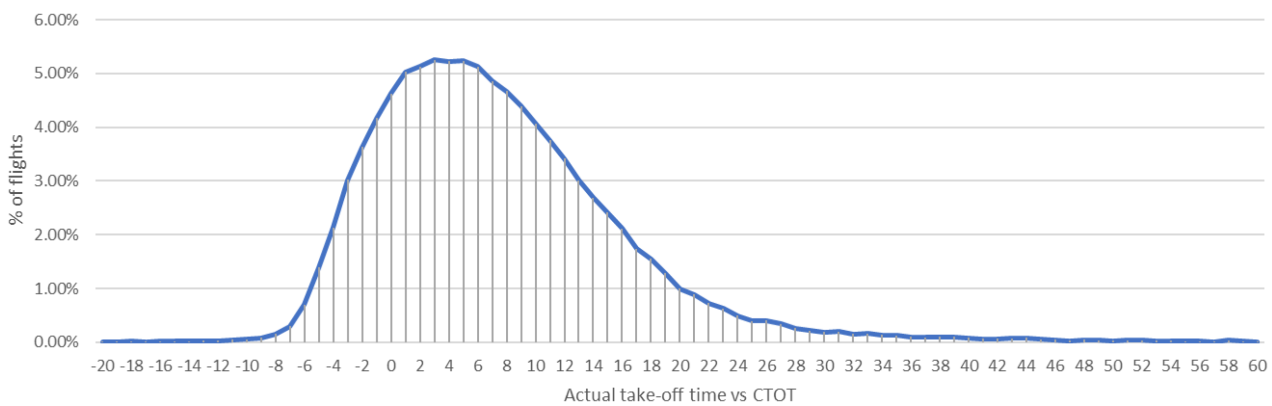

Figure 10 – Take-off time variation with GDP-assigned CTOT for Australian domestic departures to Melbourne in 2019 (in minutes).

5. Concept for Integrated TBO/LR-ATFM

Some of the key uncertainty sources affecting today's LR-ATFM have been characterized in the previous section. It was shown that the RTA capability of the FMS is capable of delivering flights to the meter points, both in cruise and in descent phases of flight, even in real world conditions, well within ± 20 seconds (Section 4.1). Moreover, ground-based arrival manager systems, even under the worst conditions, can predict ETAs within ± 2 minutes (Section 4.2) 20 minutes from crossing a metering point. On the contrary, accurately predicting the push-back time, is still an issue that, depending on the lookahead time, airline and airport, can be achieved with accuracy between ± 4 minutes in the best cases, and ± 20 minutes in the worst (Section 4.3). Increased use of TBO can help manage these uncertainties but key questions remain, for example how far to extend the range of metering operations and what is the optimal number of metering tiers. Effective integration of TBO in support of LR-ATFM, for example by better integrating pop-up flights, helps manage demand/capacity balance commensurate to uncertainty in the system. For example, there is no point in holding aircraft on the ground for 5 minutes when the constraint is 10 hours into the future.

Increased data exchange can mitigate the issues discussed in Section 4 and support a successful TBO/LR-ATFM concept in the future. Each of the uncertainty sources discussed will require the definition of the data content, update rate, data sources, etc. The following list describes some of areas of improvement that can have the biggest impact:

- Provide improved wind forecast data to AMAN and FMS,
- Increase sharing of FMS intent data (e.g., speed profiles, cost index, Extended Projected Profile (EPP), etc.) to the ground systems (AMAN, TBFM),
- Improve the harmonization between international TBO systems, e.g., between TBFM and AMAN
- Increase the update rate of airlines push back time with confidence intervals through the Collaborative Decision Making (CDM) process.

In summary, Table 3 shows the main uncertainties affecting TBO integration with LR-ATFM and the improvements that can mitigate these issues.

Table 3 – Uncertainties affecting LR-ATFM and potential mitigating factors.

Uncertainty Source	Flights Affected	Potential Improvements in Support of LR-ATFM
FMS trajectory delivery uncertainty	Long haul	- Improved wind data into the FMS - Exchange of AMAN time constraints to the FMS
Arrival Manager (AMAN) schedule uncertainty	Short and long haul	- Improved wind & convective weather data for ETA predictions - Improved Airport Arrival Rate (AAR) predictions - Improved data exchange for internal departure pushback times
Push back time uncertainty	Short haul	- Improved airline data exchange with ANSPs

6. Further Work

A common question posed is how accurate does the available information need to be to support LR-ATFM? The answer to this question very much depends on the operational scenario. For example, an airport for which most of its demand departs from origins more than 4 hours away, LR-ATFM may be successful with a 4-hour horizon as most of the aircraft are airborne and therefore demand can be predicted with reasonable accuracy, as demonstrated in Sections 4.1 and 4.2. On the contrary, the effectiveness of LR-ATFM for an airport with significant short haul demand will much likely be lower due pushback uncertainties making demand predictions much less reliable (see Section 4.3). In addition, airports that experience large capacity variations due weather, like for example Melbourne (YMML), require accurate capacity predictions as well as demand predictions. Future work will aim to develop a theoretical model that allows ANSPs to determine the LR-ATFM system performance and data accuracy for successful implementation based on factors unique to that aerodrome (e.g. ratio of long haul vs short haul demand, capacity variations, fleet mix, etc.). These theoretical accuracies will be compared to the 'state of the art' in terms of FMS and TBO capabilities, and methods will be proposed to manage the integration of pop-up flights within a stream of flights subject to LR-ATFM. Lastly, data exchange requirements will be defined for each of the uncertainties described.

7. References

[1] Enea, G. & Porretta, M., A comparison of 4-D trajectory operations envisioned for NextGen and SESAR - Some preliminary findings, Proceedings of ICAS 2012.

[2] Nikoleris, A., Chatterji, G., Almog, N., and Palopo, K., Arrival delay absorption using extended metering with speed control, 12th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference and 14th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, 2012.

[3] ICAO, Global TBO Concept, V. 0.11.

[4] Shultz, M., Lubig, D., Rosenow, J., Itoh, E., Athota, S., Duong, V., Concept of Long-Range Air Traffic Flow Management, SESAR Innovation Days, 2020.

[5] McDonald, G., Bronsvoort, J., Concept of Operations for Air Traffic Management by Managing Uncertainty through Multiple Metering Points, Air Transport and Operations Symposium, 2012.

[6] Chen, H., Solak, S., Value of Extended Time-Based Metering for Optimized Profile Descent-Based Arrival Operations, Transportation Research Record: Journal of the Transportation Research Board (TRB), 2016.

[7] Jones, J., Lovell, D., Methods for Curbing Exemption Bias in Ground Delay Programs Through Speed Control, Transportation Research Record, 2014.

[8] Enea, G., McPartland, M., Bonin, T., Evaluation of Aircraft Speed and Wind Modeling Accuracy in Automation for Trajectory Based Operations, US/Europe ATM Seminar, 2021.

[9] Enea, G., Sgorcea, R. M., Timberlake, J. M., Osborne, S., Symionow, W., & Davison, T, Operational Integration of Required Time of Arrival (RTA) with Time-Based Management (TBM): Concept of Operations and Human-in-the-Loop Simulation Results, AIAA AVIATION Forum, June 2018.

[10] RTCA, "Guidance for the Usage of Data Linked Forecast and Current Wind Information in Air Traffic Management (ATM) Operations", DO369, June 2017.

[11] Balakrishna, M., Becher, T. A., MacWilliams, P. V., Klooster, J. K., Kuiper, W. D., & Smith, P. J. (2011, October). Seattle required time-of-arrival flight trials. IEEE/AIAA 30th Digital Avionics Systems Conference (pp. 2D4-1), 2011.

[12] Isaacson, D., Hayashi, M., Gong, C., Wong, G., Tang, H., Laboratory Evaluation of Dynamic Routing of Air Traffic in an En Route Arrival Metering Environment, AIAA AVIATION Forum, June 2018.

[13] Hayashi, M., Isaacson, D., Tang, H., Evaluation of a Dynamic Weather-Avoidance Rerouting Tool in Adjacent-Center Arrival Metering, 13th USA/Europe ATM R&D Seminar, June 2019.

[14] Engholm, C., Robasky, F., Banerjee, A., and McPartland, M., Examination of Mode S EHS Wind Observations for Use in Wake Vortex Mitigation Applications, AIAA Aviation Technology, Integration, and Operations Conference. June, 2018.

[15] McPartland, M., Opportunities to Leverage Aircraft-Derived Atmospheric Observations Data, MIT Lincoln Laboratory Air Traffic Control Workshop, Washington DC, 5 December 2017.

[16] Levitt, I., Nouragas, P., Romano, C., Rubino, T., Suech, M., Research, Development, Test & Evaluation in the Trajectory Based Operations Integrated Test Environment, The ITEA Journal of Test and Evaluation 2020; 41: 118-127.

[17] Enea, G., et al., Automating Trajectory Prediction Performance Analyses for the FAA Traffic Management Advisor, AIAA Guidance Navigation and Control Conference, Boston, MA, 2013.

[18] Vanwelsenaere, A, Ellerbroek, J., Hoekstra, J., Westerveld, E., "Analysis on the impact of pop-up flight occurrence when extending the arrival management horizon." US/Europe ATM Seminar, 2017.

[19] Farley, T, Foster, J., Hoang, T., Lee, K., "A time-based approach to metering arrival traffic to Philadelphia." In First AIAA Aircraft Technology, Integration, and Operations Forum, Los Angeles, California. 2001.

[20] Badrinath, S., Balakrishnan, H., Joback, E. and Reynolds, T.G., 2020. Impact of off-block time uncertainty on the control of airport surface operations. Transportation Science, 54(4), pp.920-943.

[21] Jones, J., Lovell, D., Ball, M., "Combining Control by CTA and Dynamic En-route Speed Adjustment to Improve Ground Delay Program Performance", 11th USA/Europe Air Traffic Management R&D Seminar, Lisbon, Portugal 2015.

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