

Impact of General Aviation Operations on Airport Performance Through Fast-Time Simulations at Charlotte Douglas International Airport

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NASA, in partnership with the Federal Aviation Administration and commercial airlines, deployed the Integrated Arrival, Departure, and Surface (IADS) traffic management system at Charlotte Douglas International Airport (CLT) in 2017 for field evaluation. The system features new capabilities of data exchange and integration, collaborative surface metering and scheduling, which has demonstrated operational benefits of reducing delay time and fuel consumption. General Aviation flights, however, are not currently included in the surface metering programs because of their different operational procedures and lack of reliable predictability in departure time. Thus, their impact on the system performance is not well understood. This paper presents a study of the impact of General Aviation traffic at CLT using fast-time simulations.

I. Introduction

In the United States there are more than 200,000 General Aviation (GA) aircraft in active use (including Part 91 and Part 135 operations) that are estimated to log more than 20 million flight hours annually [1]. They are used for a variety of purposes including personal, business, and instruction. The number and proportion of GA operations varies by airport. At Charlotte Douglas International Airport (CLT), for instance, an average of 30 departure and 30 arrival flights per day account for about 4% of all airport operations. The numbers are based on a three-month operation data set from July to December in 2019. As a comparison, the daily numbers at Dallas Love Field Airport (DAL) are over 60 each, and accounts for 20% of airport operations. Whereas the overall proportion of GA operations at CLT is small, the potential exists for some of these GA flights to impact surface operations. For example, they may compete with other air traffic, including commercial and cargo flights, for airport resources like runways. GA flights have less predictable departure schedules than commercial operations and, at CLT, do not have communication with the ramp tower before taxi, presenting a unique challenge for trajectory-based surface operations.

A. Integrated Arrival, Departure, and Surface (IADS) Traffic Management System

In September of 2017, NASA, in close collaboration with the Federal Aviation Administration (FAA) and industry, deployed the Integrated Arrival, Departure, and Surface (IADS) traffic management system at CLT as part of Airspace Technology Demonstration 2 (ATD-2) project for a three-year field evaluation. The IADS system has demonstrated operational benefits through its capabilities of data exchange and integration, collaborative surface metering, departure scheduling for overhead stream insertion, and real-time metrics reporting [2]. The objective of the IADS system is to balance demand and capacity to achieve more efficient traffic movement on the surface and overhead stream insertion.

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Surface metering is used when the predicted demand exceeds the airport capacity during departure banks. Holding flights at the gate transfers excess taxi time from the departure runway queue back to the gate, prior to engine start. As of March 31, 2020, it is estimated a total of 3,832 hours of engine run time reduction that resulted in 5,075,981 pounds of fuel savings and 15,634,022 pounds of CO₂ emission reduction [3].

Surface scheduling and metering is enabled by the availability and quality of flight readiness time. Major airlines participating in the ATD-2 field evaluation provide an Earliest Off-Block Time (EOBT) for each departure flight. The EOBT represents the best estimate of a flight's earliest pushback time. A good quality EOBT helps the scheduler achieve accurate demand prediction at each runway and hence, achieve reliable scheduling to keep the surface less congested while maintaining overall airport throughput. Along with other data inputs, the surface scheduler uses the EOBTs to predict takeoff times of departure flights and calculate recommended gate holds. Gate hold advisories are communicated to Ramp Control through the ATD-2 Ramp Traffic Console (RTC) interface.

Airlines are motivated to improve the accuracy of EOBT data for the benefit of reduced excess taxi time and fuel savings achieved through surface metering. A preliminary study of EOBT quality impact on surface metering [4][5] shows that the EOBT accuracy has a direct impact on the length of the departure gate hold time assigned by ATD-2's surface scheduler.

To date, GA operations have not been included in surface metering at CLT. One reason is that, unlike commercial flights at CLT's main ramp, pilots departing from the GA ramp area do not contact the Ramp Tower prior to taxi. At the main ramp, the Ramp Controller communicates gate hold advisories for surface metering. In contrast, GA flights' first communication is with the Ground Controller at the FAA's Airport Traffic Control Tower (ATCT). Other challenges in GA operations include less-predictable departure times and the ability to communicate up-to-date readiness and intent information to the ATD-2 scheduler. Excluding GA flights before they enter the Airport Movement Area (AMA) from surface metering and scheduling may have a potential impact on the efficiency of airport operations that has not been investigated.

B. Mobile App Technology Enables Two-Way Communication with GA Operations

A mechanism is needed to enable two-way communication between GA operations and the ATD-2 scheduler prior to their entry into the AMA. In response to that need, The MITRE Corporation has developed a prototype Mobile Application (App) to enable two-way information sharing between GA pilots and NASA's IADS traffic management system [6] [7].

MITRE has conducted a field test of their prototype Mobile App technology at CLT with a small group of Corporate Flight Operators. Using a mobile device, pilots submit a ready time to the ATD-2 scheduler. This ready time, referred to as a "Ready-to-Taxi Time", or RTT, represents the pilot's best prediction of when they will arrive at the edge of the GA ramp area and be ready to contact Ground Control for their taxi clearance to enter the AMA. The RTT submitted by GA pilots is analogous to the EOBT submitted by airlines for departure flights at the main ramp. It provides ATC and the ATD-2 scheduler with more accurate and up-to-date departure readiness information. In return, the GA pilot receives flight-specific schedule information, generated by the ATD-2 scheduler, such as assigned runway and expected takeoff time, and information about traffic management restrictions in place. Fig. 1 shows an example timeline of how a GA pilot may incorporate using the Mobile App to submit readiness information into their pre-departure procedures.

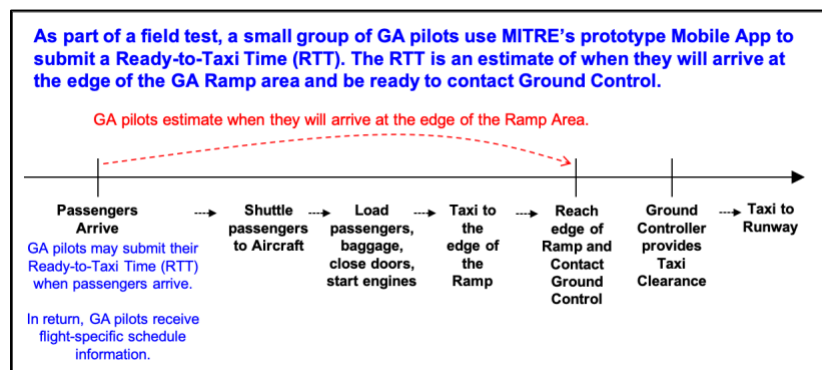


Fig. 1 Example timeline showing how a Corporate GA pilot may incorporate the Mobile App into their pre-departure procedures.

MITRE's field demonstration has shown that Mobile App technology can enable two-way communication flow between GA operators and surface schedulers. However, the communication procedures and requirements related to surface metering for GA flights have not yet been explored. Although not investigated in this field test, Mobile App technology has the potential to support the inclusion of GA flights in surface metering. For example, Mobile App technology might be used to provide metering hold advisories to GA pilots. Although this research has included primarily business aviation (BA) flights, other GA aircraft, cargo, and military flights have the same communication limitation and similar impacts on airport performance. They are included in the GA flights in this study.

C. Research Objective

Because of the GA flights' unique operational challenges, their impact on surface operations at CLT, particularly during surface metering, has not been fully understood. Research questions include: 1) whether GA flights have an unintended advantage over commercial airline flights which adhere to metering advisories at the gates? and 2) within a traffic bank, what GA traffic concentration

affects the airline flights the most? Since the grand scheme of surface metering depends on quality of predictability for performance, questions exist around whether including GA flights with RTT data in surface metering might improve overall runway throughput, taxi times, delays, and fuel consumption.

Note that the concept of surface metering “gate holds”, as applied to commercial flights at a parking gate, is that the aircraft is held at the gate, prior to push back. How it would be applied in GA operations has yet to be explored. It may mean that a GA flight holds somewhere in the GA ramp area, and possibly, delays engine start. However, for the purpose of this simulation, the term “gate hold” is applied generally to GA operations to mean they were held prior to entering the AMA. Specific procedures for applying “gate holds” in GA operations are beyond the scope of this simulation.

This paper investigates the impact of GA flights on the efficiency of airport operations using IADS’s surface metering programs at CLT. The study uses fast-time simulations and explores two sets of variables. The first is the GA traffic demand that is quantified by the number of GA flights in the overall flight traffic at the airport and their flight times during traffic peak hours. The other variable is the GA flight readiness information, RTT, including provision and accuracy.

The paper is organized as follows: Section II describes the simulation environment including system setup, traffic scenarios, metrics and measurements, and the RTT model development. Section III presents the simulation results using the given scenarios and RTT model. The paper concludes with a summary in Section IV.

II. Simulation environment description

A. Airport

The simulations used the CLT airport in a south simultaneous traffic flow configuration. Fig. 2 shows the airport layout at CLT. While Runway 18R is for arrival only, Runways 18C and 18L are dual-use runways for both departures and arrivals in this runway configuration. A Fixed Base Operator (FBO), where some GA/BA passengers meet their pilot, is located at the General Aviation Ramp on the east side of the airport, shown in the green box in Fig. 2.



Fig. 2 CLT airport diagram

B. Simulation setup

The simulations in this paper use the same configuration that was built and validated in the previous study about the impact of EOBT uncertainty [4] with the addition of a newly developed RTT model for GA flights, as shown in Fig. 3. NASA’s Surface Operations Simulator and Scheduler (SOSS) [8] was used for these simulations. SOSS connects to the ATD-2 Tactical Surface Scheduler through the Surface Modeler. The traffic scenarios are the inputs to the simulator and define the GA traffic level and demand density, as well as scheduled airline flights. The EOBT Model provides the EOBT updates for the airline aircraft in the main terminals. The RTT Model provides the estimated readiness times and accuracy for GA flights. The Surface Modeler used for fast-time simulations is adapted from ATD-2’s Surface Model used in real-time field demonstration, which is used for data exchanges and integration. One of the core concepts is to group aircraft by their priorities and predictability of flight readiness in scheduling [9]. When the predicted traffic demand exceeds the runway capacity and the predicted excess taxi time is above a preset threshold, surface metering is triggered. The Tactical Surface Scheduler schedules flights from high-priority group to low-priority group. In the simulations, both airline departures at gates that provide EOBT updates and GA aircraft providing an RTT estimate at stand are placed in the same high-priority group. The GA aircraft with no RTT estimate are placed in the low-priority group for scheduling priority and are exempt from surface metering, and, therefore, start taxiing from the parking stand whenever they are ready, emulating the current GA ramp operation without Mobile App communication.

C. Simulation configurations

In this study, four simulation configuration groups are considered. They are designed to support two sets of simulation variables as described in the research objectives. The baseline traffic scenario for all groups is derived from actual operation data from Bank 2 traffic at CLT on February 14, 2018. There is a total of nine traffic banks daily at CLT. Bank 2 is one of the busiest banks in the morning traffic. The typical traffic pattern in Bank 2 is that the departure demand peaks before the arrival demand starts to build up.

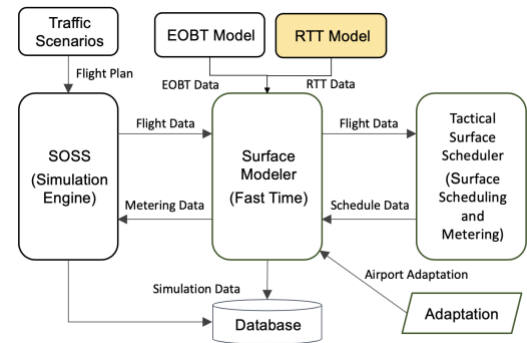


Fig. 3 Fast-time simulation setup

In this baseline scenario, there are 85 airline departures and 83 airline arrivals, respectively. Of the 85 departures, 43 take off from Runway 18C and 42 from 18L, respectively. Of the 83 arrivals, 5, 30, and 48 land on Runways 18C, 18L and 18R, respectively.

1. Simulation Group 1: GA flight request distribution

The purpose of the first simulation group was to investigate the impact of GA flights' requested departure time distribution. Four different departure time distribution patterns were examined, with each scenario having ten GA flights: 1) uniformly distributed over the bank, 2) concentrated in the beginning of the bank, 3) concentrated in the middle of the bank, and 4) concentrated in the end of the bank. GS flights in this simulation group did not provide RTTs and so were exempt for surface metering. It was expected that GA traffic demand at the peak time, i.e., case 3, would have the largest impact on the airport performance in a surface metering situation.

2. Simulation Group 2: Number of GA flights

The second simulation group increases the number of GA flights uniformly distributed in the bank to examine any adverse impact to airline flights, such as increase of taxi times or gate hold times (when metering is on). As with Group 1, GA flights did not provide RTTs.

3. Simulation Group 3: RTT percentage

In the third simulation group, a certain percentage of GA flights were assumed to provide RTTs with similar accuracy as observed in MITRE data described in section E. The percentage of GA flights providing RTTs was varied for ten uniformly distributed GA flights. Those GA flights submitting RTTs are assigned the same scheduling priority as the airline flights that have EOBTs at main terminals and are expected to comply with any assigned metering hold at the parking stands. The performance (e.g., taxi time) of the GA flights will be examined together with airline flights.

4. Simulation Group 4: RTT accuracy

In the last simulation group, all ten uniformly distributed GA flights were assumed to provide RTTs with varying accuracy. The RTT model generates the various accuracy levels used in the simulations. The expectation was that as the RTT accuracy improves, taxi time reduction will occur for both airline and GA flights during surface metering.

D. Performance metrics

To analyze the impact on the efficiency of airport operations, a set of performance metrics were considered. They included gate hold time of metered GA and airline flights, time series of gate hold time, taxi out time of GA and airline flights, time series of taxi out time, and runway throughput.

E. RTT model

In this section, we describe how the RTT accuracy model is developed using a data driven approach. For this work, we have used the data collected by MITRE for GA flights that departed from CLT between October 20th, 2017 and September 17th, 2019. The proposed RTT model is a combination of two probabilistic quantities: 1) the timing of the updates up to the Actual RTT (ARTT), and 2) the accuracy of the updated RTTs as a function of the timing. The proposed statistical model that generates RTT accuracy is used in the fast-time simulation for evaluating the impact of RTT accuracy on airport surface operations.

1. RTT Data Analysis

GA/BA flight data collected by MITRE was used for the RTT data analysis. Out of 1,656 GA flights in this data set, 301 flights submitted at least one RTT and had AMA entry times from Airport Surface Detection Equipment, Model X (ASDE-X). The AMA-entry time represents the GA flight's *Actual* RTT, that is, the time they arrived at the edge of the GA ramp area. In this analysis, two main variables were analyzed: 1) RTT accuracy, and 2) RTT update interval. The RTT accuracy is defined as the difference between the ARTT and pilot's last RTT estimate. The RTT update interval represents the time difference between two RTT updates of the same flight, or between the last RTT update time and ARTT.

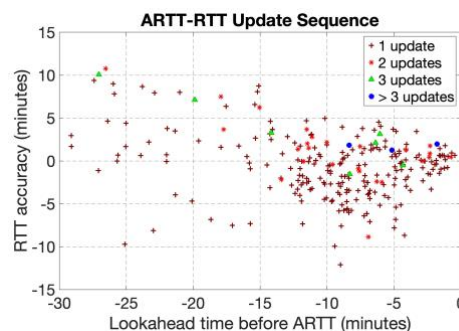


Fig. 4 RTT accuracy changes over time

Fig. 4 shows the RTT accuracy changes in the lookahead time window [-30 min, 0 min] as time approaches the ARTT. The plot represents the RTT estimate values submitted by the pilots within the lookahead time window. This plot shows that in general, the RTT errors tend to decrease to negative values as the time progresses, which implies that the RTT prediction becomes more

conservative, as it approaches ARTT. The majority of the GA flights (85%) submitted their RTTs once (dark red markers), approximately 10% GA flights submitted two RTT updates (red color), and about 5% provided more than two RTT updates.

2. RTT Model Development

For the RTT model development, a two-step approach was used, which was introduced in the EOBT modeling in [4]. First, the RTT update times of each flight were modeled within a [-30 min, 0 min] lookahead time window as the time approached ARTT. Then, the RTT accuracy was modelled at each update time calculated in the first step. The model produced RTT accuracy distribution similar to the actual RTT error distribution using the probability distributions provided by commercial software libraries like Apache Commons Math package [10] and MATLAB [11].

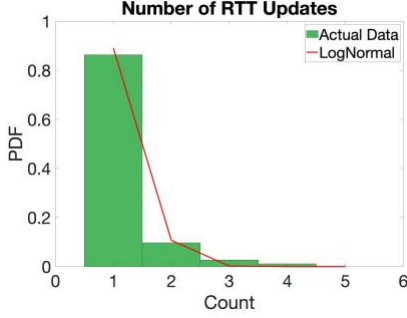


Fig. 5 Number of RTT updates

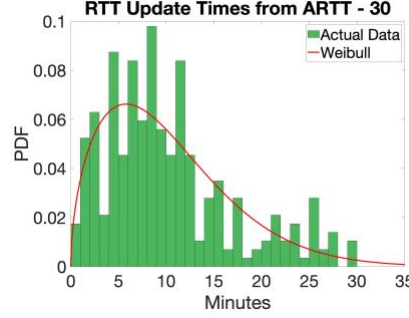


Fig. 6 RTT update time

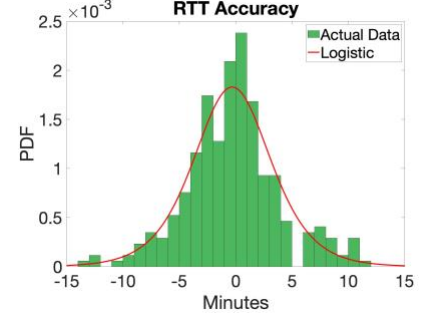


Fig. 7 RTT accuracy distribution

In the first step, the following two variables were considered: 1) the number of RTT updates per flight (referred to as PD1), and 2) the time distance from the reference time (i.e., ARTT) to the time when the RTT value is updated (referred to as PD2) within the [-30 min, 0 min] lookahead time window. To model the number of times the RTTs are updated for a single flight, the log-normal probability distribution, which has two parameters (μ and σ), was selected since it best matched with the actual data among various distributions tested. The log-normal distribution is a continuous probability distribution; hence, the values were rounded to the closest integer for computing the number of RTT updates.

For the RTT update time distance modeling, the Weibull distribution was selected. In the RTT model, the time distance between two updates can be modelled as a 'size' in time, given the number of RTT updates obtained from the log-normal distribution. The Weibull distribution, which has only two parameters (A and B), showed the best fit to the RTT data samples among various continuous distributions available in the Apache Commons Math package and MATLAB. From the actual data analysis, probability distributions of these two values were fit, as shown in Figs. 5 and 6. The histogram bar graphs (green) and regression curves (red) represent the actual data and the modelled distributions, respectively. The RTT update times, X_k , for each flight can be modelled using the values randomly sampled from these two distributions and expressed in Eq. (1).

$$X_k = -\text{random}(PD2), \quad k = 1, 2, \dots, \text{random}(PD1) \quad (1)$$

In the second step, a linear regression model was developed, as expressed in Eq. (2), to fit the average accuracy trend along the lookahead time. In (2), x and y represent the lookahead time with respect to the ARTT time and the mean RTT error (ARTT-RTT) at x , respectively, with the regression coefficients, c_0 and c_1 .

$$y = c_0 + c_1 * x \quad (2)$$

Next, a sequence of probability distributions was fitted to the actual RTT error data (referred to as PD3). The logistic probability distribution model was the closest to the actual RTT error distribution provided by the actual data. Fig. 7 shows the histogram of actual RTT accuracy values, and the red line in the chart shows the selected Logistic probability distribution model. The Kullback-Leiblar divergence (also called relative entropy) [12] was used to measure how much one probability distribution was different from the reference probability distribution. The Kullback-Leibler divergence of the selected model with respect to the actual distribution was 0.4064, the lowest, or the best, fit of all candidate models.

The RTT accuracy, Y , can be modelled using Eq. (3):

$$Y = c_0 + c_1 * X_k + \text{random}(PD3) \quad (3)$$

where X_k is the RTT update time from the previous model in Eq. (1).

From the data analysis using the actual RTT data at CLT, the following parameters were calculated in TABLE I.

Table I Parameters used in the RTT Model

RTT Model	Probability Distribution or Regression Model	Parameters
RTT update time	PD1: Log-normal	$\mu = 0.114848, \sigma = 0.303685$
	PD2: Weibull	$A = 11.3599, B = 1.54735$
RTT accuracy	PD3: Logistic	$\mu = -0.306186, \sigma = 2.27737$
	Linear Regression	$c_0 = -2.538, c_1 = -0.1908$

3. RTT Model Validation

With the given parameters in Table I, the RTT values were generated from the proposed RTT model for model validation. The two scatter plots in Figs. 8 and 9 show the actual RTT error and the generated RTT errors using the model proposed in Eq. (3), respectively, along the lookahead time window [-30 min, 0 min] as the time approaches ARTT. The RTT values from the RTT accuracy model cannot be exactly the same as the actual RTTs for an individual GA flight, but it is shown that the distributions are visually quite similar and the Kullback-Leibler divergence is small (0.0389).

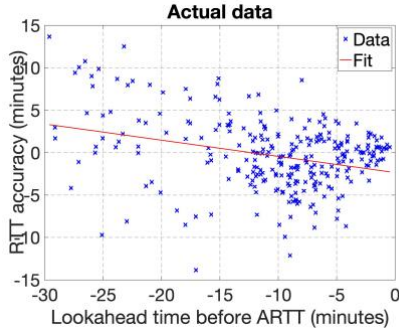


Fig. 8 Actual RTT accuracy

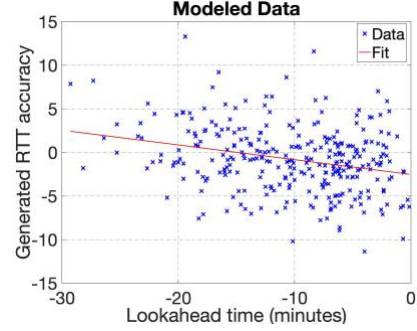


Fig. 9 Modeled RTT accuracy

III. Simulation Results

This section presents the simulation results and analyses of the four simulation groups. During Bank 2 at CLT, almost all GA flights use the east runway (18L/36R) which is closest to the GA ramp areas. In the simulations, all GA flights were assigned to Runway 18L. The results shown in the analysis are for Runway 18L only.

A. Simulation Group 1: GA flight request distribution

In this simulation group, ten GA flights were added to the baseline scenario. This number reflects the Bank 2 non-passenger flight statistical analysis. Their flight ready times from the GA ramp were distributed in the bank in four ways:

- Case 1: uniformly distributed over the whole bank,
- Case 2: in the beginning 30 minutes of the bank,
- Case 3: in the middle 30 minutes of the bank, and
- Case 4: in the last 30 minutes of the bank

Twenty Monte Carlo simulation runs were conducted for each case. Figs 10 and 11 show the average total gate hold times and the average total taxi-out times, respectively, over the twenty simulation runs. Error bars indicate 95% confidence level. Since the GA flights provided no RTTs in this group, they were not subject to metering (and zero gate hold time). In Case 2, where the GA traffic concentration was in the beginning of the bank, airline flights had longer gate hold and taxi-out times, rather than Case 3 as originally expected. It reveals that the GA traffic was competing with the airline traffic for the runway at the beginning of the bank. Additionally, because the GA aircraft immediately started taxiing into the AMA, after being designated as “ready”, and joined a departure queue earlier, they became higher priority in the scheduler than the airline aircraft at the gate. This resulted in longer gate holds and taxi-out times for the airline flights. Case 3, where the GA traffic concentration was in the middle of the bank, had the second largest impact to airline flights. This is because although the airline departure traffic began to decrease, there was sufficient demand on this dual-use runway due to the inbound arrivals. Case 4, where the GA traffic was in the end of the bank, had the least impact on the airline flights. Also, in Case 4, the total GA taxi-out time increased compared to Cases 2 and 3. The probable reason for the increase in taxi out time is that the arrival traffic on the dual-use runway at the end of the bank caused the GA aircraft to wait longer for the runway use.

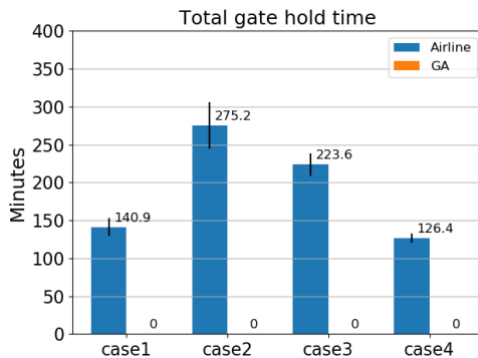


Fig. 10 Total gate hold time of group 1

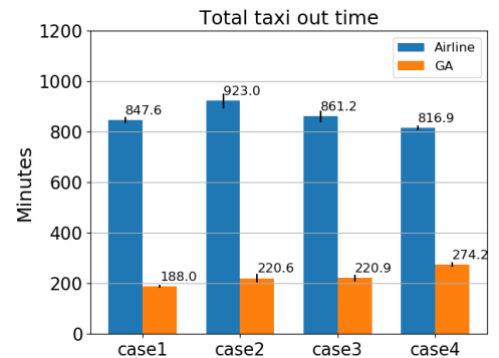


Fig. 11 Total taxi out time of group 1

Figs 12 and 13 plot the time series of the gate hold time and taxi-out time, respectively. The time series is made of a sequence of vertical bars in five-minute bins. In the gate hold time series shown in Fig 12, the left bars represent the average total gate hold times of aircraft whose readiness time lies in those bins, and the right bars represent the average total gate hold aircraft count. Airline and GA aircraft are separated and stacked. In this simulation group, GA aircraft were at the parking stand and can leave freely and not subject to any holds and so only airline aircraft have hold times and visible bar heights as shown in Fig. 12. For taxi-out time shown in Fig 13, each bar shows the average total taxi out time of the aircraft who's actual off-block time lies in that bin. Airline and GA aircraft taxi-out times are stacked in the plot.

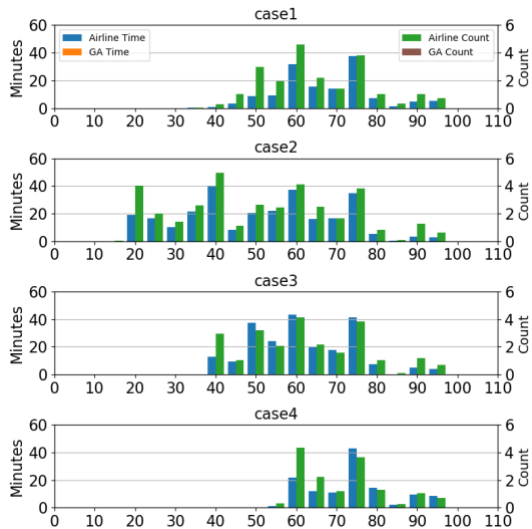


Fig. 12 Gate hold time series of group 1

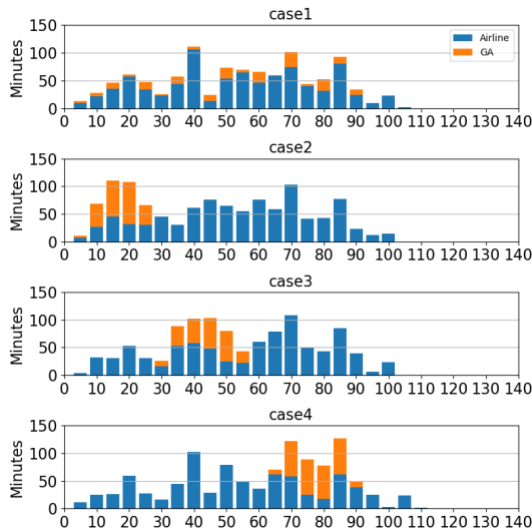


Fig. 13 Taxi out time series of group 1

In the time series for Case 2, surface metering of the airline flights started early around 20 minutes into the bank, and so the GA flights dominated the early part of the bank as shown in the taxi out time series and ‘pushed’ the airline flights to metering hold. Case 3 shows the similar metering start time to Case 1, but higher metering time bars because of the GA traffic concentration in the middle of the bank. Case 4 shows the least impact on airline aircraft metering which is consistent with the total numbers in Fig. 11.

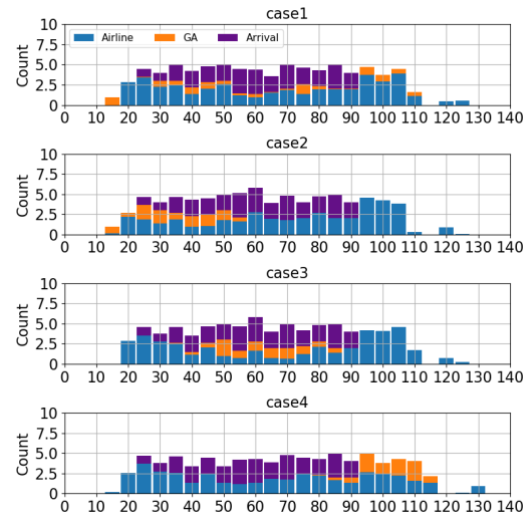


Fig. 14 Runway throughput chart of group 1

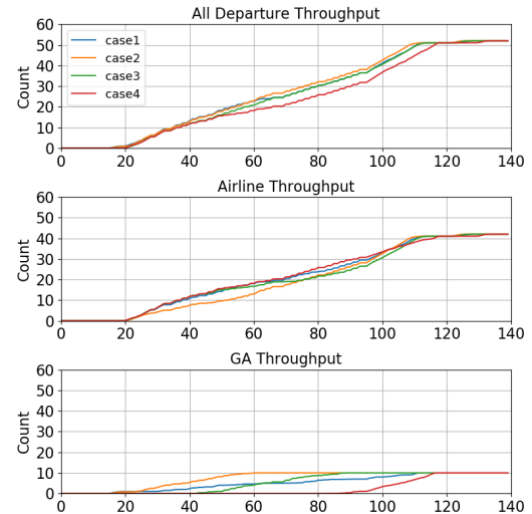


Fig. 15 Cumulative runway throughput of group 1

Figs 14 and 15 show the runway throughput metric. A departure runway operation is registered at takeoff and an arrival runway operation occurs at landing. The stacked bar charts in Fig. 14 measure the average numbers of runway operations in five-minute bins. Fig. 15 plots depict the cumulative operations for departures only to focus on airline and GA departure throughputs. In Case 2, the bar chart shows the GA aircraft took a significant portion of runway takeoff slots in the early part of the bank and pushed airline departure aircraft to later takeoffs, resulting in takeoff delay of airline aircraft. This is also observed in the cumulative throughput plots in Fig. 15 where the airline departure (in the middle plot) of Case 2 exhibited lower throughput up to about 70 minutes into the simulation time compared to the other cases. A similar situation can be seen in Case 3, in which the GA aircraft concentration in the middle of the bank caused lower airline flight throughput from 60 to 105 minutes. The highest runway throughput in five-minute bins

happened in Cases 2 and 3, at 60 minutes into the simulation time. It is about 5.5 flights combining departures and arrivals, which translate to an average of 55 seconds of separation time, indicating the runway was saturated then.

The results in this simulation group show that GA traffic concentrated in the beginning 30 minutes of the bank had the largest impact on airline flights, in metering hold time, taxi out time, and throughput. One reason is that airline departure demand starts early in the bank, which is then overlapped by GA traffic. Another reason lies in the unpredictability of GA operation, which tends to cause longer gate holds from the surface scheduling algorithm and longer taxi-out times for airline aircraft.

B. Simulation Group 2: Number of GA flights

In this group, six different numbers of GA flights were added to the baseline scenario. Their readiness time perturbation was evenly distributed over the entire traffic bank. Table II shows the numbers of GA flights in each of the six cases. Twenty simulation runs were conducted for each case. Statistically, Case 6 of this group is the same as Case 1 of Simulation Group 1.

Table II Number of GA flights

Case No	1	2	3	4	5	6
Number of GA Flights	0	2	4	6	8	10

Figs 16 and 17 show the average total gate hold times and the average total taxi-out times, respectively, over the Monte Carlo simulation runs. When GA traffic increased, the airline flights experienced longer metering hold times, as expected. At the same time, the total taxi-out time of the airline flights also showed an increasing trend with Case 2 as an outlier, which probably was due to the demand timing of the two GA flights with respect to the airline flights in the baseline scenario. The increase of GA traffic and its less predictability had a negative impact on the airline flights in both gate hold and taxi-out times, or on the metering effectiveness for taxi out time reduction. The increased taxi time of GA flights shown in Fig. 17 was due to the increased number of GA flights.

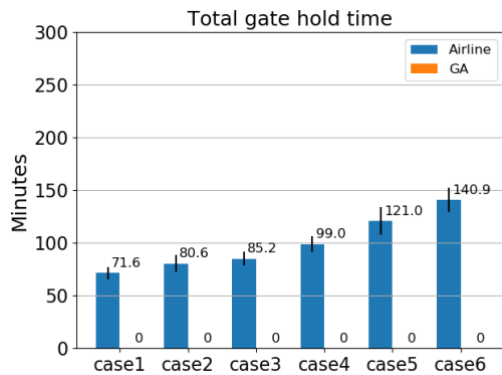


Fig. 16 Total gate hold time of group 2

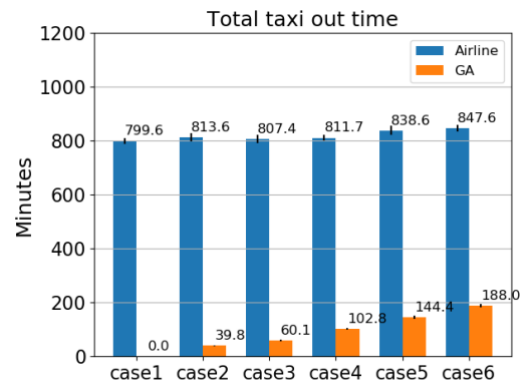


Fig. 17 Total taxi out time of group 2

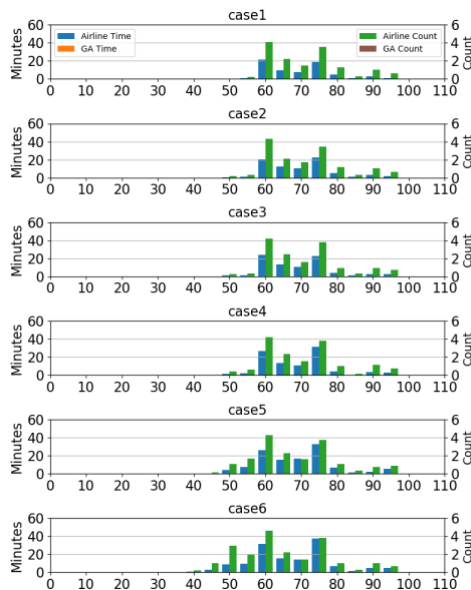


Fig. 18 Gate hold time series of group 2

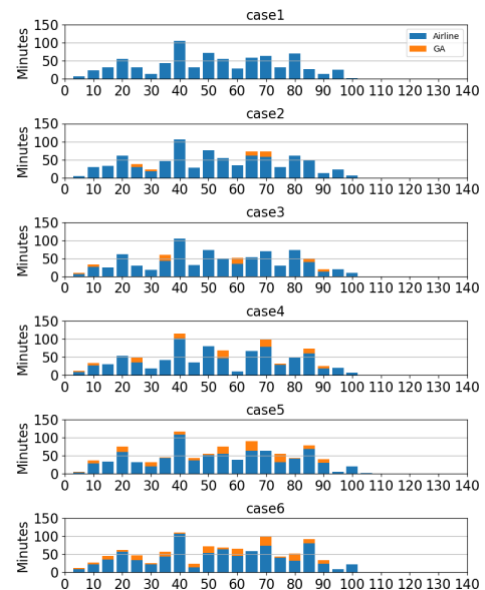


Fig. 19 Taxi out time series of group 2

The time series of gate hold and taxi out times are depicted in Figs 18 and 19. When the number of GA flights increased gradually, the metering started earlier. Because the GA traffic was evenly spread across the bank, however, the system was able to handle the impact over the bank.

The runway throughput comparisons among the six cases are shown in Figs 20 and 21. The cumulative airline flight throughputs, in the middle graph in Fig. 21, show delayed throughputs as the number of GA flights increased. This is consistent with the combination of the increased gate hold time and taxi out time seen earlier. It implies takeoff delay of the airline flights, which can be seen in the time series of bar charts around 100 minutes as more airline flights were pushed to take off late.

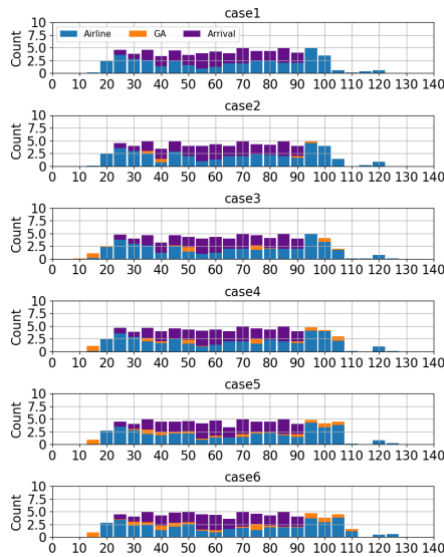


Fig. 20 Runway throughput chart of group 2

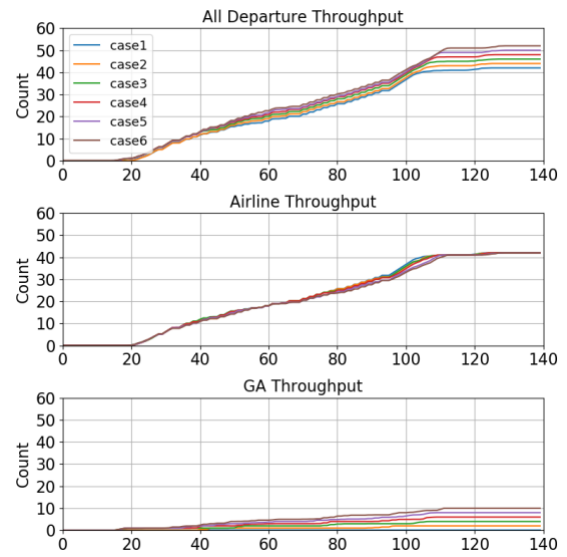


Fig. 21 Cumulative runway throughput of group 2

Overall in this simulation group, the simulation results show that the increase of GA traffic affected the airline flights with earlier metering start times, higher hold times, taxi out times and takeoff delays. In particular, because of the less predictability of GA traffic demand, the effectiveness of surface metering to mitigate taxi out times was affected negatively.

C. Simulation Group 3: Percentage of GA flights having RTTs

The RTT model was introduced in Simulation Group 3 and provided the RTT values for GA flights prior to departing the parking stands in the GA hangar. The RTT model was configured to match the accuracy of the actual data from MITRE. Ten GA flights had their ready times perturbed uniformly over the entire bank in the baseline scenario. The percentage of the GA flights that provided their RTTs were varied in six cases: 0%, 20%, 40%, 60%, 80% and 100%. The 0% case represents the current operations without Mobile Applications, whereas the 100% case assumes that all the GA flights provide controllers with the estimated AMA entry times in advance. The GA flights which provided RTTs were considered in the high priority group in runway scheduling and had to comply with the metering hold at parking stand. Forty simulations were run for each case. This doubled number of simulations runs helped expand the statistical sample size to achieve a good accuracy of each target percentage of GA flights that provided RTTs.

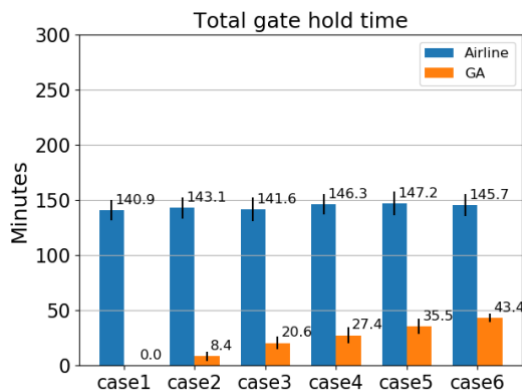


Fig. 22 Total gate hold time of group 3

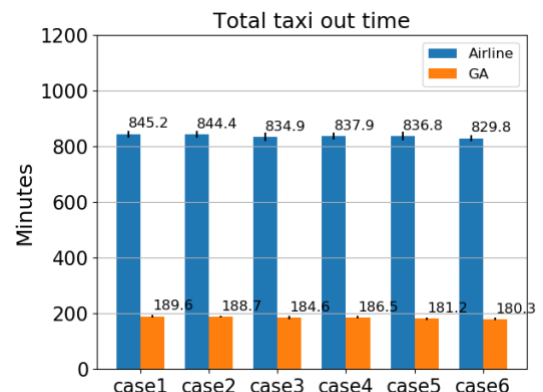


Fig. 23 Total taxi out time of group 3

Figs 22 and 23 show the average total gate hold times and the average total taxi out times, respectively. Fig. 22, shows that the total hold times of the GA flights increase as more GA flights provided RTTs, but the hold times of the airline flights show no statistically significant difference. This implies that the impact on the gate hold time of airline flights by GA flights with or without RTTs is

small. GA flights that submit RTTs compete with airline flights for slots from the scheduler and hold at park stand. In contrast, the GA flights that do not provide RTTs directly affect the airline flights by leaving the parking stand freely when ready. Nonetheless, the overall gate hold times of both airline and GA flights increased when more GA flights had RTTs. In correlation with the increase in metering hold times, the taxi out time chart in Fig 23 shows a decreasing trend in both airline and GA flights. It indicates that when a greater percentage of GA flights submitted RTTs and complied with the metering times, the interruption to the metering ecosystem dropped and benefitted the taxi out time reduction.

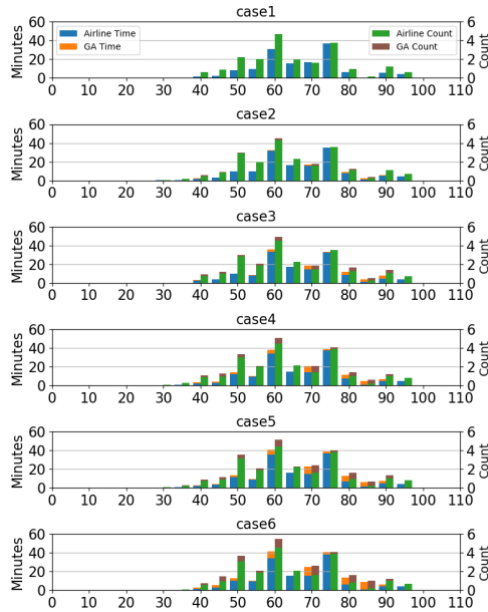


Fig. 24 Gate hold time series of group 3

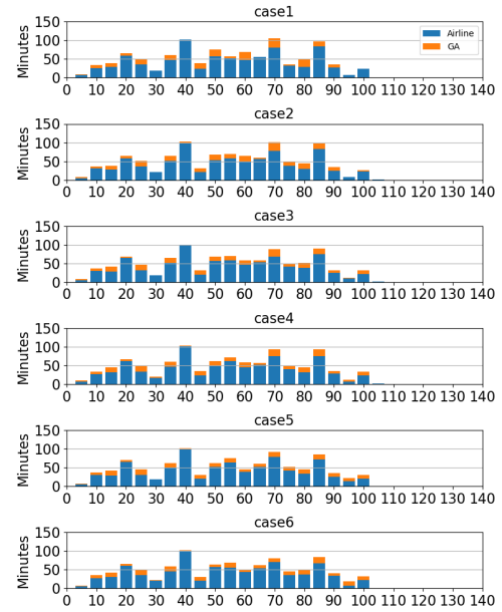


Fig. 25 Taxi out time series of group 3

The time series bar charts of metering hold and taxi out times are displayed in Figs 24 and 25, respectively. The metering hold time charts show that the percentage of GA flights submitting RTTs did not accelerate nor delay metering start times, because of the same reasons as described in the total number analysis, i.e., the gate hold time of airline flights by GA flights with or without RTTs is small. The metering hold time distributions of the airline flights are very similar to each other. The increase of GA flights' metering hold count and time is evident as more RTTs had been submitted. At the same time, the taxi-out times of both airline and GA flights decreased across the bank, consistent with the results in the total numbers.

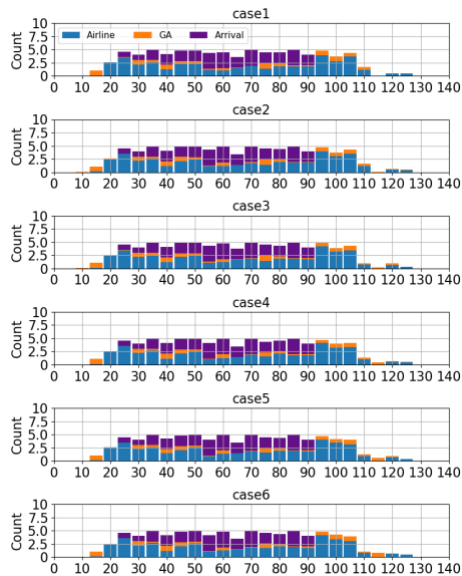


Fig. 26 Runway throughput chart of group 3

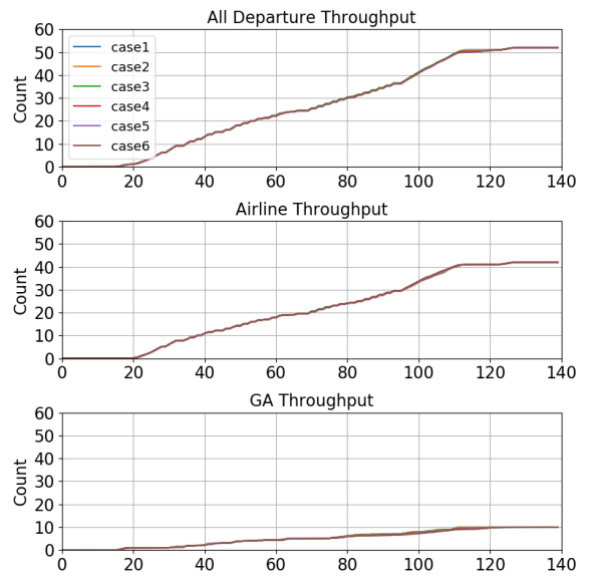


Fig. 27 Cumulative runway throughput of group 3

The runway throughputs are depicted in Figs 26 and 27. No obvious differences are found between cases in either plot. That indicates that the RTT provision of GA flights can increase metering hold time but decrease taxi out times of both airline and GA aircraft, helping maintain departure throughput.

In summary, the results show that overall taxi out times can be reduced when more GA flights provide RTTs and are in compliance with metering hold times. In other words, GA flights submitting RTTs and complying to metering times can help improve the airport performance.

D. Simulation Group 4: GA flight RTT accuracy

In Simulation Group 4, four different RTT accuracy levels of GA flights were tested, as shown in Fig. 28. Case 1 is the ideal case where the pilots' estimated RTTs are exactly the same as the actual RTTs. Case 3, the baseline case, is the current level of RTT accuracy from the data collected by MITRE. Cases 2 and 4 have the accuracy levels better and worse than the baseline case, respectively, for comparison. The horizontal axis is the lookahead time towards the actual RTT. The vertical axis is the RTT accuracy measured as the difference of the actual RTT and the estimated RTT by pilots. The data of the plots were collected from actual simulations.

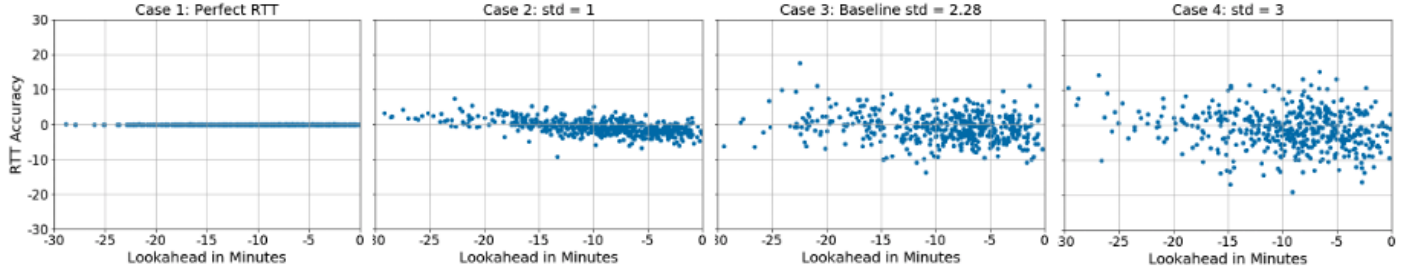


Fig. 28 RTT accuracy cases

In each case, ten GA flights were uniformly added across the baseline traffic scenario with the varied RTT accuracy level. Forty simulations were conducted for each case as well.

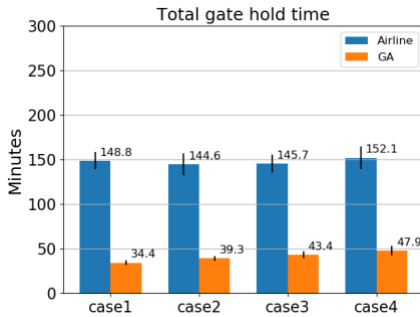


Fig. 29 Total gate hold time of group 4

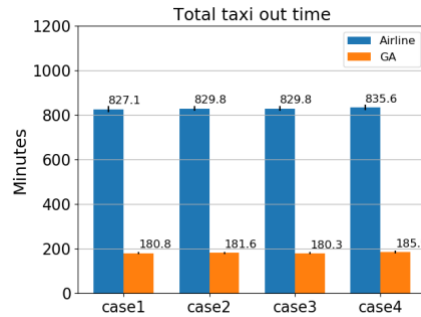


Fig. 30 Total taxi out time of group 4

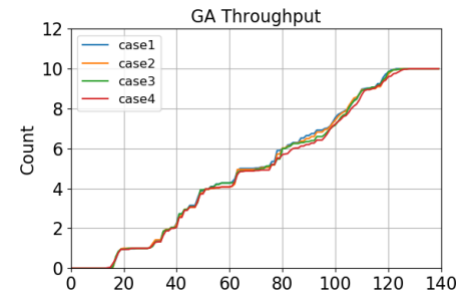


Fig. 31 Cumulative runway throughput of GA flights of group 4

Figs 29 and 30 show the comparison among the four RTT accuracy levels for metering hold and taxi out times, respectively. The metering hold times of GA flights went up steadily when RTT accuracy became worse. However, the additional hold times did not translate to taxi out time reduction. The reason likely lies in the fact that the added hold times were induced primarily by the inaccuracy of RTT prediction rather than scheduling. In particular, the conservative prediction errors (i.e., estimated RTT is later than ARTT) resulted in unnecessary hold times and consequently takeoff delays as seen in the runway throughput plot, Fig. 31.

For airline flights, no statistically significant differences are observed in the first three cases. In Case 4, the taxi out times of both airline and GA flights had a small but noticeable amount of increase, compared to the averages of the other three cases, possibly due to the increased uncertainty from the RTT prediction errors. The time series of metering hold and taxi-out times, and the runway throughputs, not shown in the paper, had little difference among the four RTT accuracy levels.

The simulation results in this group show that the RTT accuracy affected mainly the GA flights' throughput. The RTT accuracy at or better than the baseline from the actual data had no significant impact on the airline flights. On the other hand, RTT error worse than the baseline level may have a negative impact on both airline and GA flights due to the increased prediction errors.

IV. Conclusions

In this study, fast-time simulations were used to investigate the impact of GA flight operations on airport performance. The ATD-2 surface metering scheduling algorithm was used for Bank 2 traffic hours at CLT. The objectives of the study are to investigate how the current GA operations may affect surface management efficiency benefits, such as taxi out time reduction from surface metering, and potential merits of including GA flights in the surface scheduling program. The simulations were conducted in four simulation configuration groups. The first two groups focused on the GA departure demand concentration and the number of GA flights in the bank. They were designed to study the impact of current GA operation. In the next two simulation groups, an RTT model was developed based on the actual operational data from MITRE. The model sets percentages of GA flights providing RTT predictions

and varies the RTT accuracies in the simulations. These two simulation groups studied how airport performance under surface metering were affected by GA flights submitting RTTs to the scheduler system, through their mobile devices for example.

The simulations in the first two groups show that:

- The concentration of GA departure traffic *at the beginning* of the bank had the most significant impact on airline departures. It resulted in longer metering hold and taxi-out times for airline flights. It also triggered the scheduler to start surface metering earlier. GA traffic concentration *in the middle* of the bank had the second largest impact on airline flights' performance. GA traffic concentration *at the end* of the bank and evenly spread out across the bank had the least impact on airline flights. However, GA departure concentration at the end of the bank had the longest taxi-out times because of the arrival traffic demand for the same runway during the second half of the bank.
- The increase of GA traffic affected the airline flights by initiating an earlier surface metering time, longer hold times, longer taxi-out times, and longer takeoff delays. In particular, less predictability of GA flights appeared to affect the metering effectiveness in reducing taxi-out time for airline flights.

The results from the next two simulation groups show that:

- When more GA flights provided RTTs and followed metering hold advisory, the overall taxi-out times were steadily reduced by a relatively small amount (probably due to the small overall GA traffic level), and at the same time the runway throughputs and takeoff delays remained the same. This finding indicates readiness information from GA flights via mobile devices, such as MITRE's prototype Mobile App, is beneficial to airport performance with surface metering.
- When the RTT accuracy is the *same* as or *better than* the baseline level, no statistically significant impact on airline flights was seen in all performance metrics. When RTT errors were *larger* than the baseline level, both airline and GA flights showed longer taxi-out times due to the increased uncertainty introduced by the prediction errors. For GA flights, larger RTT prediction errors caused longer metering hold times that subsequently led to takeoff delay.

Despite the relatively small percentage of GA traffic at CLT, the results showed the clear impact of the current GA-operation levels on airport performance in the surface metering environment. Obtaining readiness information from more GA flights may also impact surface operations. Further research may consider other airports such as DAL where GA operations make up a greater percentage of the traffic demand.

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References

- [1] Federal Aviation Administration, "General Aviation and Part 135 Activity Surveys – CY 2017," https://www.faa.gov/data_research/aviation_data_statistics/general_aviation/CY2017
- [2] Y. Jung, *et al.*, "Airspace Technology Demonstration 2 (ATD-2) Phase 1 Concept of Use (ConUse)," NASA/TM-2018-219770, February 28, 2018.
- [3] NASA ATD-2 team, "ATD-2 Benefits Mechanism," Publications of the ATD-2 Subproject, 2020
- [4] H. Lee *et al.*, "Fast-Time Simulation for Evaluating the Impact of Estimated Flight Ready Time Uncertainty on Surface Metering," 38th Digital Avionics System Conference, San Diego, California, Sep 2019.
- [5] S. Badrinath *et al.*, "Evaluating the impact of uncertainty on airport surface operations," 2018 AIAA Aviation Forum, Atlanta, Georgia, Jun 2018.
- [6] P. Diffenderfer *et al.*, "Concepts for Delivering IFR Clearances & Exchanging Pre-Departure Data Using Mobile Devices," 2018 Integrated Communications Navigation and Surveillance (ICNS) Conference, Apr 2018.
- [7] P. Diffenderfer *et al.*, "Using Mobile Devices for IFR Clearance Delivery and Release and Data Exchange," AIAA Aviation Forum Atlanta, Georgia, June 2018.
- [8] R. D. Windhorst *et al.*, "Validation of simulations of airport surface traffic with the Surface Operations Simulator and Scheduler," AIAA Aviation Technology, Integration and Operations Conference, Los Angeles, California, Aug 2013.
- [9] W. Coupe *et al.*, "Scheduling Lessons Learned During Phase 1 Field Evaluation of the ATD-2 Integrated Arrival, Departure, Surface Concept," 13th USA/Europe Air Traffic Management Research and Development Seminar (ATM2019), Vienna, Austria, June 2019.
- [10] Apache Commons Math Library, <https://commons.apache.org/proper/commons-math>
- [11] MATLAB, <https://mathworks.com/products/matlab.html>
- [12] S. Kullback, "Information Theory and Statistics," John Wiley & Son, 1959, reprinted in 1978: ISBN 0-8446-5624-9.