Analysis of Impacts of Terminal Restrictions on Departures in D10 TRACON

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The D10 – Dallas-Fort Worth Terminal Radar Approach CONtrol (TRACON) is an air traffic facility that controls and manages aircraft and airspace that consists of multiple airports located in the North Texas area. From an air traffic management standpoint, one of the main challenges in the D10 TRACON is the departure fix capacity as multiple airports compete for resources. This problem is magnified when en route demand/capacity imbalance and inclement weather around the TRACON reduce the capacity at the terminal fixes. This leads to multiple, dynamic Traffic Management Initiative (TMI) restrictions being issued by the Air Traffic Control (ATC) on departing flights. This, in turn, propagates delay to the surface of each airport within the metroplex. The NASA Airspace Technology Demonstration 2 (ATD-2) Phase 3 is deployed in D10 to demonstrate new technologies developed to manage the Integrated Arrival, Departure, and Surface (IADS) traffic in a metroplex environment where multiple airports are interacting and sharing resources at the terminal boundary. This paper uses the ATD-2 terminal restriction data collected in the D10 TRACON to quantify the impact of restrictions on the demand, analyze the relation between terminal restrictions and departure taxi time on airport surface, and establish relationships between restrictions and surface delay. We found that the restrictions on departure flights have a direct adverse effect on departure excess taxi time on the airport surface.

I. Introduction

Inefficiency and lack of predictability are the two most challenging issues that the National Airspace System (NAS) is facing today in order to satisfy the ever-increasing air transportation demands. In an airport metroplex environment such as the D10 TRACON where multiple airports compete for shared resources, these challenges are magnified by demand/capacity imbalance and inclement weather around the terminal boundary which further reduce the capacity at the terminal fixes leading to multiple, dynamic TMIs being issued on departing flights. This, in turn, can propagate delay to the surface of each airport within the TRACON [1].

NASA has been collaborating with the Federal Aviation Administration (FAA) and industry partners to develop and demonstrate new concepts and technologies [2-6] for the Integrated Arrival, Departure, and Surface (IADS) traffic management system under the Airspace Technology Demonstration 2 (ATD-2) sub-project [7, 8]. The primary goal of the ATD-2 sub-project is to improve the predictability and the operational efficiency of the air traffic system in metroplex environments while maintaining or improving throughput by enhancing and integrating arrival, departure and surface prediction, scheduling, and management systems. The ATD-2 sub-project is broken up into three different

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phases. Phases 1 and 2 were deployed at Charlotte Douglas International Airport (CLT) [9] and provided enhanced operational efficiency and predictability of flight operations through data exchange and integration, surface metering, departure scheduling and electronic negotiation of release times of controlled flights for overhead stream insertion.

ATD-2 Phase 3 builds upon Phases 1 and 2 by extending the coordinated scheduling of arrivals, departures, and surface traffic to support the management of departure demand/capacity imbalances in a multi-airport airspace. When inclement weather constrains the capacity at a given fix in the metroplex, the Phase 3 system aids Flight Operators in the decision to reroute the flights over an alternative departure fix by assessing the delay savings on a set of pre decided alternative routes [10]. The D10 Metroplex is home to two major hub airports, Dallas/Fort Worth International Airport (DFW) and Dallas Love Field Airport (DAL), where ATD-2 field demonstration partners American Airlines and Southwest Airlines have a large presence in the respective airports. The D10 Metroplex also experiences high traffic demand and frequent traffic delays due to inclement weather. All of these factors made D10 Metroplex a good choice for ATD-2 Phase 3 field evaluations.

In this paper, we present our research to identify the drivers of surface delay in D10 and understand the relation between terminal restrictions and surface delay. The motivation of our research is to help improve methods to reduce delays on the airport surface when TMIs are in effect on the terminal boundary.

This paper first provides the background on the D10 TRACON and National Traffic Management Logs (NTML) restriction data. The background then introduces the ATD-2 restriction data collected in the D10 TRACON and the systematic approach taken by ATD-2 to transform the NTML parsed data into labels for categorizing the type of restrictions to have a high-level view that captures the overall complexity of the restriction scenarios. Finally, we leverage the ATD-2 restriction data to analyze departure excess taxi time and quantify the impact of different types of restrictions and find correlations between the terminal restrictions and surface delay.

II. Background

A. D10 TRACON and Restrictions

The D10 TRACON airspace is centered on DFW in North Texas and extends outward approximately forty miles. It contains DFW and DAL in close proximity to each other along with several busy general aviation airports, a regional cargo hub, and a Naval Air Station Joint Reserve Base [11]. These airports are labeled beginning with "K" in Fig. 1.
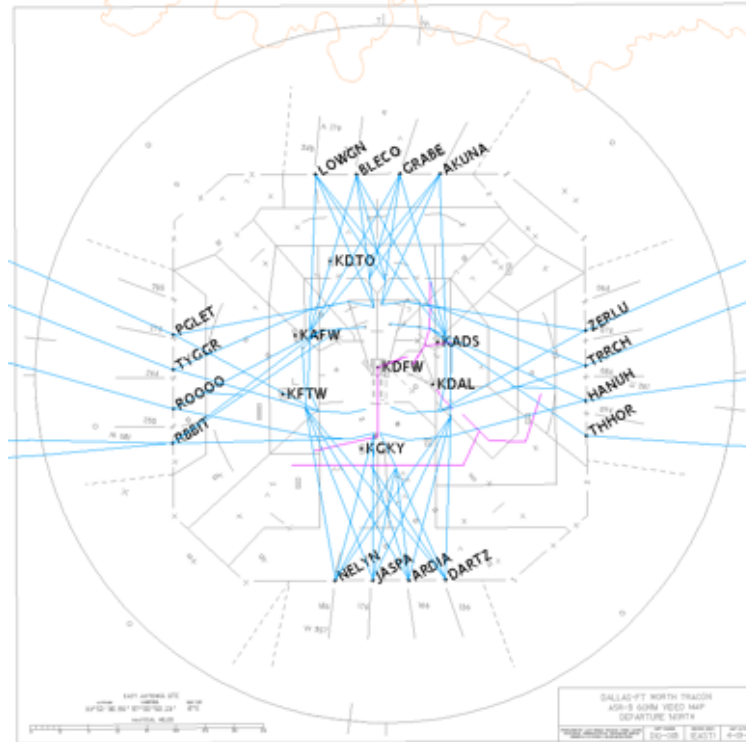

Fig. 1 D10 airspace and departure fixes.

There are 16 departure fixes on the terminal/center boundary, and these are shared among all the airports. These departure fixes are arranged in groups of four along the North, East, South, and West departure gates, see Fig. 1. Although all airports in the TRACON contribute to the demand at the departure fixes, 65-70% of the D10 traffic is generated by operations at DFW and DAL, which is why the analysis in this paper focuses on those two airports.

Departure fix closure and Miles-in-Trail (MIT) for departure flights are two common restrictions issued by Center and TRACON to address demand/capacity imbalance at the terminal boundary [12]. In 2019, most MIT restrictions at the TRACON/Center boundary lasted for an hour, whereas most fix closures lasted for two hours as seen in Fig. 2 where the horizontal axis is the actual duration of the restriction and the vertical axis is the originally scheduled duration. The intensity of the color indicates the frequency such that the darker the color the more data points fall on that (x, y) value. It is clear from this figure that whereas MITs and fix closures may last the entire predicted duration, many are often cancelled earlier than originally planned due to weather subsiding or moving away from the boundary.
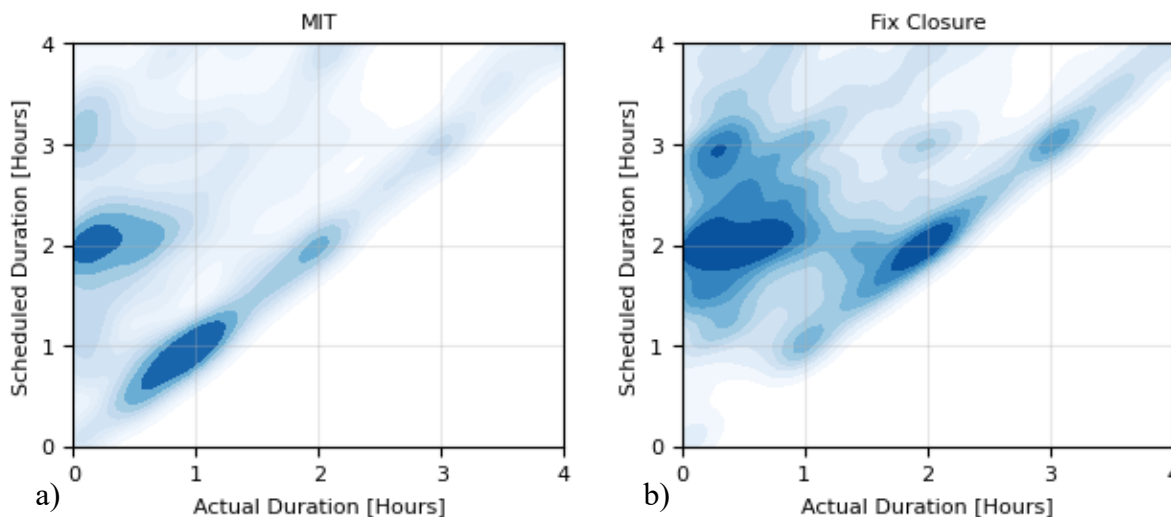

Fig. 2 Predicted vs. actual restriction duration. (a) MIT durations. (d) Fix closure durations.

When restrictions are applied at the terminal boundary, the effects manifest at airports within the terminal as surface delay and excess taxi time for departing flights. Figure 3 shows that the restricted flights at DFW experienced much higher excess departure taxi time than unrestricted flights between July and December in 2019. In this figure the vertical axis shows the counts of flights subjected to MIT or fix closures and the horizontal axis shows the departure excess taxi time in minutes which is calculated as the difference between actual taxi time and unimpeded taxi time. A positive x-axis value means the actual taxi time was longer than unimpeded taxi time. Figure 3(a) shows unrestricted flights, Fig. 3(b) shows flights subjected to different MIT only restrictions, Fig. 3(c) shows flights subjected to one or more departure fix closures only, and Fig. 3(d) shows flights with a combination of MIT and fix closures. The mean and standard deviation of excess taxi time get worse as the number of TMI restrictions increase or as they get more severe. This is strong evidence that the terminal boundary restrictions have a real impact on departure taxi times at the airports within the TRACON.

B. National Traffic Management Logs (NTML)

Traffic Management Specialists within ATC facilities strategically manage the flow of air traffic to minimize delays and congestion due to system stressors such as inclement weather, heavy traffic volume, and equipment failures. ATC facilities are required to log all TMIs and coordinate the implementation of some initiatives with the Air Traffic Control System Command Center (ATCSCC) and to communicate the initiatives to Traffic Management Specialists at all affected facilities, as well as to controllers within their facility. Every affected facility is then also required to log the information and communicate it to the controllers. The FAA developed the National Traffic Management Log (NTML) to provide a single system for automated coordination, logging, and communication of TMIs throughout the National Airspace System [13, 14].

Oftentimes in practice these NTML logs were either incomplete due to missing data or untimely because Traffic Management Coordinators (TMCs) get busy, enter the restrictions after the fact and have to estimate when the

restrictions started and stopped which may be inaccurate. The timeliness and accuracy of entries in the NTML logs can sometimes decrease as the complexity of the operations increases.

ATD-2 worked in collaboration with FAA, and TMCs at DFW and DAL to change how NTML entries were made so that the restrictions can get published to FAA Operational Information System (OIS) and Systemwide Information Management (SWIM). This effort included standardizing the input so that it could be parsed in an automated way and developing the technologies to parse the data [15]. This eliminated having to ask TMCs to make additional entries in ATD-2 beyond what they already make in NTML.
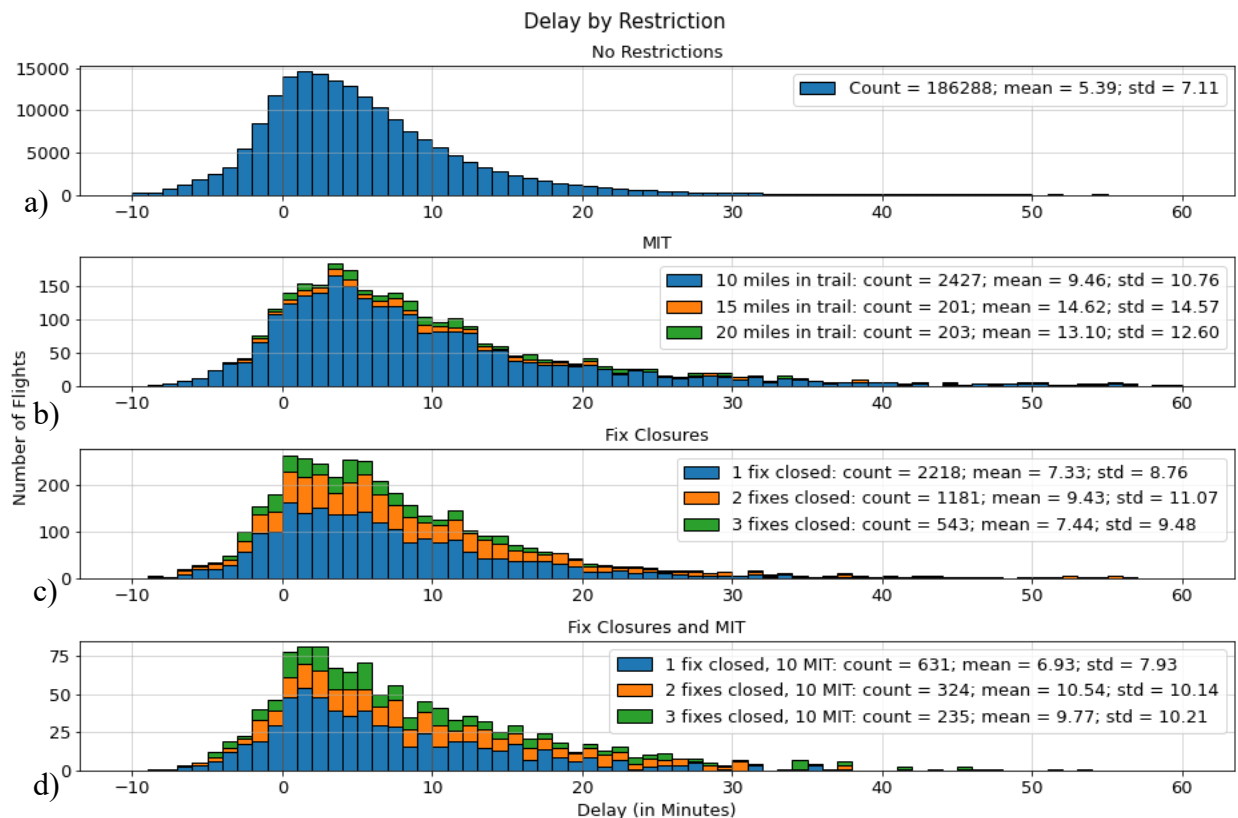
Fig. 3 Departure excess taxi time at DFW. a) No restrictions. b) MIT only. c) Fix closure only. d) Fix closure and MIT combined.

C. ATD-2 Data

The ATD-2 IADS system is powered by real-time FAA System Wide Information Management (SWIM) data feeds including Traffic Flow Management System (TFMS), SWIM Terminal Data Distribution System (STDDS), SWIM Flight Data Publication Service (SFDPS), Time Based Flow Management (TBFM), Terminal Flights Data Manager (TFDM), and Terminal Automation Information Service (TAIS) [16]. These SWIM data feeds are complemented by other data sources such as ramp surveillance and gate information provided by the airlines.

The SWIM data feeds contain valuable data, but can provide inconsistent information on the same flight that is difficult for consumers to understand. Without deep knowledge of TFMS, TBFM, and TFDM along with FAA air traffic systems En Route Automation Modernization (ERAM) and Standard Terminal Automation Replacement System (STARS), the consumption logic may not lead toward the benefit the community desires [17]. Much of this work is embodied in the Fuser [18] service which is illustrated in Fig. 4 where the Fuser is shown running within the ATD-2 IADS systems in CLT and North Texas (NTX).

The Fuser aggregates flight data from multiple FAA sources, Airline data, and 3rd party data into a unified source. Flight information is organized by individual flights (one take-off and one landing) using the Globally Unique Flight Identifier (GUFI). As new messages are received, the flight file is updated. Clean and accurate data is assured through the use of transformation and mediation processes which enforce business rules on the received data. Fused data is sent to the Surface Trajectory Based Operations (STBO) surface model which tracks, updates, and disseminates information on key surface events. Actual surface event data is used in conjunction with derived data and model

processing logic to produce a single cohesive view of airport operations. At a rate of once every ten seconds, the surface modeler leverages this view of surface operations to generate surface trajectory predictions for both departures and arrivals. The Fuser leverages heuristics and analysis on which data source is best to use for a specific field and produces to the information in a common well-defined data model [19].

To consuming SWIM data, the IADS system publishes the Terminal Flight Data Manager (TFDM) Terminal Publication (TTP) feed back to SWIM which can be consumed within the SWIM Research and Development (R&D) environment. The ATD-2 TTP feed on the SWIM R&D matches the specifications of the future TTP feed to foster industry innovation in preparation for TFDM [20].
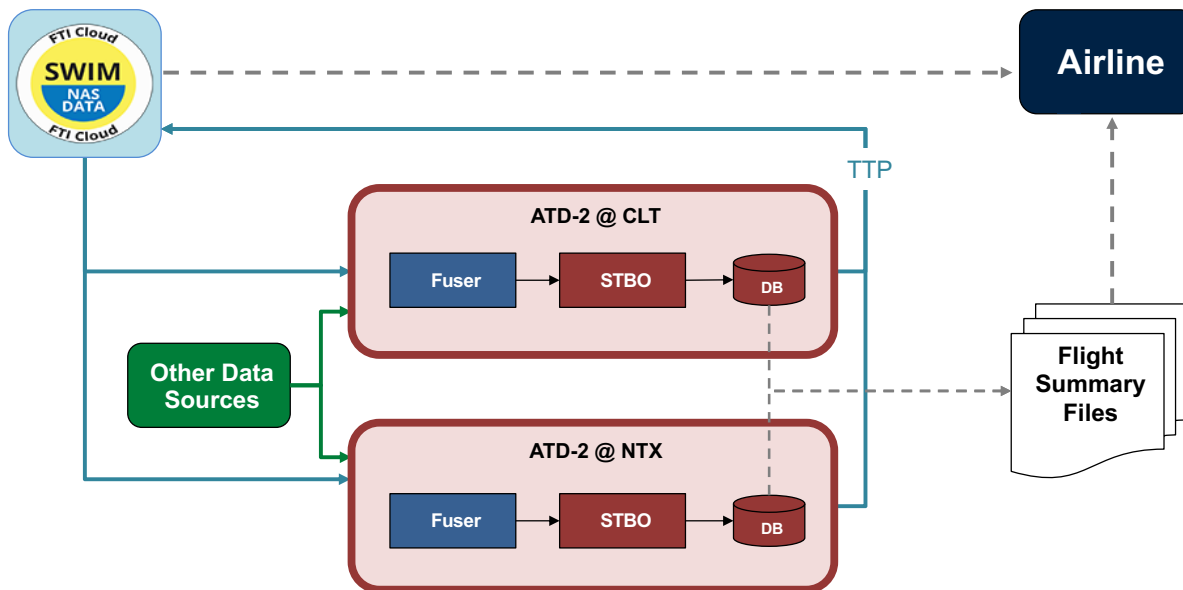
Fig. 4 Data architecture and data flow between SWIM, ATD-2, and airlines.

The data written to the database is valuable but often too verbose to be used effectively for analysis. To address this problem, ATD-2 developed the Flight Summary and TMI summary reports to serve analysts and user needs. These reports help standardize the ATD-2 approach to handling such conditions as human inputs, business logic, measurement convention, complexities of data mediation, order of processing messages, and changes from earlier versions of ATD-2 software. These reports are generated every morning for post-operations analysis on the previous day's operations. These Flight Summary and TMI summary reports are the data sources for analyses presented in the following section.

III. Analysis

We analyzed D10 data covering a six-month period to understand the major drivers of surface delay at DFW and DAL. We did this by training a Machine Learning (ML) model to predict excess departure taxi time on D10 data. Once we had a reasonably accurate ML model, we identified data features that were most important for the model to make predictions. We then analyzed these data features in detail to understand why these are important and how they affect surface delay.

A. Data Inputs

In the D10 TRACON, the ATD-2 system has collected Flight Summary data since November 6, 2017 and TMI data in since June 12, 2019. The Flight Summary report and TMI Summary reports are generated every morning for post operations analysis on the previous day's operations. The Flight Summary report contains each unique flight as a row containing over 500 columns of unique data elements and predictions captured at some discrete points in time. The TMI Summary report contains each unique TMI as a row containing about 25 columns of unique data elements providing details on each TMI in effect during the operational day.

In this paper we use ATD-2 Flight Summary and TMI Summary reports for DAL and DFW from July 1, 2019 to December 31, 2019. From the ATD-2 TMI Summary report we use the start and end time of each MIT and fix closure to understand how long each restriction lasted and which terminal resources were affected by it. From the ATD-2

Flight Summary report we use the pushback (OUT), takeoff (OFF), and excess Airport Movement Area (AMA) taxi time for each flight. Because most holds take place in the AMA and excess taxi time is usually zero in the ramp area, we used excess AMA taxi time as our measure of surface delay. For each flight the STBO model derives undelayed taxi time from nominal taxi speed and expected taxi route. The excess AMA taxi time is calculated as the difference between actual AMA taxi time and undelayed AMA taxi time for that flight. From the ATD-2 Flight Summary report we also get information on whether the flight was subject to any MITs or fix closures. This enables us to identify restricted flights.
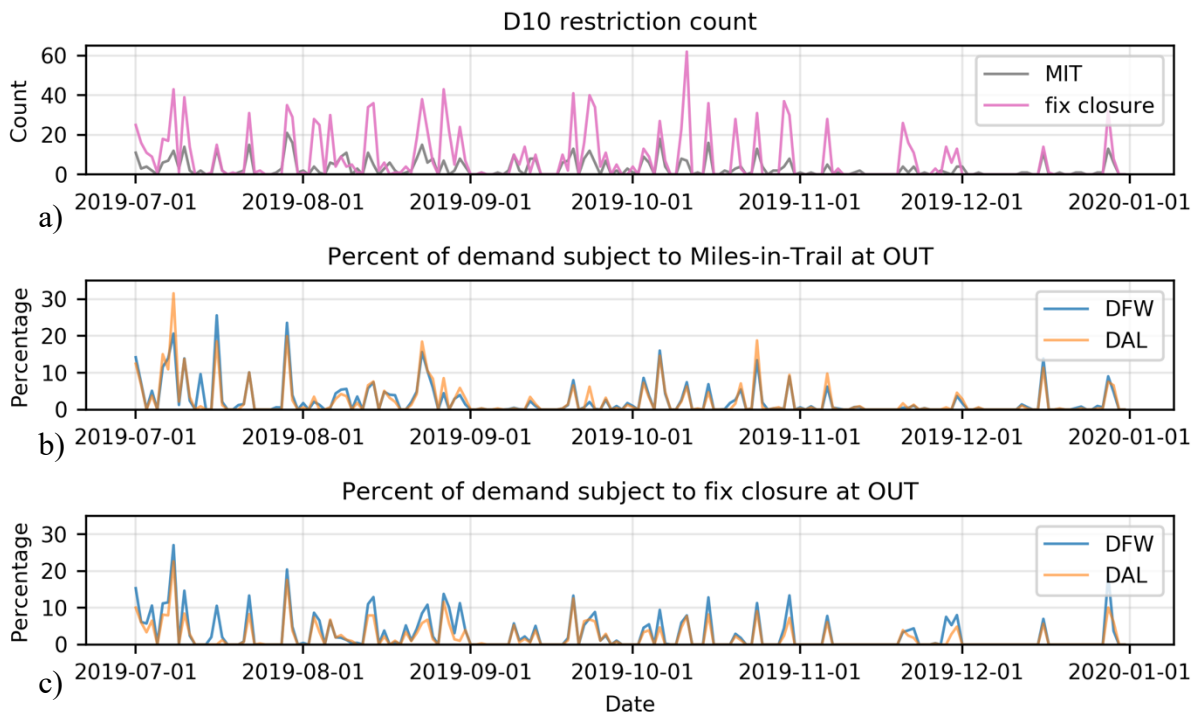
Fig. 5 Daily restricted departures at DFW and DAL. a) Daily count of restrictions. b) Daily percentage of flights subject to MIT restrictions. c) Daily percentage of flights subject to fix closure restrictions

Figure 5 uses ATD-2 TMI Summary report data to show the counts of MIT and fix closures affecting departures at DFW and DAL during the six-month period analyzed in this paper. During this time the number of unique fixes closed throughout the day often surpassed 30 with that number crossing 40 on some days, see Fig. 5(a). For a given day, there are fewer MIT restrictions than fix closures because ATC often initially responds to weather events with closing multiple fixes and putting a single MIT restriction on the compressed flow. Figure 5(b) shows the percentage of departure flights from DFW and DAL that are subject to an MIT restriction at the OUT event. Figure 5(c) shows the percentage of departure flights from DFW and DAL that are subject to a fix closure at OUT. Because fix closures and MIT restrictions often go hand in hand, the percentage of flights that are subject to the different types of restrictions is similar.

B. Machine Learning Model for Surface Delay Prediction

Machine Learning (ML) models are algorithms that have been trained to recognize patterns in data. In this paper, we build a simple ML prediction model for departure excess taxi time at DFW using ATD-2 data described in the previous section. The motivation here is to identify patterns and features in data that play an important role in determining surface delay.

Decision Tree (DT) learning is one of the most widely used non-parametric supervised learning methods. A DT creates a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. DTs are simple to understand and interpret and require little data preparation. DTs are also known to perform well even if its assumptions are somewhat violated by the true model from which the data was generated. Committees of ML models, also called ensembles, have the potential to improve on the accuracy of a single ML model and provide a computationally scalable approach to handling massive data.

We built a Gradient Boosted Decision Tree (GBDT) using *scikit-learn* [21] Python library. GBDT follows a sequential learning approach where each new learner in the ensemble is built only after the existing learner has been trained and evaluated. At each iteration a set of weights $w_1, w_2, ..., w_N$ is applied to the training sample such that those training examples that were incorrectly predicted in the previous iteration have their weights increased (or boosted). The motivation is to combine several weak models to produce a powerful ensemble.

For our analysis, we created a simple GBDT using *scikit-learn* version 0.24.2 GradientBoostingRegressor class [22] using non-default parameter values as given in Table 1. A data dictionary of features used in this ML model is provided in Appendix. We chose to evaluate two different window sizes, 15 minutes, and 30 minutes, to look at the count of prior operations because we have no statistical evidence of the correct window size. The GBDT is immune to collinearity and is therefore robust to having both features. There were 162,045 restricted flights with fully defined features in our data, with which we used a 70/30 train/test split for our ML model resulting in a training set consisting of 113,431 flights and a test set of 48,614 flights. For comparison we also created a naïve prediction model which always predicts the average excess AMA taxi time of all the flights in the training set.

Table 1.   Parameter definitions and values used for GBDT model

Parameter	Definition	Value
n_estimators	The number of boosting stages to perform	500
max_depth	Maximum depth of the individual regression estimators	4
min_samples_split	The minimum number of samples required to split an internal node	10
learning_rate	Controls how quickly the model is adapted to the problem	0.1
loss	Loss function to be optimized ('ls' refers to least squares regression)	'ls'

Figure 6 compares the performance of the ML model and naïve model. In this figure, the error in predicted excess taxi time in minutes is given on the horizontal axis and the count of flights for each error value is given on the vertical axis. The green bars represent the ML model errors and the blue bars represent the naïve model errors. The mean values of the two types of errors is the same, meaning that on an average, the ML model performed about the same as the naïve model. However, because mean values are easily affected by extreme values it is important to consider the standard deviation as well as the overall distribution of errors. The ML model prediction errors are centered around zero minutes indicating accurate prediction for a large number of flights. Also, a tighter standard deviation for the ML model indicates overall smaller prediction error for the remaining individual flights. On the other hand, the naïve model errors are centered around –4 minutes, meaning that it overestimates the delay for a large number of flights. The larger standard deviation of the naïve model indicates a wider range of prediction error. In other words, even though the mean errors were same for the two models, the ML model was closer to the truth.
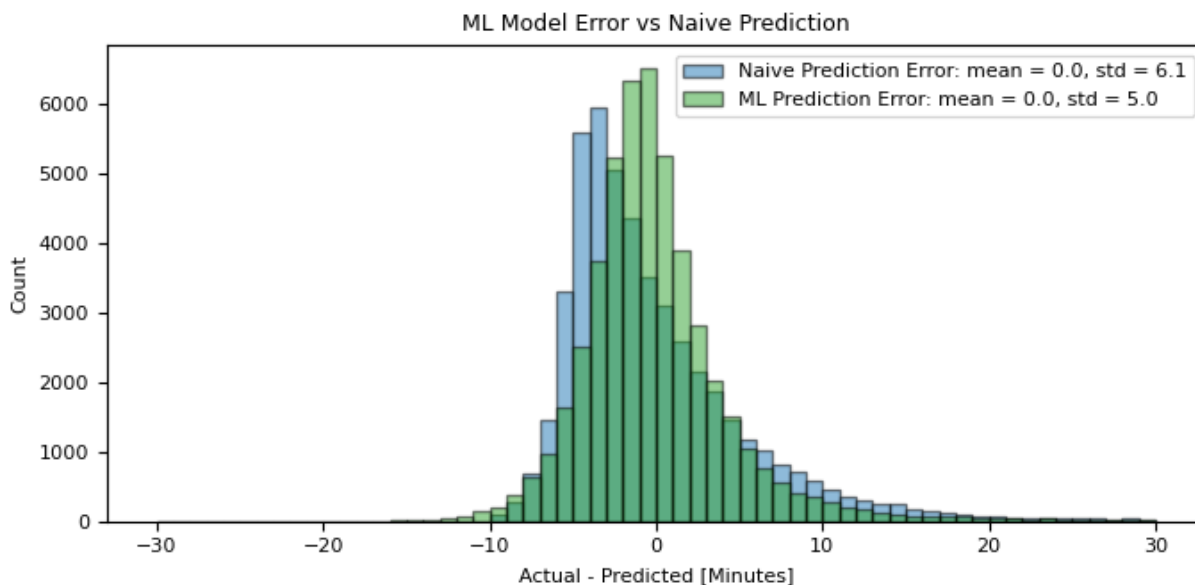
Fig. 6 ML model vs. naïve prediction error for departure excess taxi time

To understand how the different data features contribute to predictions in our ML model we looked at feature importance. Feature importance is a technique for assigning scores to input features used in a predictive model where the score indicates the relative importance of each feature when making a prediction. In Fig. 7 four features clearly stand out. The first is the local minute of the day which is indicative of departure banks. A bank is a concentrated period of demand during which the traffic patterns ebb and flow. Departure banks often result in surface delays due to the sheer volume of operations taking place in a short window of time. The next two features measure the volume of operations. The fourth feature is a function of restricted demand immediately prior to takeoff.
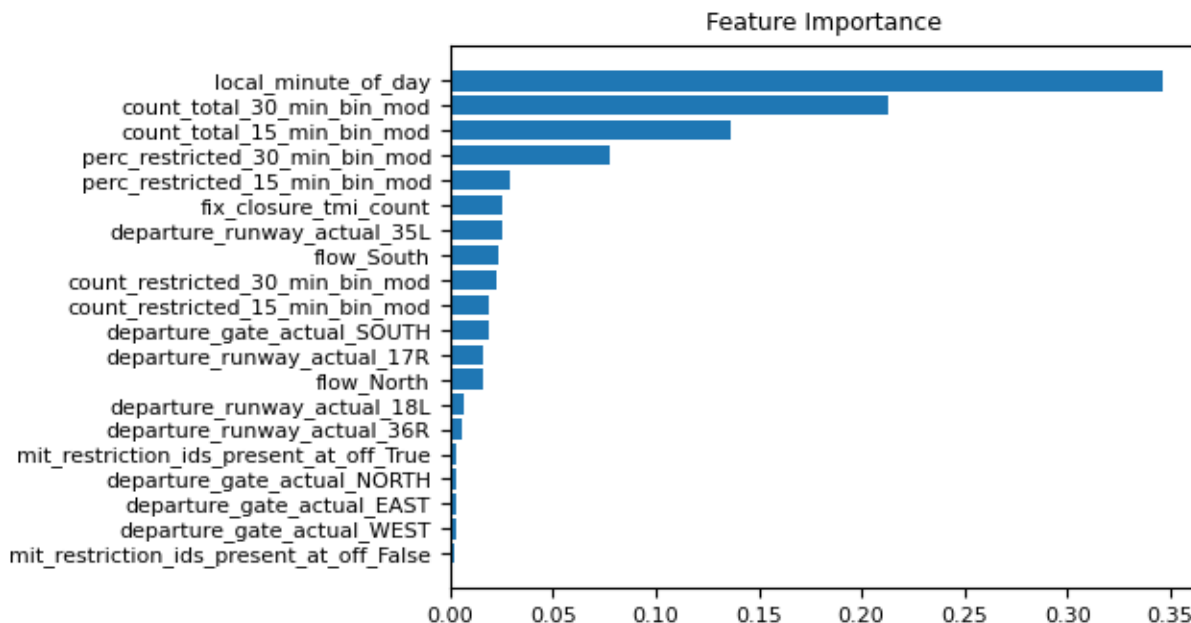

Fig. 7 ML model feature importance.

Based on the feature importance identified by our ML model, the factors that most influence the excess taxi time of a flight are volume of runway operations, and fraction of restricted runway demand around takeoff. In the next section we analyze these features to understand why they are important.

C. Data Driven Statistical Analysis

We looked at 158,351 unrestricted and 162,272 MIT restricted departures from DFW using our data. MIT restricted departures experienced longer excess taxi out time compared to unrestricted flights as shown by the long right tail of restricted flights in Fig. 8(a). The restricted flights on an average took close to twice as long as unrestricted flights.

At DFW, runways 17R/35L and 18L/36R are the primary departure runways. We looked at the impact of restrictions by runway, Fig. 8(b), and terminal departure gate, Fig. 8(c), separately and found similar trends for restricted and unrestricted flights. In both these graphs the median and Inter Quartile Range (IQR) of the restricted flights (orange boxes) is consistently larger than the unrestricted flights (blue boxes) from the same runway or to the same gate, confirming that MITs at terminal boundaries directly affect delay on the airport surface.

We analyzed the relation between runway load and excess taxi time by looking at the number of same runway operations in 15-minute and 30-minute windows prior to takeoff for each flight and found that the demand for the runway has a major impact on departure delays. Consider flight f which took off at t minutes. If in the prior 15 minutes (t-15 to t-0) at least 1 flight departed that was restricted, we make note of how many total flights departed during this time N_t and how many of this total were restricted N_r. The reason we only note this if at least 1 flight that departed during this time was restricted is to limit our focus to occasions when restrictions were in effect. Using (N_t, N_r) to form a coordinate system of cells, we color plot the frequency or number of instances when flight f was unrestricted in 9(a), and when flight f was restricted in 9(b). Note that the two figures use different scales, as shown. In these figures, the number of operations increases from left to right, and the number of restricted flights increases from bottom to top. Because within each column the total number of flights is fixed, higher values of restricted flights count (y-axis) also indicate greater percentage of restricted flights. It is clear from Fig. 9(a) that the number of operations reduces as the percentage of restricted flights increases. The concentration of darker color cells in the lower left quadrant of Fig. 9(b)

shows that when there are multiple restricted flights operating close to each other, the runway throughput is lower. This is because each of these flights needs to maintain a mandated amount of distance between them.
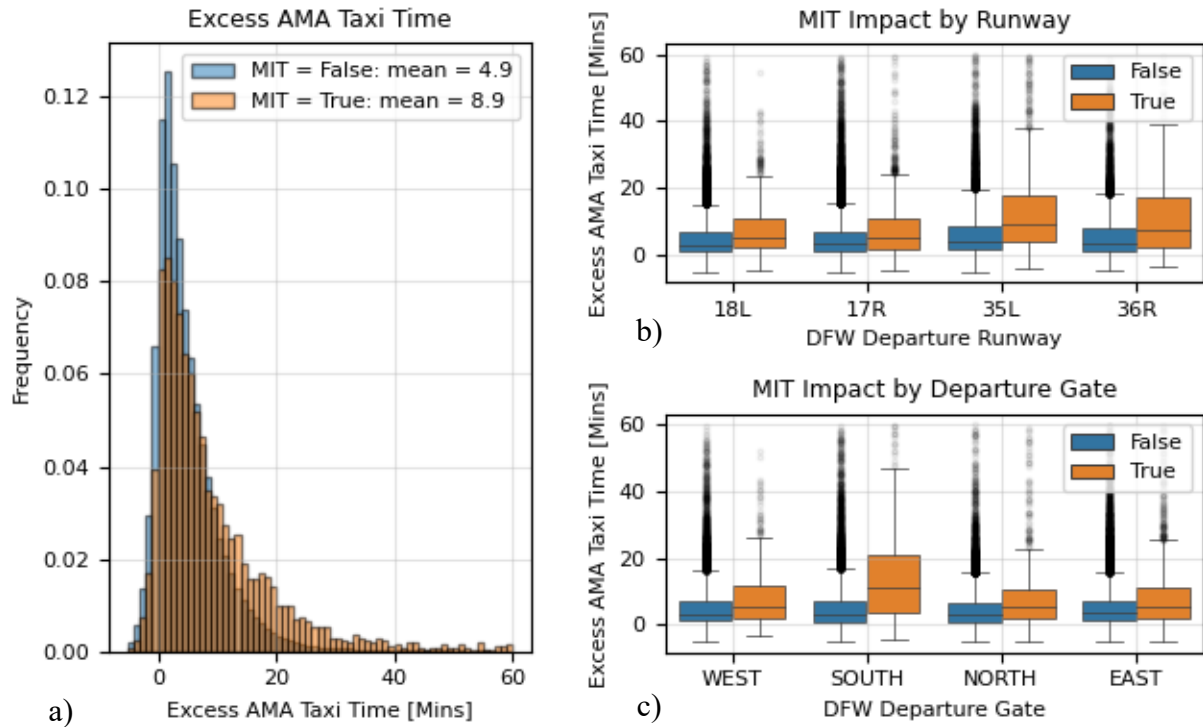

Fig. 8 a) Impact of terminal restrictions on excess taxi time. b) Impact by departure runway. c) Impact by terminal departure gate.

Figure 10(a) shows the distribution of departure flights with varying counts of operations from the same runway in the 15-minute and 30-minute periods prior to take-off. In the last 15 minutes before takeoff, a flight may see as many as 20 departures ahead of it from the same runway, although numbers above 15 are not very common. If we expand this window to 30 minutes, the number of preceding departures goes as high as 40, although numbers above 30 are uncommon. Further investigation of data may be needed to understand the unusually high number of operations in both window sizes.
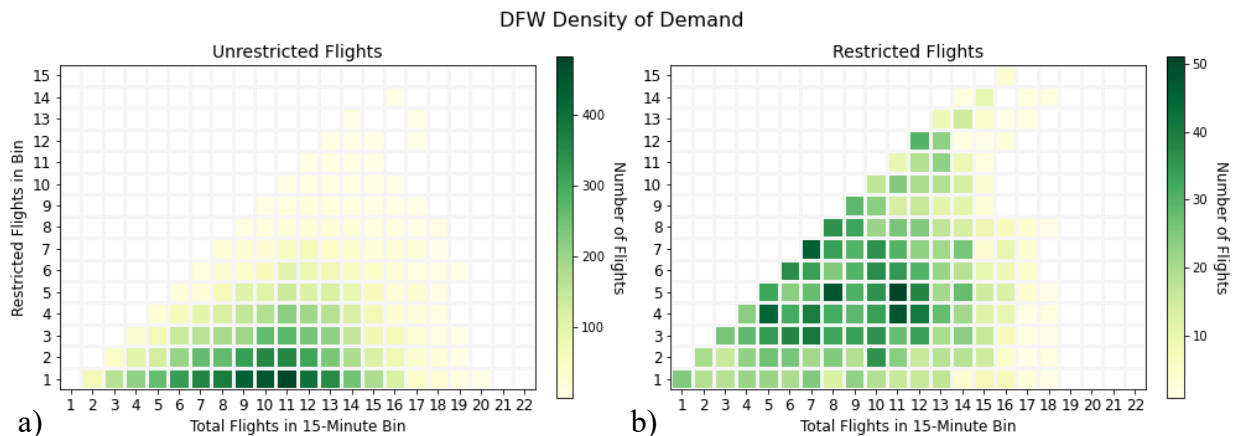
Fig. 9 Runway demand at DFW with 15-minute look back window for (a) unrestricted flights (b) restricted flights

We use the horizontal axis of Fig 10 (a) to divide the flights into different groups based on the number of operations. In Fig. 10 (b) we analyze the excess AMA taxi time for each of these groups. When there are no MIT
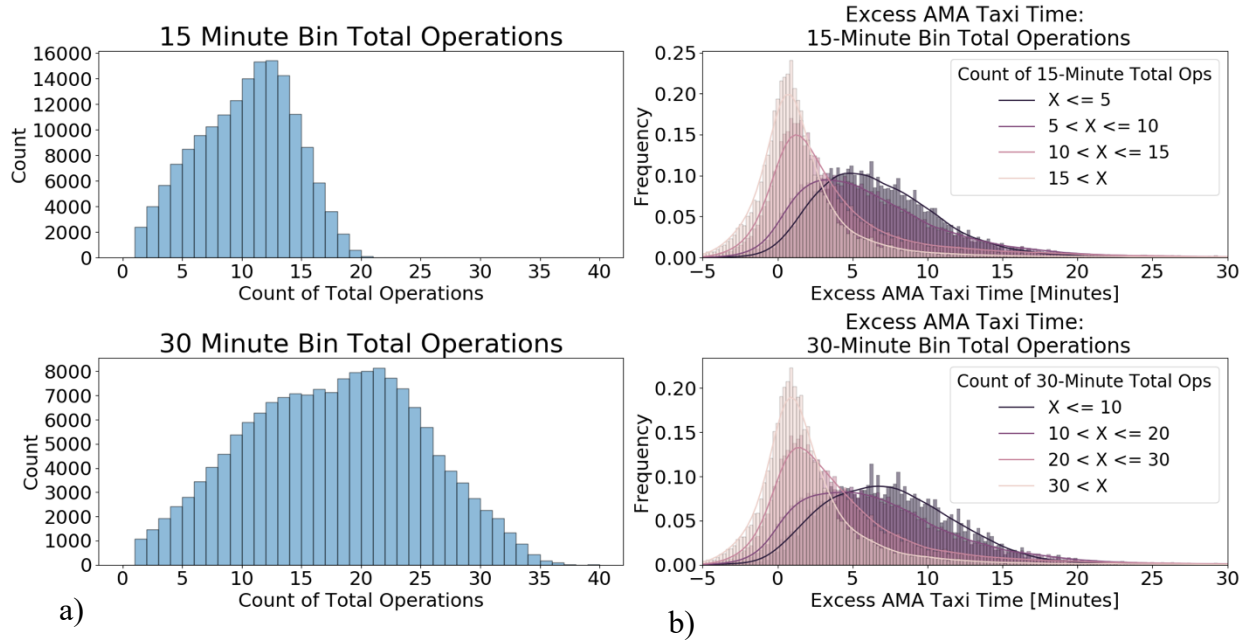
Fig. 10   a) Number of same runway operations in 15-minute and 30-minute window. b) Restrictions decrease runway throughput and increase taxi time.

restrictions present, aircraft can take off quickly one after the other, resulting in a high runway throughput. This means aircraft spend less time in the runway queue. This is reflected in low excess taxi time values for the group with the highest number of operations in Fig. 10 (b). As the MIT restriction starts to get more severe, aircraft need greater separation between them, resulting in lower runway throughput. This means the aircraft spend longer time in the runway queue. This is reflected in increasingly longer excess taxi time for each group as the number of operations decreases.

Note that the excess taxi time characteristics of respective groups in both 15-minute and 30-minute windows in Fig. 10 (b) are almost identical. For this reason, we chose to focus on only the 15-minute window for the remainder of this analysis.
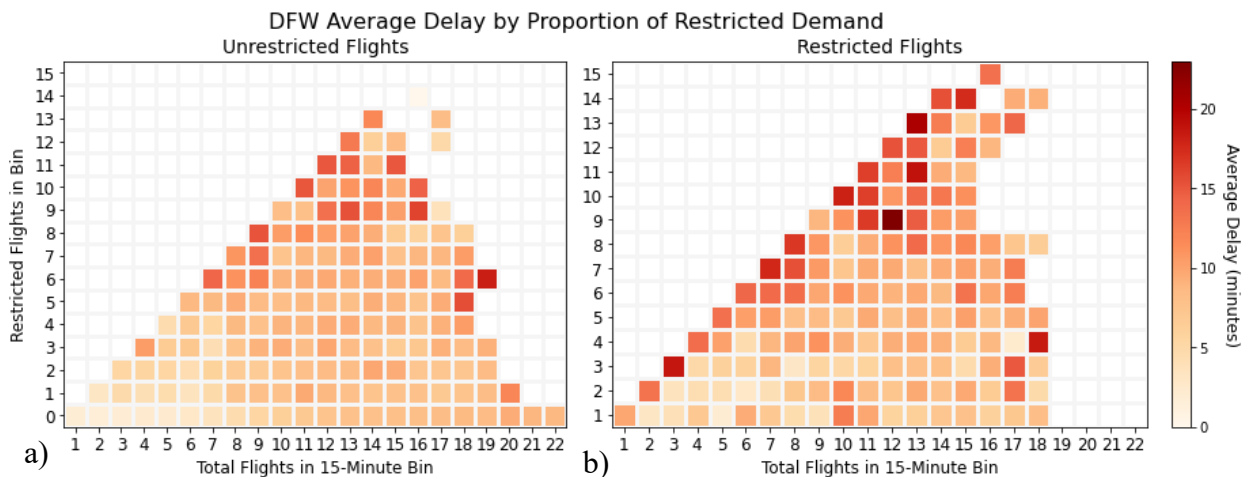
Fig. 11   Average delay by proportion of restricted demand for (a) unrestricted flights and (b) restricted flights.

To further cement the relation between restrictions, runway throughput, and excess taxi time we assessed the delay values for each cell in Fig. 9 (a) and (b). These results are shown in Fig. 11 (a) and (b) respectively. Note that Fig. 11 uses the same coordinate system as Fig. 9. Whereas in Fig. 9 we were looking at the frequency of operations for each (N_t, N_r) cell, in Fig. 11 we are looking at excess taxi time for each (N_t, N_r) cell. The intensity of color in each cell in

Fig. 11 represents the amount of delay. Once again, because within each column the total number of flights is fixed, higher values of restricted flights count (y-axis) also indicate greater percentage of restricted flights. In Fig. 11(a), for a given row the delay value doesn't change much going from left to right. This shows that adding more and more unrestricted flights to runway volume doesn't affect taxi times much. However, as we go from bottom to top, taxi times get progressively higher. This shows that as the percentage of restricted demand increases, so does the delay because a restricted flight in front of other flights in a queue will pass on some of its delay to subsequent flights and if those flights are also restricted then they will get this delay on top of their own delay. This also explains the comparatively higher delay values seen in Fig. 11(b). The diagonal in Fig. 11(b) represents the case where 100% of the demand is restricted, the delay values are highest for these cells.

IV. Discussion

Our analysis shows that the most important driver of surface delays is the runway operations volume and percentage of restricted demand operating around the same time. As the restrictions get more severe the delays increase. Operations volume decreases as the fraction of restricted operations per unit time increases. This decrease in runway operations also adversely affects surface delay as flights have to wait longer in the runway queue. The worst delays are seen when there are multiple restricted flights using the same runway. The results of our analysis show that in general, terminal restrictions such as MIT have a direct adverse effect on surface delays. The analysis results may vary from airport to airport, although the general trend may hold across different airports.

When restrictions are applied on the terminal boundary there may be available alternative routes that might be free of restriction and subject to less delay. When this situation occurs, a flight that is originally routed through a constrained departure route may be rerouted through an alternative departure route with less or no constraints which results in less surface delay, thus resulting in a delay saving. The ATD-2 IADS Phase 3 system aids Flight Operators in the decision to reroute the flights over an alternative departure fix by assessing the delay savings on each alternative route defined by each flight operator's Trajectory Option Set (TOS) [23]. The TOS is a set of alternative routes that each have an associated Relative Trajectory Cost (RTC) specified by the Flight Operators' (FO) own cost factors. The delay savings for each route in the TOS is compared to its RTC to determine when the delay savings on an alternative route rises above the RTC threshold value. In addition to computing the delay savings for individual flights, the IADS Phase 3 system also calculates the overall savings at a system level resulting from a reroute of a single flight. The savings at the system level is important for the FOs as they may be able to see how rerouting a single flight can benefit the air carrier, the larger fleet, as well as the airport or the metroplex [24].

The IADS Phase 3 TOS reroute capability was intended to be evaluated in D10 during the IADS Phase 3 Stormy 2020 Field Evaluation between May and September 2020. Prior to the start of the Field Evaluation in March 2020, air traffic demand dropped sharply due to impacts of COVID-19. The Phase 3 system was nonetheless built and deployed to the North Texas Metroplex in March of 2020. This provided the means to passively collect predictions from the Phase 3 system in a shadow mode to evaluate the type of TOS reroute opportunities that arise. The results of this shadow evaluation during Stormy 2020 can be found in [25]. Lessons learned from the Stormy 2020 Shadow Evaluation will be incorporated into the Phase 3 Field Evaluation in 2021.

V. Conclusion

In this paper, we identified and analyzed several factors that affect taxi times on the surface at airports within D10 airspace. We began by describing the D10 TRACON and summarizing terminal resections like MIT and fix closures which are used to meet demand that exceeds capacity at the terminal boundary. We also summarized how NTML logs have been used to communicate and coordinate initiatives across facilities and what their shortcomings were. We then summarized how NASA's ATD-2 sub-project worked closely with FAA and stakeholders in D10 to create consistently reliable terminal restriction data for the TRACON. We looked at a six-month period using ATD-2 data to show that a significant fraction of traffic at DFW and DAL is subject to MIT and fix closure on most days.

Next, we created an ML model using ATD-2 data to identify what factors play a significant role in driving the delay on airport surface when restrictions are present on the terminal boundary. Our ML model identified runway operations volume and percentage of restricted operations per unit time as the most important factors.

We did an in-depth analysis of our data to understand why these features are important. The results of our analysis agreed with our ML model. We showed that operations volume decreases as the restricted demand increases. This decrease in runway operations also adversely affects surface delay as flights must wait longer in the runway queue. The worst delays are observed when there are multiple restricted flights using the same runway. We established that there is a clear relation between surface delay and TMIs applied at terminal boundary, like MIT.

Finally, we introduced TOS reroute capability developed in ATD-2 Phase 3 and currently deployed at D10 metroplex for field evaluation as a solution to reduce delays under terminal restrictions by rerouting flights over an alternative fix by assessing delay savings on alternative routes.

Appendix

local_minute_of_day: Minute of the day in local time.

count_total_15_min_bin_mod: Count of all flights taking off from the same runway in 15-minute window prior to OFF.

count_restricted_15_min_bin_mod: Count of MIT restricted flights taking off from the same runway in 15-minute window prior to OFF.

perc_restricted_15_min_bin_mod: Percentage of MIT restricted flights taking off from the same runway in 15-minute window prior to OFF.

count_total_30_min_bin_mod: Count of all flights taking off from the same runway in 30-minute window prior to OFF.

count_restricted_30_min_bin_mod: Count of MIT restricted flights taking off from the same runway in 30-minute window prior to OFF.

perc_restricted_30_min_bin_mod: Percentage of MIT restricted flights taking off from the same runway in 30-minute window prior to OFF.

fix_closure_tmi_count: Count of fix closure TMIs present at OFF.

mit_restriction_ids_present_at_off_True: One hot encoding variable indicating no MIT restrictions were recorded for the flight at takeoff.

mit_restriction_ids_present_at_off_False: One hot encoding variable indicating no MIT restrictions were recorded for the flight at takeoff.

departure_runway_actual_17R: One hot encoding variable indicating use of runway 17R for departure.

departure_runway_actual_18L: One hot encoding variable indicating use of runway 18L for departure.

departure_runway_actual_35L: One hot encoding variable indicating use of runway 35L for departure.

departure_runway_actual_36R: One hot encoding variable indicating use of runway 36R for departure.

flow_North: One hot encoding variable indicating North flow operations

flow_South: One hot encoding variable indicating South flow operations.

departure_gate_actual_NORTH: One hot encoding variable indicating use of North terminal gate for departure.

departure_gate_actual_EAST: One hot encoding variable indicating use of East terminal gate for departure.

departure_gate_actual_WEST: One hot encoding variable indicating use of West terminal gate for departure.

departure_gate_actual_SOUTH: One hot encoding variable indicating use of South terminal gate for departure.

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