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Implementation of Long-Range Air Traffic Flow Management at Large Hub Airports: An International Perspective*

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***Abstract*—Many international airports have operations with a diverse mix of flight times. When demand/capacity imbalances are predicted to occur, traditional traffic management techniques often exempt long-haul flights which can cause inequity and extra delay to the short-haul flights. Long-Range Air Traffic Flow Management (LR-ATFM) concepts are designed to more equitably share delay across all flights. Using a simulation model, this paper presents results on how different uncertainty sources affect the management of long- and short-haul flights in international airport hubs. Case studies from the United States (Newark), Australia (Melbourne) and Japan (Tokyo Haneda) are presented. The objective of the simulation is to establish a relationship between (1) push-back uncertainty of short-haul flights, (2) estimated time of arrival uncertainty of long-haul flights, and (3) the ratio of short- and long-haul flights on the sequence stability and system delays. Results on these metrics are reported in the paper to discuss different scenarios when LR-ATFM is applied or not. The results provide insights into how LR-ATFM strategies could be more effectively implemented in the future.**

Keywords-Long-Range Air Traffic Flow Management; Trajectory Based Operations; Airports.

I. Introduction & Previous Work

Large international airport hubs receive flights from both short-haul and long-haul destinations. As a result, traffic management into these hubs needs to handle flights of very different durations, which are impacted by different uncertainty sources. Moreover, when Traffic Management Initiative (TMI) programs are implemented to manage demand/capacity imbalances, such as Ground Delay Programs (GDPs), the long-haul flights are typically excluded. Therefore, short-haul flights are usually over-penalized with delays. Managing schedules with diverse duration flights can be supported by extending initiatives such as time-based control via Trajectory-Based Operations (TBO) farther from the destination airport. This type of approach is usually referred to as Long Range-Air Traffic Flow Management (LR-ATFM).

Although various implementations and flight trials of early LR-ATFM concepts can be traced back to the Bay of Bengal Cooperative ATFM System (BOBCAT) in 2007 [1], a clear definition of LR-ATFM is only recent. In 2022, CANSO [2] described it as: "The integration of ATFM solutions to deliver a collaboratively balanced flow of long-haul and short-haul aircraft to an ATM resource (airport, waypoint, or sector of an airspace)." CANSO's concept suggests to manage short-haul flights using GDPs and long-haul flights with some form of time-based metering (TBM). In all cases, the responsibility to meet the time constraint of the long-haul flights is passed to the crew at different timelines, ideally as early as possible. The International Civil Aviation Organization (ICAO) in 2018 had already introduced the terminology in the context of a joint flight trial between ANSPs of Singapore and New Zealand [3] but had not clearly defined the concept. CANSO's definition addresses the main objective of the concept and points to the differences between long-haul and short-haul flights, and the different uncertainties they are subject to. These were defined in a recent study [4] using two case studies from the United States and Australia. The three main uncertainty sources were defined as:

1. Departure Push-Back Time predictability (mostly for short-haul flights),

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2. Scheduled Time of Arrival (STA) predictability, and

3. Flight Management System (FMS) Estimated Time of Arrival (ETA) predictability.

The ICAO Global TBO concept [5] lays out the requirements to implement TBO in a globally harmonized way. A foundational characteristic of Global TBO operations is the increased reliance on data sharing in a collaborative environment. This will be key to mitigate the innate sources of uncertainty affecting LR-ATFM. In [6], a concept of operations for LR-ATFM focused on the Asia-Pacific Region is presented based on [3]. 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 [7] 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 [8], 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 longer the range, the more fuel savings can be achieved.

One of the key tools to manage demand/capacity imbalances is the use of GDPs. Jones and Lovell [9] 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. Lastly, the accuracy of a state-of-the-art scheduler was studied in [10] where the authors looked at the effect of improved wind information to improve TBO systems performance, and describe some of the enhancements to the automation necessary to take advantage of the improved wind data.

Using a simulation model, this paper looks at the effects of different shares of long- and short-haul flights into the schedule of international hubs. Case studies from the United States, Australia, and Japan are used to illustrate the problem. Actual data on push-back time uncertainty and data from an actual FMS are used to characterize some of the above-mentioned factors affecting LR-ATFM in the simulation model.

The rest of this paper is organized as follows: Section II describes the international airports used as case studies. Section III describes the uncertainty data used as inputs to the simulation model. Sections IV and V describe the simulation model and the results respectively. Using the simulation results, a discussion with some proposed mitigations is presented in section VI. The paper ends with some conclusions and next steps in section VII.

II. CASE STUDIES

In this section, to illustrate typical schedules at large airports in different world regions, operational characteristics at New York Newark, Melbourne and Tokyo Haneda airports will be briefly described. The data presented in this section is also used to identify the share of long-haul (more than 2 hours) and short-haul flights (less than 2 hours) used as input parameters to the simulation model described in section IV.

A. *Newark Liberty*

Newark Airport (EWR/KEWR) is one of the busiest airports in the United States (US). The high demand and limited runway capacity leads to it also being one of the most affected by delays, especially when wind and other weather conditions are not favorable. In fact, in 2019 it was the airport generating the largest number of GDPs in the US. The arrival demand profile for a representative day in 2019 (Tuesday, November 5th) 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).

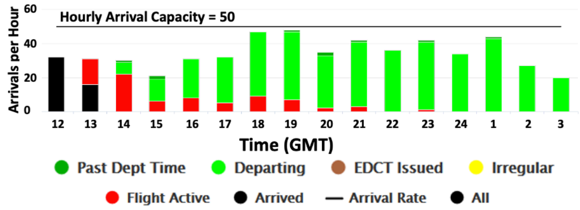

Figure 1. Representative EWR daily arrivals demand on November 5 2019 at 13:30Z. Black represents flights already landed, red have taken off from their origin, and green are scheduled to depart. The black line is the airport arrival rate of 50 per hour on this day (https://www.fly.faa.gov/aadc/).

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. If flights were to be grouped in 3 groups: flight time under 1 hour, flight time between 1 and 2 hours, and flight time more than 2 hours, the data indicates that 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. In the simulation presented in in section IV, these will be grouped into short-haul (less than 2 hours) and long-haul (more than 2 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 and a large standard deviation of 131 minutes.

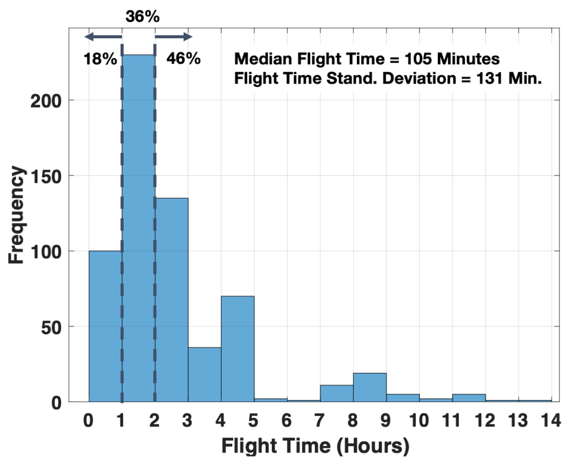

Figure 2. Representative EWR arrival demand flight time distribution in 2019.

Of the 100 flights of the day with less than one hour of flight time that could be defined as pop-ups, the majority came from Boston (22), 10 from Pittsburgh, and 8 from Washington Reagan (DCA) and Albany. 8 flights came from Canadian airports, 6 from Toronto, and one each from Montreal and Quebec City each. 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 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 currently excluded from any initiative to control demand such as GDP, Airspace Flow Programs (AFP), etc.

The hourly distribution of short- and long-range flights arriving at EWR in 2019 for the same day discussed in Figure 1 is shown in Figure 3. Short-haul flights are not present in the early hours of the morning when most flights are long-haul.

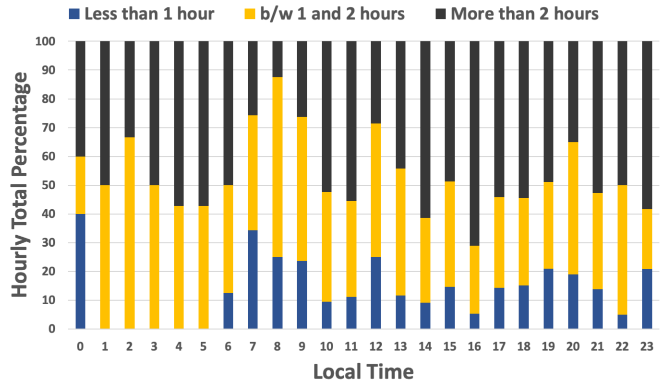

Figure 3. Representative EWR distribution of flight time groups by arrival hour in 2019 (local time).

B. *Melbourne*

Melbourne Tullamarine Airport (MEL/YMML) 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 capacity of 40 arrivals per hour can be reached in Visual Meteorological Conditions (VMC) when utilizing Land 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 the time between 6am and 11pm local time during 2019. This was 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 4 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 include Sydney (23%), Adelaide (7%) and Brisbane (10%; flight time can be under 2 hours depending on prevailing winds). 15% of flights have a flight time less than 1 hour coming from nearby airports such as Canberra (4%) and Hobart (5%). 41% of flights have a flight time of more than 2 hours. Similar to Newark, the vast majority of flights (85%) have a flight time less than three hours. The longest flight into Melbourne in 2019 was from Vancouver, with a maximum flight time exceeding 17 hours.

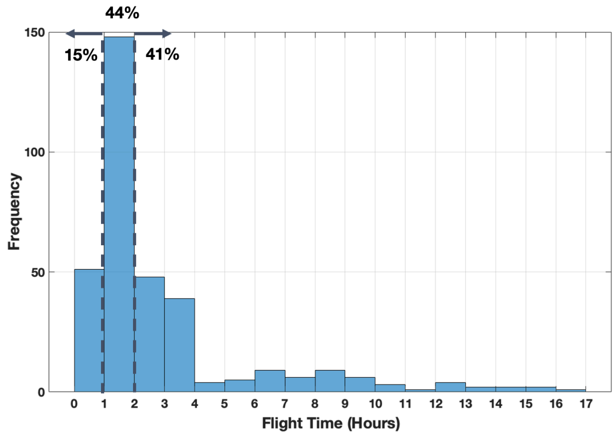

Figure 4. MEL arrival demand flight time distribution for 2019.

Figure 5 provides a distribution of flight time by local arrival hour at Melbourne (averaged over 2019). As can be seen, most international 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 have 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 and exempt from GDPs. This, in combination with the typical capacity and demand imbalances at Melbourne Airport, make it a prime candidate for the implementation of LR-ATFM.

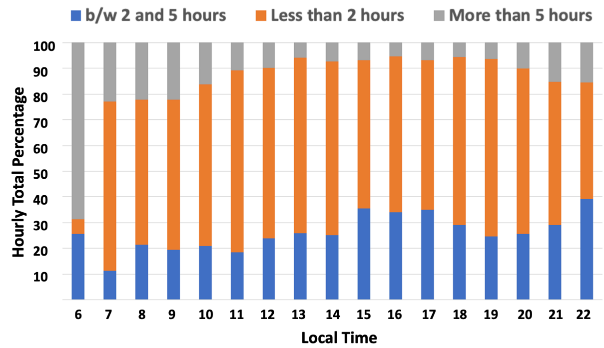

Figure 5. Representative MEL distribution of flight time groups by arrival hour in 2019 (local time).

C. *Tokyo*

Tokyo International (Haneda) Airport (HND/RJTT) is the busiest hub airport in Japan, which services both domestic and international flights. On a typical day in 2018, for example, about 17% of all arrivals were international, with the remaining 73% being domestic flights. The flight times of all domestic flights on a sample day in January 2018 are shown in Figure 6.

As seen from the figure, most of the domestic flights (75%) are between 1 and 2 hours, flights shorter than 1 hour represent 18% of all domestic arrivals, and flights longer than 2 but shorten than 3 hours constitute the remaining 7%. Note that no domestic arrival exceeds this 3-hour limit, the longest flights depart from the southern island of Okinawa. International flight data is available for the portion of the Fukuoka Flight Information Region (FIR) only, so these flights are not included in the histogram. The shortest international flights come from Seoul (South Korea) and can be under 3 hours.

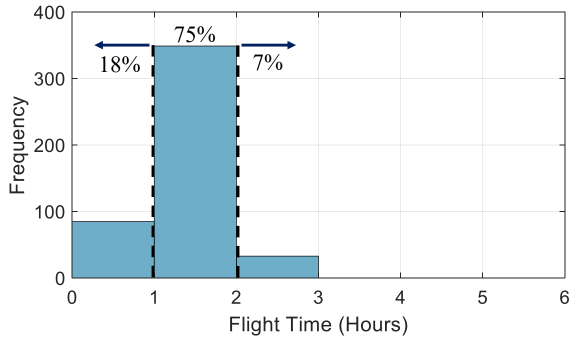

Figure 6. Representative HND arrival demand flight time distribution on a sample day in 2018 (domestic only).

The hourly distribution of the arrivals for a sample day in 2018 is shown in Figure 7. Night and early morning arrivals are mostly international flights, which is similar to Melbourne. For most of the day, flights longer than 2 hours represent a very small percentage of all arrivals, which might limit the effect of any in-flight ATFM initiatives such as the LR-ATFM.

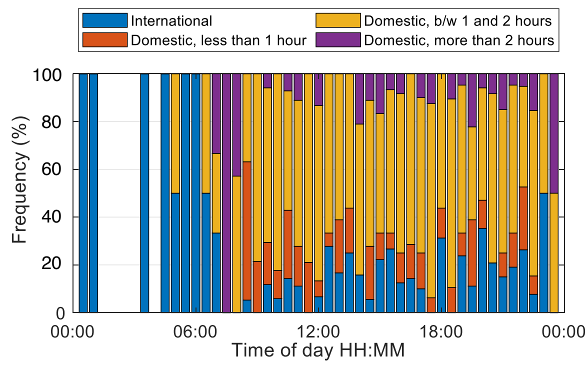

Figure 7. Representative HND distribution of flight time groups by arrival hour on a sample day in 2018 (local time).

III. Input Data

The objective of the simulation runs (described in the next section) is to help explain the relationship between (1) push-back uncertainty of short-haul flights, (2) ETA uncertainty of long-haul flights, and (3) ratio of short- vs long-haul, on sequence stability (slot changes for LR-ATFM flights and/or assignment of too much delay). To achieve this goal, real data distributions were investigated to identify appropriate inputs to the simulation model, which will be described in this section.

A. *Departure Push-Back Time Uncertainty Data*

One of the major sources of uncertainty for ATC is the departure push-back time. This mostly impacts short-haul flights that do not have time to speed up or slow down in a short cruise phase. This issue is even more evident for aircraft taking off inside the metering horizon (called "pop-up" flights) and notoriously create problems for time-based arrival management systems. To quantify this source of uncertainty to LR-ATFM in the simulation model, data for the United States and Australia were compared.

In [11] Badrinath *et al.* studied the accuracy of predicted push-back times (called Earliest Off Block Time (EOBT) in the US) as a function of forecast lead-time compared to the actual push-back time. Data from 2018 showed that the EOBT relative to actual push-back time error can vary significantly between airports, between airlines at the same airport, and with the lookahead time. Not surprisingly, in general, the closer the EOBT estimate is made to the actual push-back, the greater the accuracy. EWR had a Standard Deviation (STD) in the EOBT time error of around 8.9 minutes at 40 minutes lookahead, and of 3.1 minutes at 10 minutes lookahead. In other words, forty minutes before taking off, the system was able to predict the best-performing airline push-back times with around ±10 minutes accuracy. Other airports in the US presented double these levels of uncertainty.

Reference [4] presents the variation in actual take-off with the 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 block time is often not available and hence GDP compliance is determined using the take-off time as a reference. 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 were more than 15 minutes late (late non-compliant). Although the vast majority of flights departed compliantly, this still means a window of 20 minutes exists 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 and therefore needs to be considered in the simulation.

B. *Scheduled Time of Arrival (STA) Error Data*

Past studies have shown that errors in the wind model used by the ground automation can cause inaccuracies in the calculated STAs [10]. Errors depend on the wind conditions of the day and can vary from 20 to 40 seconds on average at a 20 minutes look-ahead time. These translate to 1.7-3.3% of the remaining flying time. The error decreases the closer the aircraft is to the metering point.

C. *FMS Estimated Time of Arrival (ETA) Error Data*

The uncertainty in the FMS trajectory prediction was modeled by looking at the earliest and latest times the aircraft can be at the destination with varying cruise altitudes and weights. This is based on the Cost Index (CI) parameter which airlines use to have the FMS calculate speeds in terms of cost of time over cost of fuel. The lowest CI determines the latest, and the highest CI the earliest the aircraft can arrive at the destination. The CI is not known by the ground automation tasked to predict the aircraft trajectory and metering time because this is often a proprietary parameter set by the airlines depending on their business objectives for any given flight.

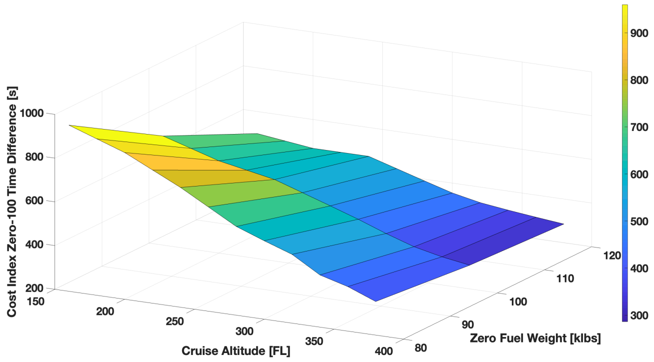

Figure 8. Arrival time difference vs CI, Zero-fuel Weight and Cruise Altitude.

The FMS used to generate these flight profiles was an actual GE Aerospace FMS for a very common single-aisle aircraft in a simulated environment using a typical configuration. That makes the numbers representative and justifies the smaller sample size as mostly trends are of interest here. The determination of earliest/latest was performed for a typical short-haul flight from Boston (KBOS) to Newark (KEWR) (typically less than one hour flight) with a range of cruise altitudes from FL160 (16,000 feet) to FL380 (38,000 feet). The latter is possible but unlikely for a short flight. The zero fuel weights (dry weights) varied from 80 klbs to 120 klbs with a constant fuel weight of 20 klbs. Figure 8 shows the time difference between the earliest (CI=100) and latest (CI=0) arrival times over these parameters. The maximum time difference of more than 900 seconds is observed at the lowest cruise altitude of FL160. The lower the cruise altitude, the more the arrival times can vary.

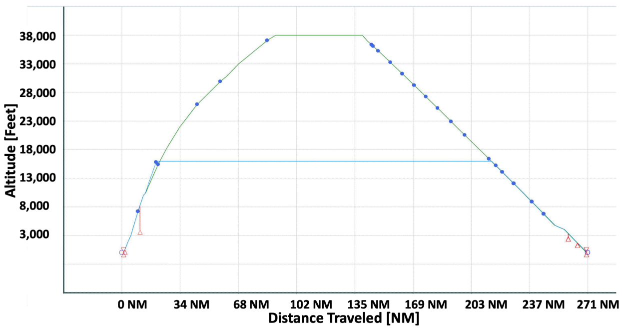

Figure 9. Vertical profile for flights using FL160 (blue line) and FL380 (green line) cruise altitude.

This is because the lower the cruise altitude, the longer the cruise phase will be (see Figure 9). A longer cruise phase will allow for more speed variance, whereas speeds are more prescribed in climb and descent due to also having to satisfy other constraints for energy management. An increase in the time difference can be observed when the zero-fuel weight is lowered because the aircraft will be able to climb faster and be in cruise longer.

The variability in the arrival time is used to illustrate that even with a perfect performance model, the ground system is still impacted by uncertainty driven by the CI used by the airline to fly the aircraft. In the case presented, on the flight between KBOS and KEWR which is usually less than one hour, there could be a variability of 15 minutes (900 seconds) just by using different CIs. This level of uncertainty, 25%-time error, is obviously an extreme, so smaller values, described in the next section will be used in the simulation runs. Anecdotally, some airlines use CIs as low as 6 (slow and low fuel burn) and up to 60, for faster arrival and higher fuel burn. This difference would cause an arrival time change on the same KBOS-KEWR flight of 7.5 minutes, or about 12% of the total flight time.

IV. Simulation Model

An ATFM simulation has been developed in order to explore key LR-ATFM issues in more detail. The simulation is a simplified queuing model which accounts for capacity and demand at different airport resources in order to calculate delays at different parts of the system, but does not capture interactions between arrivals and departures explicitly. Real world uncertainty sources were modeled with error distributions that will be discussed. Results were obtained by running multiple simulations in a Monte Carlo fashion and averaging the outcomes. More details on earlier versions of the simulation model can be found in [12].

The share of international flights potentially subject to LR-ATFM is varied from 0% to 60%. From now on, this will be denominated long-haul flights, since in the US there are domestic flights that are more than six hours long (coast-to-coast). This high percentage of long-haul flights is not consistent with the data shown in section II for EWR, MEL, and HND, but testing the impact of high shares of long-haul flights was one of the objectives of the simulation. In the simulation, these are the only flights subject to LR-ATFM delays of 2 minutes maximum. The maximum delay absorption through deceleration in the enroute phase allowed for LR-ATFM of 2 minutes is in accordance with past research results [13] for Fukuoka FIR. This value is small compared to other regions such as the Melbourne FIR in Australia where higher amounts of delays can be absorbed through speed control, and therefore is not representative of other airspaces. Nonetheless, it was considered to be a good starting point for this research. Extensions to this model will be discussed in the conclusions and are subject of future research.

In the simulation, the domestic flights, usually less than 2 hours, denominated short-haul are the only operations subject to ground delays. Again, this assumption comes from the original model developed for the Japanese airspace.

The purpose of the ATFM simulation is to calculate estimated departure times based on the ground delay program for domestic (short-haul) flights, LR-ATFM delays imposed on long-haul flights and resulting arrival times for given traffic flow and control parameters. The key parameters are the maximum allowed LR-ATFM delay, set to 2 min as discussed above, and the airborne delay buffer (maximum vectoring time in the terminal area) set to maintain runway pressure, equal to 9 minutes. This buffer accounts for departure time and flight time prediction uncertainties, so when the predicted airborne delay of each flight is less than this value, no ground delay or LR-ATFM delay is assigned. Ground delays of short-haul aircraft can be indefinitely long, but the LR-ATFM delays of long-haul arrivals are limited to 2 min [12] [13].

The ATFM simulation starts with initial sequencing, which is based on the expected time of arrivals (ETAs) obtained prior to departure of each flight. Required separation on arrival is set to 2 minutes, so the initial ETA queue is recalculated every time an ETA is updated to ensure this separation minimum is met (see Figure 10). The difference in the initial ETA and projected ETA adjusted for separation for each flight is the arrival delay and it is tallied as a key metric in the simulation. When the arrival delay exceeds the 9-minute buffer, ground delays on short-haul flights and LR-ATFM delays on long-haul flights are applied. Note that since the LR-ATFM delays cannot exceed 2 minutes, sequence changes might be necessary, i.e., long-haul flights might have to "overtake" short-haul ones. One of the main goals of LR-ATFM is to provide more equity in delay distribution, as discussed in past work [14]. Actual departure and arrival times, however, might change due to uncertainties in departure and enroute flight times, so the calculated departure times (ground delays) and LR-ARFM delays are updated periodically.

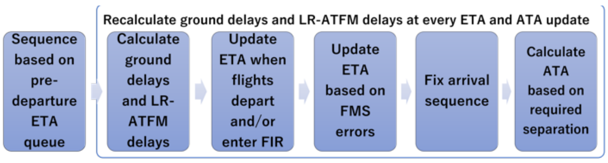

Figure 10. Delay calculation flow.

The uncertainties modeled in this ATFM simulation are departure time uncertainties and flight time prediction uncertainties, due to both FMS CI settings and STA error in the ground system. In the real world, departure time uncertainties depend on airport of origin, weather conditions, airline and other factors as discussed in section III.A. In this ATFM simulation, departure time uncertainties are modeled by a normal distribution with a mean of zero and standard deviation of 5, 10, or 20 minutes. This is not completely consistent with the actual data from the US and Australia presented in section III.A for EWR and MEL, where aircraft are more likely to depart late but was used for simplicity. Nonetheless, this is enforced in the simulation. In fact, when a flight is assigned a ground delay, it cannot depart earlier than the assigned time. This assumption as well is not completely realistic, in the US flights subject to ground delay programs can leave slightly early if ATC allows them. This is not reflected in the simulation. As a result of these assumptions, ground-delayed flights and non-ground-delayed flights departure errors are modeled separately.

Long-haul arrivals' ETAs are also subject to uncertainties due to limited information sharing among different flight regions, so these are modeled analogous to domestic departure time uncertainties. Note that there are no pop-up flights in the simulation. The total number of flights in the original ETA sequence and the final Actual Time of Arrival (ATA) sequence is always the same. The order in the sequence obviously changes from the original and the number of swaps are tallied as a predictability metric. This will be discussed in the next section.

Since the simulation model could not encompass both FMS and STA errors, these uncertainties were combined into a single distribution. In Section III.B an STA error between 1.6% and 3.4% because of wind data error was presented, while in Section III.C, a maximum time error of 25% was shown. A compromise was chosen for the simulation runs and combined flight time prediction uncertainties are modeled by a normal distribution with mean of zero and standard deviation of 2% and 5% of the predicted flight time. Therefore, longer flights are described by higher uncertainties. A summary of the parameters varied in the simulation is presented in Table 1.

TABLE 1. EXPERIMENTAL MATRIX.

Simulation Parameters	Metric	Values Simulated
Push-back Uncertainty Distribution	Standard Deviation	5, 10, 20 minutes
STA/FMS Error Distribution	Standard Deviation	2%, 5% of flight time
Long- vs Short-Haul Mix of Flights	Percentage	40%, 70%, 100% short-haul flights

Monte Carlo simulations with 300 runs are performed for each sample traffic to account for the uncertainties described above. The metrics used are ground delay of short-haul flights, controlled enroute delay of long-haul flights, airborne delays (vectoring) in the terminal area and extra delays as compared to the non-ATFM-control case due to flow control (Figure 11) for all flights. ATFM delay include the airborne delays introduced using LR-ATFM to long-haul flights (max 2 minutes per flight, airborne) and by the use of GDPs for short-haul flights (no limit, absorbed on the ground).

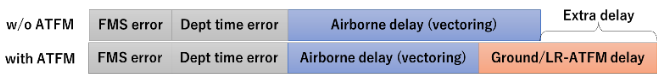

Figure 11. Extra delays introduced by LR-ATFM and GDPs.

V. RESULTS

A. *Delay Analysis*

The original schedules for each traffic mix are shown in Figure 12. Short-haul arrivals are shown in blue, long-haul (LR-ATFM-target) arrivals are shown in pink.

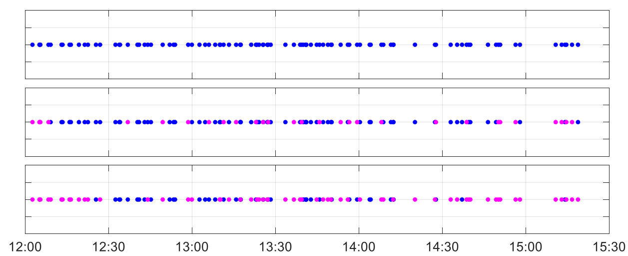

Figure 12. Pre-departure schedule in the simulation time (x-axis) for short-haul (blue dots) 100% (upper panel), short-haul 70%- long-haul (pink dots) 30% (mid panel) and short-haul 40%- long-haul 60% (lower panel) traffic.

Figure 13 presents results for these traffic mixes, consisting of short-haul only (d100), short-haul 70% (d70) and short-haul 40% (d40) traffic. The remaining traffic is considered long-haul and subject to LR-ATFM. FMS2 and FMS5 stand for the FMS error standard deviation, 2% and 5% of the flight time respectively. In each Monte Carlo run, the total delays of all 100 flights are calculated. These are then averaged over all 300 Monte Carlo simulation runs and shown on the vertical axis of the figure. The horizontal axis shows the departure time prediction standard deviation (sigma) error of 5, 10, or 20 minutes.

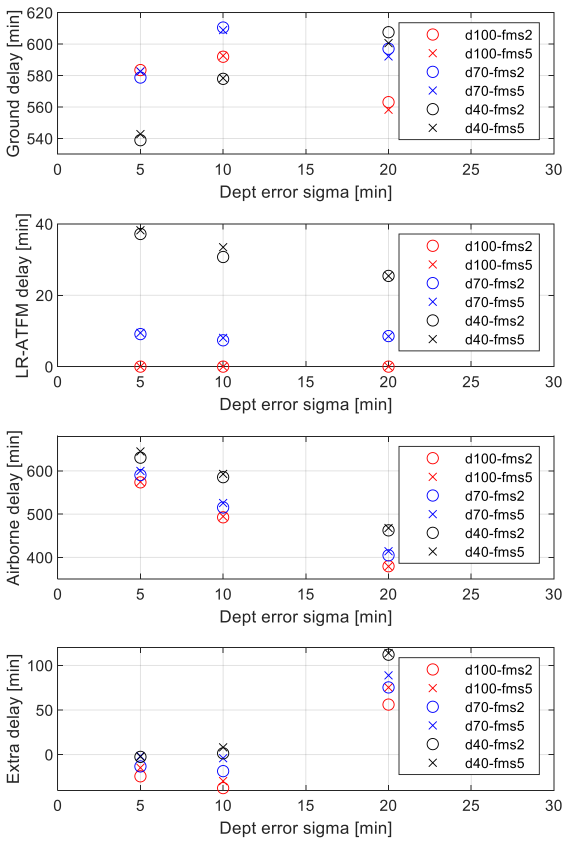

Figure 13. Total simulated delays (all flights).

From the top panel of Figure 13, no significant dependence of the ground delay on departure time errors for the existing traffic is observed. While the simulation allows for ground delay recalculations once every uncertainty is removed from the system (for example, after each departure and arrival), the relatively short sequence (about 3 hours) and constraints on the freezing horizon on ground delay updates (40 minutes prior to departure) limits the departure time error effect. The same can be said for FMS errors.

From the second panel of Figure 13, it is seen that the LR-ATFM delay increases when more long-haul aircraft are present in the queue, but this impact might be limited due to the small amount of delay which can be absorbed by these aircraft. Larger departure time errors decrease the LR-ATFM delays, but this is considered to be due to the decreased sparsity of the arrival traffic, a phenomenon discussed in more details below. Airborne delays (third panel) decrease substantially for larger departure time errors. Because of the normal distribution used, such errors allow for early departures (not completely realistic), which in turn spreads the arrival times over a larger time interval.

From the original schedule at the start of the simulation, the pre-departure ETAs of all 100 aircraft are between 12:00 and 15:20. In the real world, arrivals are constrained by traffic preceding and following this window, as the delay propagates, but this is not explicitly modeled in the current set of simulations. To account for such arrival delay accumulation, the number of aircraft arriving in this window, i.e., the number of flights with ATAs within this window, is investigated for all simulated traffic patterns. This can be considered a measure of total throughput. The results are shown in Figure 14. For departure error sigma 5 minutes, between 93.8 and 94.9 flights arrive in the initial ETA window, depending on the number of domestic aircraft and FMS error. The values are not integer as they are averaged over all 300 Monte Carlo simulations. These numbers drop to 89.0-89.7 for departure error sigma 20 minutes cases, which indicates reduced traffic density and thus reduced airborne delays. This result also shows the impact of departure error on throughput. The bigger the departure error, the smaller the number of flights is processed in the original arrival window. The share of short-haul and FMS errors has a smaller effect as can be seen in Figure 14.

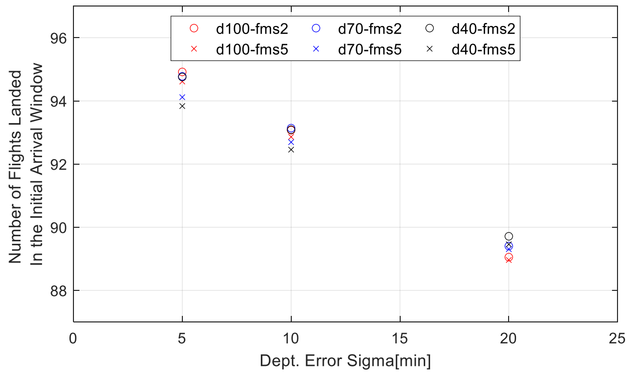

Figure 14. Traffic arrival sparsity for various simulation cases.

Extra delay (bottom panel of Figure 13) increases for large departure errors as well. Flights subject to ground delays are not allowed to depart early, i.e., compared to the non-ATFM control case which is used as a baseline of the extra delay, more flights are delayed.

No direct dependence of the delays on the FMS errors is observed. The main reason for these results is the timing of the final arrival sequencing, which is performed after the FMS errors are fixed in the developed simulation. In reality, flight time uncertainties are present after the arrival sequence is frozen, which causes increases in airborne delay. Comparison with such sequencing timing is a subject of future work.

B. Position Shift Analysis

To study the schedule predictability of different scenarios, the number of positions shifts was collected. Position shift is defined as the difference in the pre-departure estimated arrival sequence and the final one (see Figure 15). Because over the entire traffic of 100 flights this is a zero sum, when calculating the total position shifts for each arrival sequence at each Monte

Carlo run, both negative and positive position shifts are defined as positive ones when calculating the overall number of shifts for each traffic scenario. Nonetheless, positions shifts are also very workload-intensive for ATC. Therefore, they show a measure of goodness of each scenario.

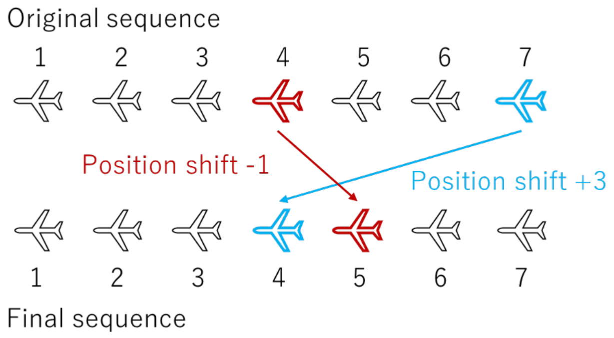

Figure 15. Position shift definition.

Figure 16 and Figure 17 show the position shifts for two traffic patterns: 100% and 40% short-haul, respectively. First, comparing both figures, it can be concluded that introducing flights subject to LR-ATFM (Figure 17), which cannot be subject to ground delay, increases significantly both the total number and frequency of position shifts. This is due to the fact that lang-haul flights subject to LR-ATFM can absorb only a limited amount of delay through speed reduction and overtake domestic flights in the final sequence, causing many shifts.

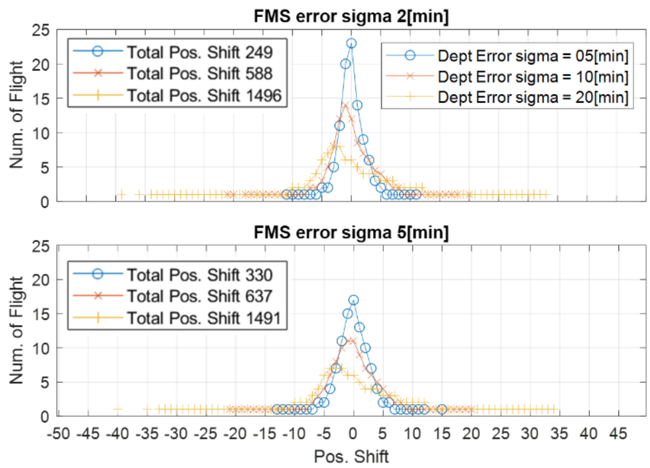

Figure 16. Short-haul traffic 100%.

Next, an increase in the departure time prediction error leads to more position shifts. The frequency of large position shifts also increases. As shown in the upper panel of Figure 16, for example, the maximum number of position shifts of a single flight for departure error sigma 5 minutes is only 11, compared to 39 for the departure error sigma 20 case. Since there is no aircraft mix (100% are short-haul), Figure 16 also illustrates the departure error is the main reason for position shifts in the arrival sequence. Comparing the lower and upper panel of the figures implies that a larger FMS error increases both the total number of position shifts and the maximum values, but this increase is more visible for smaller departure errors. In fact, for both traffic mixes, the total position shifts in case of departure errors sigma 20 minutes are more for FMS error sigma 5, but the difference in the FMS error sigma 2 case is negligible and is most likely due to the nature of Monte Carlo simulations.

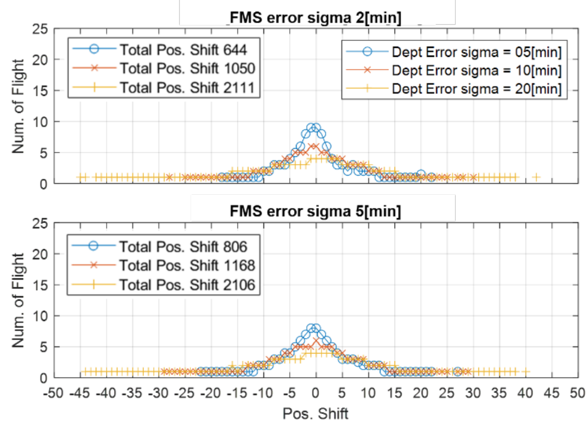

Figure 17. Short-haul traffic 40%.

C. LR-ATFM contributions to delay absorption equity

Numerical simulations for the same traffic patterns but without the LR-ATFM control were conducted to investigate the LR-ATFM contributions to delay absorption equity. The delays analogous to those presented in Figure 13 are shown in Figure 18. Compared to the LR-ATFM case, the ground delays (top panel) increase regardless of the departure and FMS errors. In other words, the LR-ATFM assigns some of the delays to flights which are not subject to the GDP, thus contributing to more fair delay distributions. LR-ATFM also allows to shift some of the delays to the long-haul flights that otherwise would not be affected by any delays, which is similar to how current operations work in all the countries evaluated in this paper. As a result, the LR-ATFM delays in Figure 18 are all zero, these delays are shifted to the short-haul flights and absorbed as ground delays. From an equity point of view, the absence of LR-ATFM reduces the distribution of delays over penalizing the short-haul flights. No significant changes in the airborne delay (third panel) are seen, results supported by past work as well [14].

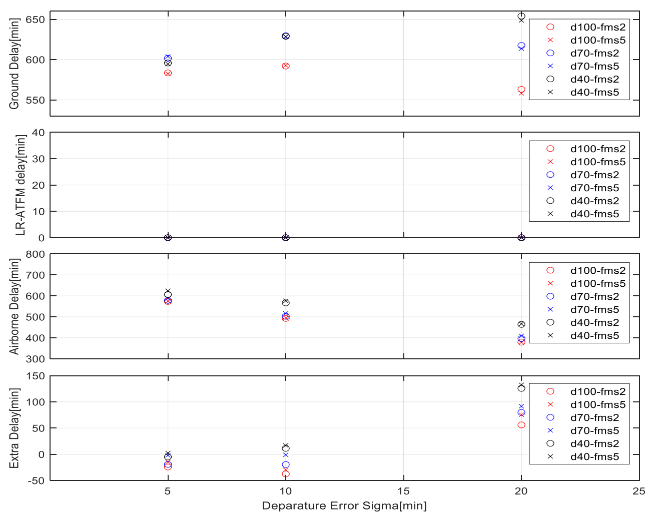

Figure 18. Total simulated delays without LR-ATFM (all flights).

LR-ATFM contributes to more predictability as well, reducing the number of position shifts, as seen from Figure 19 where the number of additional positions shifts compared to the same scenario with LR-ATFM (Figure 17) are presented in the parentheses. Positions shifts increase across all scenarios because LR-ATFM controls are not applied here to pre-condition the sequence. Therefore, there is more need to overtake flights. This, as mentioned before, significantly increases ATC workload.

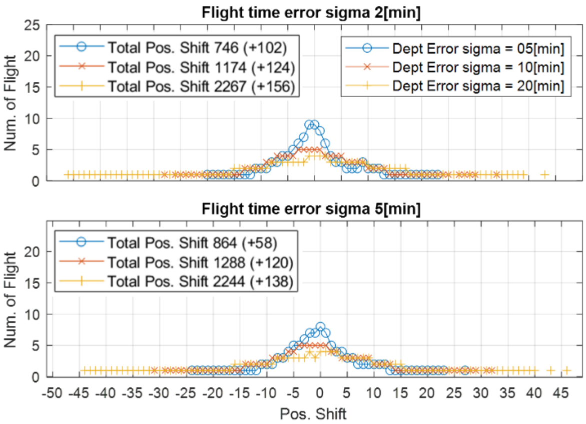

Figure 19. Domestic traffic 40% position shifts without LR-ATFM case.

VI. Discussion and Potential Mitigations

LR-ATFM is the meeting point between flow management, which is concerned with ensuring the *rate* of aircraft arriving at an airport is consistent with its capacity, and tactical arrival management, in which individual aircraft are assigned actual arrival *times*. The point at which this transition occurs from arrival rate to arrival times is often not a clear boundary and should be better defined. In fact, most ANSPs operate flow management and tactical arrival management by different systems with limited integration. As LR-ATFM essentially connects these environments, it is inherently complex and dependent on the operational scenario.

But what is a successful LR-AFTM implementation? The ideal situation is one where long-haul flights get a fixed arrival time as early as possible to optimize flight efficiency, and where this does not lead to (increased) inequity in delay allocation and access (to an airport or airspace) for short-haul flights which have not taken off yet. The preliminary results of the simulation model support that LR-ATFM will not add any additional inequity in delay distribution.

One of the complexities investigated in this paper is the contribution of differing trajectory uncertainty between short- and long-haul flights. This ultimately leads to uncertainty in the prediction of demand (both short- and long-haul combined). Paradoxically, short-haul demand is more difficult to predict at large prediction horizons due to large uncertainty in departure time. Therefore, the higher the short-haul demand, the more variation one can expect in the arrival sequence, exactly as demonstrated by the simulations. The practical consequence is, that if the times in the arrival sequence are difficult to set until very late (when the majority of short- and long-haul demand is airborne), it provides little benefit to provide long-haul flights with an arrival time several hours out if this time is very likely to change.

LR-ATFM is therefore only effective (and provides efficiencies) when there is sufficient predictability of total demand (short- and long-haul) at large prediction horizons. This is either achieved through reducing trajectory errors or a sufficient portion of flights being long-haul (relative to the prediction horizon). In other words, an LR-ATFM concept that aims to provide long-haul flights with an arrival time 4 hours from arrival, but where these long-haul flights only make up a few percent of total arrivals, is unlikely to be successful. It either will result in continuously changing times for the long-haul flights, or if the assigned time is honored, more tactical management of short-haul flights to fit in the sequence (this is also likely to result in lost capacity). The net impact could therefore be that while in theory LR-AFTM allows for some sharing of delay between short-haul and long-haul flights, this sharing may actually come at a cost (i.e., increased total delay). The results of the simulations shown in Figure 13 (with LR-ATFM) and Figure 18 (no LR-ATFM) do not show any increase in the total delays imposed to the traffic scenarios. Therefore, even if preliminary and with the limitations described, they do not show an increased cost to the system.

The authors believe that pushback uncertainty for short-haul flights is therefore the key challenge to overcome for LR-ATFM to be successful. Concepts such as Airport Collaborative Decision Making (A-CDM) (or Surface CDM in the United States) could assist in improving pushback uncertainty at the departure airport for short-haul flights, which would improve sequence stability at the arrival airport. However, inherently, flights that have not yet departed will in general always be subject to more arrival time uncertainty than a long-range flight that is airborne and established in cruise. For any airport where LR-ATFM is being considered, it is therefore important that the ability to predict arrival demand (as well as capacity) at large prediction horizons is carefully assessed. LR-ATFM is a tool in the overall ATFM toolbox, and like with any tool, it may not be suitable or effective for every operational scenario (airport/airspace).

Further, the authors believe that a hybrid solution between managing flow rates (at larger time horizons) and controlling to fixed arrival times (closer to arrival) should be found. For example, in the planned LR-AFTM implementation for Australia, a concept was being considered where LR-AFTM flights were assigned a “no-earlier-than” time rather than a fixed arrival time. This allows a buffer to be applied to prevent over-allocation of delay as well as allowing some flexibility in the tactical arrival management to adjust the sequence when short-haul demand is introduced.

VII. Conclusions & Next Steps

From the preliminary simulation results presented in this paper, LR-ATFM seems to distribute delays more equitably because it introduces delay absorption to long-haul flights that are currently exempt and therefore reducing overall ground delays. Moreover, it reduces the number of positions shifts, improving the predictability and stability of the system. Although preliminary and with the limitations described above, the concept is promising. As discussed, the implementation is key to materialize the potential benefits.

In terms of potential next steps, one of the key extensions to the modeling approach is to examine the impact of the amount of delay that can be absorbed in the long-haul flights. The maximum value of two minutes used in the simulation is not realistic for most FIRs around the world that are much larger than Fukuoka. Further exploration of this parameter will be studied in future work through a parametric study of a range of feasible values. A prior limitation to extensive absorption of airborne delay in oceanic regions has been the limited surveillance and communication environments to effectively control long-haul flights. But in a future environment where international CDM, Space-Based ADS-B and satellite communication protocols are a reality, absorption of larger delays in cruise will become viable.

Such a concept needs to be supported by automation that is more sophisticated and more inter-connected between ANSPs. On such larger distance scales, factors such as winds and weather need to be integrated in the trajectory calculations. To date, no system exists that can do that across ANSPs. Winds have large impacts on the ground speed flown and weather on the routes length that will be actually flown due to deviations around weather. The longer the time and distance, the larger these uncertainties become. All these aspects should be the subject of future research that, given the nature of the LR-ATFM problem, would greatly benefit from international collaboration such as the one initiated for the development of this paper.

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