Extrapolating the Sustainability Benefits of Collaborative Digital Departure Reroute

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A method for extrapolating the benefits and delay savings of NASA's Collaborative Digital Departure Reroute (CDDR) technology to major terminal areas across the National Airspace System is developed and initial results presented for a year's worth of flight departures for 10 of the busiest terminal areas in the US. Features related to route options, delay, and weather impact are derived from Coded Departure Routes (CDR) and Aviation System Performance Metrics (ASPM) and used to predict the counts of CDDR proposed flight reroutes. Machine Learning (ML) and Linear Regression models are independently developed and trained on a year of data from CDDR deployed at the Dallas Fort-Worth terminal. Similarity in yearly count prediction trends between these two models when applied across 10 terminal areas lends confidence to the methodology. Estimates of delay per flight for each terminal area are then combined with the CDDR reroute count predictions to derive yearly benefits in terms of delay and fuel savings.

I. Nomenclature

A	=	alpha feature flight set
$D_{c,l}$	=	delay feature flight set with delay category c and threshold of l minutes
$d_c(F)$	=	average category c delay of flight set F
$n(F)$	=	number of flights in flight set F
R_l	=	route options feature flight set with l alternate routes
$S_{c,l}$	=	delay savings feature flight set with delay category c and threshold of l minutes
$s_c(F)$	=	average delay savings (category c – Airborne Delay) of flight set F
T	=	set of total flights
$W_{c,l}$	=	weather impact feature flight set with category c and impact level l

II. Introduction

NASA's Digital Information Platform (DIP) [1] provides users with easy, reliable, and secure cloud-based access to integrated flight data, convective weather, turbulence, airspace restrictions and airspace services that rely on this information. Collaborative Digital Departure Reroute (CDDR) [2] is a decision support service deployed on NASA's DIP to demonstrate and accelerate digital transformation of airspace operations. CDDR supports the tactical pre-departure reroute decision process by predicting delay savings on each alternative route in the flight operator's Trajectory Option Set (TOS) and proposing candidate reroutes when the predicted delay savings exceeds flight operator defined thresholds. Flight operators and Air Traffic Control (ATC) may then evaluate the candidate reroutes for submission and approval with the goal of reducing delay and fuel burn. NASA implemented CDDR for field evaluation [3] at the D10 Terminal Radar Approach CONtrol (TRACON) in the North Texas Metroplex in

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November 2020. Since then, the system has continued to evolve and yield delay and fuel savings benefits for NASA's airline partners operating in D10. American Airlines and Southwest Airlines, who both operate major hubs in D10, use CDDR daily to assist in pre-departure reroute planning and coordination.

DIP will continue to develop decision support services for other phases of flight in the future and NASA will perform operational evaluations of these services in the field with a focus on efficiency improvement and enabling autonomous operations. To realize the full potential value and impact of these services, it is important to establish a mechanism and process to extrapolate the benefits over the entire NAS. The present work focuses on developing such a process for CDDR.

An effort was initiated to extrapolate the benefits of CDDR to other TRACONs and estimate NAS-wide benefits. Early attempts to extrapolate CDDR benefits relied on airspace restriction data from National Traffic Management Log (NTML) via FAA's System Wide Information Management (SWIM) system to predict the number of flights that would take advantage of a CDDR proposed TOS reroute in response to Miles-In-Trail (MIT) and fix closures at other TRACONs across the NAS. However, it was discovered that reliable restriction data is not widely available. There are issues with consistency and timeliness of how ATC staff from different facilities manually enter restrictions into NTML. Restriction nomenclature varies between facilities making the data difficult to parse. Some restrictions are missed because ATC staff are busy or differences in data entry procedures result in this data being entered in a different place such that the information does not get distributed via SWIM. Therefore, a new method of CDDR benefit extrapolation using more reliable and consistent NAS-wide data sources was developed, which is the focus of this paper.

This paper presents an extrapolation of CDDR benefits to 10 of the busiest TRACONs using Coded Departure Routes (CDR), Aviation System Performance Metrics (ASPM) data, and Machine Learning (ML) modelling. Section III gives an overview of the general approach and various data sources utilized. Section IV details the development of generic TRACON features from these data sources. Section V describes how a ML model and Linear Regression model were developed and trained on D10 field data and compares the resulting predictions of numbers of flights that would utilize CDDR reroutes at the other TRACONs. Delay, fuel, and cost savings metrics per flight are described and yearly extrapolation results are presented in Section VI. Finally, Section VII presents conclusions and next steps.

III. General Approach and Data Sources

The general approach to extrapolating benefits of CDDR to other TRACONs is depicted in Figure 1. Benefits are extrapolated by combining estimated benefits per CDDR rerouted flight with predicted numbers of flights rerouted at various TRACONs. The ML model trained on D10 CDDR field data processes generic TRACON features into predicted numbers of CDDR rerouted flights per TRACON. Various data sources (discussed in the subsections below) are processed to develop the TRACON features and estimated benefits per rerouted flight.

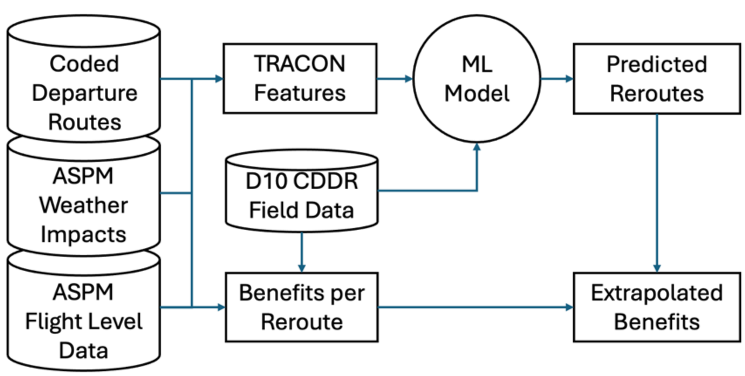

Figure 1 Benefits Extrapolation Approach

A. D10 CDDR Field Data

A year of D10 TOS Activity Reports were analyzed between May 1, 2022 and April 29, 2023 to extract numbers of CDDR rerouted flights as targets to train the ML model. These reports include, on a flight-by-flight basis, a record for each TOS route that CDDR presents to the flight operator as a candidate reroute for that flight. Only a subset of candidate reroutes is submitted by the flight operator to ATC, and only a further subset of submitted are approved by ATC for implementation. Other information helps identify the benefit use case of each Candidate. These include flags indicating whether the flight was subject to a MIT and/or Fix Closure. Any record subject to MIT or Fix Closure, either before or at the gate out event, was categorized as Traffic Management Initiative (TMI), with all others categorized as non-TMI. Records also include estimated surface delay savings, additional flight time, and estimated fuel savings from the proposed reroute. It is possible for CDDR to propose multiple TOS routes for the same flight, each recorded separately. Therefore, records were filtered to only one per flight, selecting the Submitted or Approved record, or otherwise the Candidate record proposing the shortest TOS reroute.

B. Coded Departure Routes

In its current implementation, CDDR uses only existing Coded Departure Routes (CDRs) as potential TOS reroutes for each flight. CDRs are predefined route options between busy origin-destination pairs, designed to mitigate adverse impacts of severe weather or other NAS constraining events. Over 35,000 CDRs departing over 140 airports NAS-wide have been defined [4] including airports within most of the busiest TRACONs. The top 10 busiest TRACONs with defined CDRs were selected for study in order of number of Air Carrier IFR Itinerant Operations between May 1, 2022 and April 29, 2023 extracted from the Operations Network (OPSNET) TRACON Operations Standard Report [5]. Figure 2 shows the top 12 busiest TRACONs (bubble size indicates relative number of operations), two of which do not have any CDRs (NCT and S46 shaded red), leaving the top 10 TRACONS with CDRs selected (shaded in green).

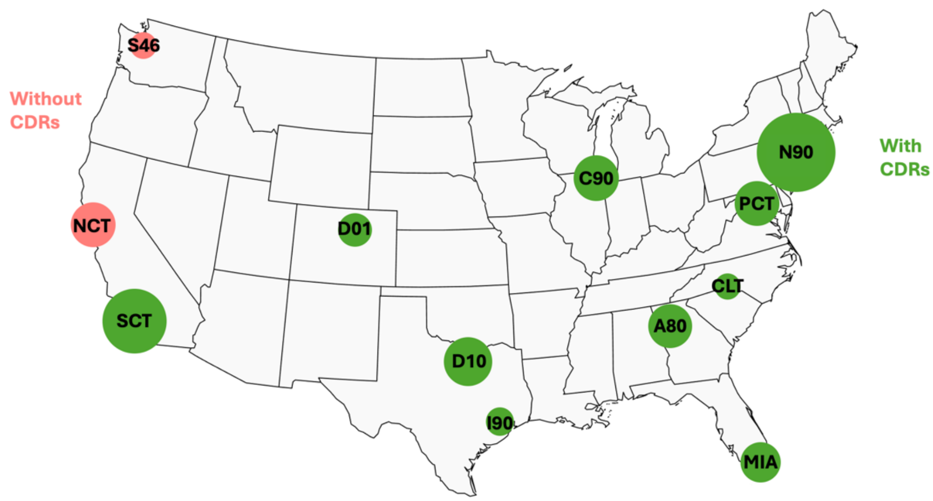

Figure 2 Top 12 busiest TRACONs with (green) and without (red) CDRs

C. Aviation System Performance Metrics

Aviation System Performance Metrics (ASPM) [6] provides data tracking specific airports and carriers operating within the United States. ASPM tracks 77 airports and 27 Carriers encompassing a vast majority of the NAS operations. ASPM offers a wide variety of analysis reports and database download options. This study utilizes the Weather Factors Details Report and the Flight Level Data Download. The Weather Factors Details Report provides data about the hourly impact of weather factors on specified airports. The Flight Level Data Download provides individual flight information and event data including gate out, takeoff, landing, and gate in times and delays.

IV. TRACON Feature Development

Categories of features related to route options, delays, and weather impacts were developed. The features were designed generically to be applicable to any TRACON with CDRs and included in ASPM. For each TRACON, flights from ASPM Flight Level Data were grouped into flight sets meeting various route option, delay, and/or weather impact criteria discussed in the subsection below. The features are then calculated as counts of flights or average delays of these feature flight sets, binned by day or week according to flight plan gate departure time. For a given flight set $F[t]$ belonging to time bin t, let $n(F[t])$ be the number of flights in the set, and let $d(F[t])$ be some average delay for all fights in the set.

A. Route Options

The CDRs that CDDR considers for reroute generally exit the TRACON in clusters referred to as departure Gates. Each Gate includes one or more departure fixes exiting the TRACON in the same general direction. When a flight's filed route is impacted by a MIT or Fix Closure, it is assumed that other routes using the same Gate may be impacted as well. Therefore, only CDRs departing via Gates other than that of the filed route (referred to as Alternate Gates) are considered as reroute options. A set of feature criteria was designed to capture sets of flights with various numbers of Alternate Gates available to them.

CDRs departing each TRACON were analyzed to define departure Gates and assign each CDR to a Gate. CDRs departing the major airport(s) within each TRACON were plotted and visually clustered to define an approximate bearing for each Gate from the TRACON center (largest major airport). Let *DepFix40* refer to the CDR fix closest to 40 nautical miles (nmi) from the TRACON center. Each CDR was then assigned to the Gate with closest bearing to the CDRs *DepFix40*. With the major airport Gates established, CDRs departing all other airports within the TRACON were assigned to a Gate similarly and plotted to visually verify, adjusting Gate bearings and manually reassigning individual CDRs if needed. Figure 3 shows a CDR Gate assignment for C90, showing just the CDRs for the major airport ORD in 3(a) and all CDRs in 3(b). The 40 nmi radius circle centered at ORD helps visually identify clusters of departure fixes along each CDR closest to the circle boundary (*DepFix40*). The large arrows identify bearings selected for Gates. Although C90 has the greatest number of airports with CDRs in this study, all airports are contained within the 40 nmi radius circle and utilize one or more of the defined Gates in a compact well-structured manner.

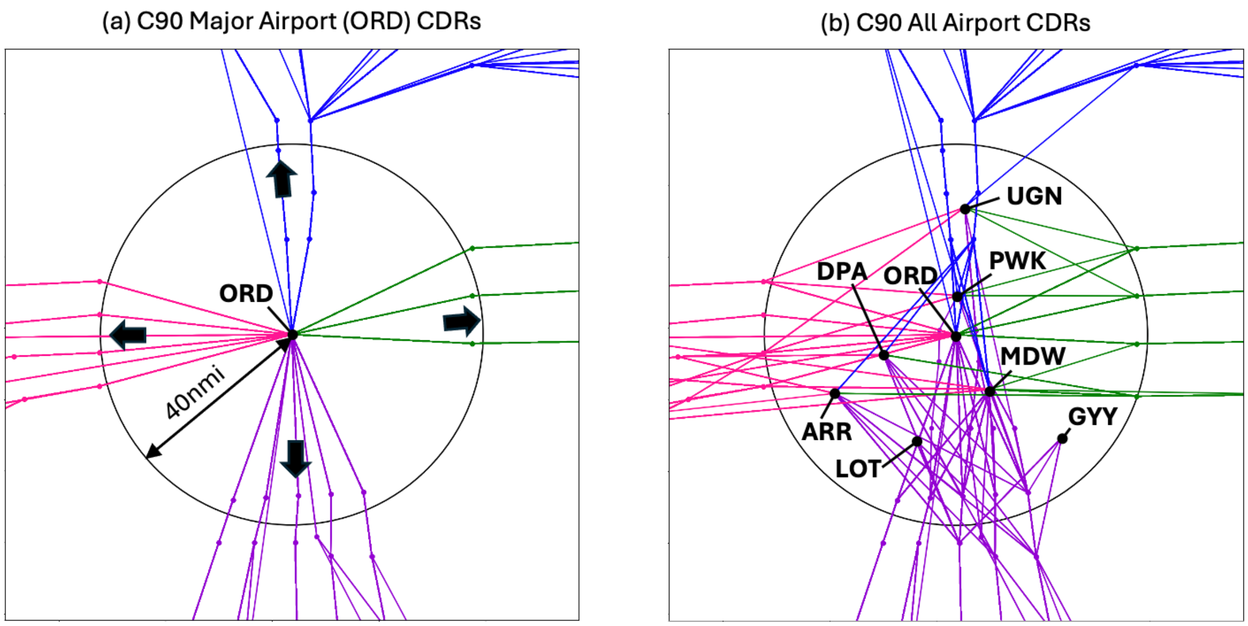

Figure 3 C90 CDR Gate Assignment

For contrast, SCT CDT Gate assignment is shown in Figure 4. SCT is much larger than the other TRACONs necessitating the use of 120 nmi rather than 40 nmi to identify departure fixes. Therefore, *DepFix120* was used to assign bearing and closest Gate. LAX CDRs also take much more direct routes to the enroute phase of flight than most other CDRs. Only when all SCT airports are plotted do some structural patterns in the routes emerge.

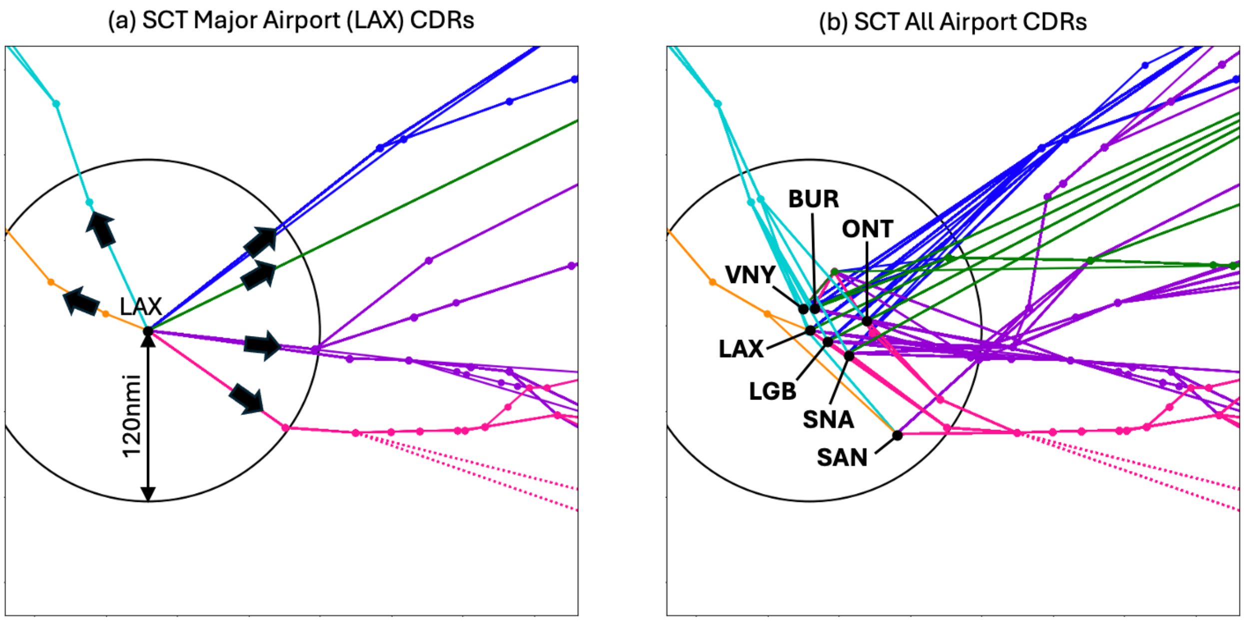

Figure 4 SCT CDR Gate Assignment

Table 1 lists the major and other airports with CDRs included in each TRACON, as well as the number of Gates defined, and number of arrival airports served by the CDRs. Note that the Rank skips TRACONs without CDRs (NCT at rank 5 and S46 at rank 11).

Table 1 TRACON CDR Airports and Gates

Rank	TRACON Code	TRACON Name	Major Airport(s)	Other Airports Included	Num Gates	Num Arr Apts
1	N90	New York	JFK, EWR, LGA	HPN, ISP, SWF, TEB	5	102
2	SCT	Southern California	LAX	SAN, SNA, ONT, BUR, LGB, VNY	6	50
3	D10	North Texas	DFW	DAL	4	171
4	C90	Chicago	ORD	MDW, GYY, UGN, PWK, LOT, DPA, ARR	4	181
6	PCT	Potomac	DCA, BWI, IAD	ADW, HEF	5	206
7	A80	Atlanta	ATL		4	183
8	MIA	Miami	MIA	FLL, FXE, OPF, PMP, TMB	7	82
9	D01	Denver	DEN	BJC, APA	4	257
10	I90	Houston	IAH	HOU	6	140
12	CLT	Charlotte	CLT		5	138

Figure 5 visually compares the resulting CDR Gate structures of the top 10 TRACONs with CDRs, where CDRs belonging to different Gates are differentiated by color. Only the major airport(s) CDRs are plotted to reduce clutter. Four of the TRACONs (D10, D01, A80, C90) display a 4-spoke structure, oriented north-south-east-west (N-S-E-W). I90 and CLT display similar CDR clustering, only expanding into in a more radial structure with more Gates. N90 and PCT are Metroplexes containing multiple major airports in proximity. SCT and MIA display radial patterns of mostly single direct routes making up a Gate rather than a cluster of routes.

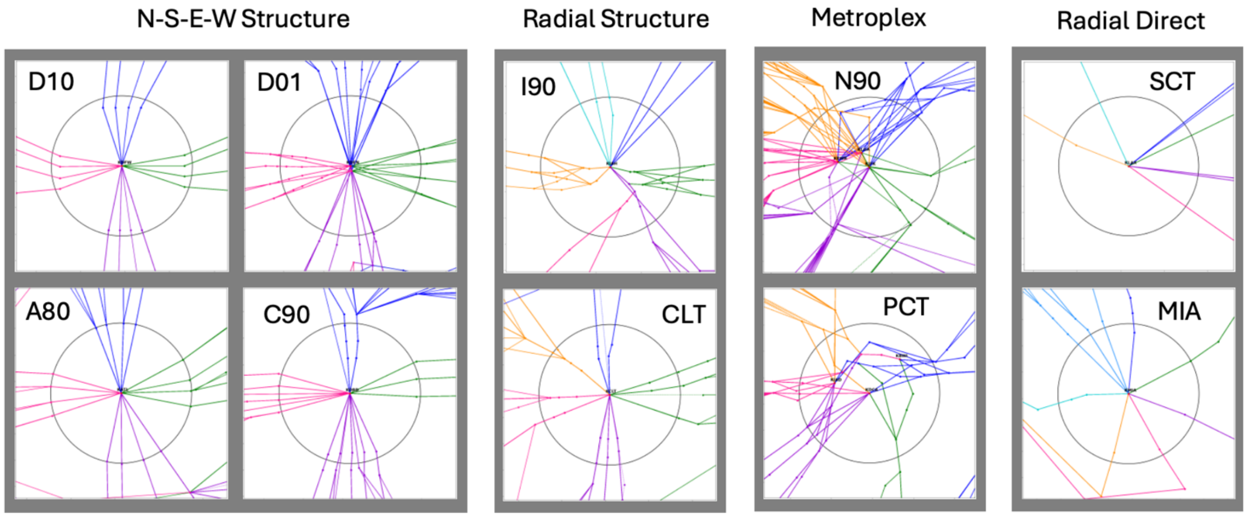

Figure 5 TRACON CDR Gate Structure Comparison

Once all CDRs are assigned to a Gate, the number of Alternate Gates available to a given origin-destination city pair is the total number of Gates assigned to CDRs between the city pair minus one (the filed route Gate). Each flight is assigned a number of Alternate Gates based on its origin-destination extracted from ASPM Flight Level Data. Let route option feature flight sets R_0, R_1, R_{1+}, and R_{2+}, include flights with 0, 1, 1 or more, and 2 or more Alternate Gates. R_0, R_1, and R_{2+} are distinct sets, whereas $R_{1+} = R_1 \cup R_{2+}$.

B. Delays

Several delays are collected or estimated for each flight enabling computation of an average delay feature for each feature flight set. ASPM Flight Level Data includes delays computed from various scheduled and actual event times from origin gate out to destination gate in. As CDDR aims to save surface delay, all delays having to do with surface or departure were extracted from ASPM Flight Level Data for feature development. These include Gate Out Delay, Taxi Out Delay, and Expected Departure Clearance Time (EDCT) Departure Delay defined as GATE_DELAY, DELAY_TO, and EDCT_HOLD, respectively in the ASPM definition of variables [7]. Additionally, let Off Delay = Gate Out Delay + Taxi Out Delay. CDDR would view any surface delay a reroute could potentially avoid as a delay savings.

For any flight in R_{1+}, an Airborne Delay was calculated as the notional difference in flight time between an assumed Primary and Alternate CDR for the flight's city pair. For this study, the Primary CDR is assumed to be the shortest CDR for the city pair. The Alternate CDR is assumed to be the shortest CDR using a different Gate than that of the Primary CDR. Airborne delay is then calculated as (alternate route distance - primary route distance) / nominal cruise speed for the flight's aircraft type. CDDR would view this airborne delay as additional flight time incurred by the reroute, or a delay expense rather than a savings.

For any given flight set F, let $d_c(F)$ be the average Delay, where the delay categories c in {*Gate*, *Taxi*, *EDCT*, *Air, Off*} represent Gate Out, Taxi Out, EDCT Departure, Airborne and Off Delay, respectively. Because Airborne Delay can be calculated only for flights in R_{1+}, $d_{Air}(F)$ may be applied only to R_{1+} flight sets or subsets.

In addition to computing delay features, delays were used to develop feature flight sets comprised of flights meeting defined delay or savings threshold criteria. Let delay feature flight set $D_{c,l}$ include flights where delay category c is greater than l minutes. For example, $D_{Gate,15}$ is the set of flights where Gate Out Delay > 15min. Delay savings features subtract airborne delay expense from surface delay savings to get a net savings. Let delay savings feature flight sets $S_{c,l}$ include flights where (delay category c – Airborne Delay) is greater than l minutes. For example, $S_{Off,0}$ is the set of flights where Off Delay – Airborne Delay > 0min. An average delay savings feature $s_c(F)$, which is the average delay saved (c-Airborne Delay) for the set of flights, may be applied only to delay savings S flight sets and subsets.

C. Weather Impacts

ASPM Weather Factors Details Report were collected for each TRACON including hourly weather impact statistics for each airport with CDRs (major and other airports listed in Table 1) between May 1, 2022 and April 29,

2023. Any airport not included in ASPM77 was assumed to have the same hourly statistics as the TRACON's largest major airport. Weather impact statistics include an impact level of None, Minor, Moderate, or Severe for the following weather impact categories: OPSNET Weather Delays (*OPSNET*), Airport Weather (*Apt*), Nearby Thunderstorms (*NearbyTS*), Enroute Thunderstorms (*EnrouteTS*), and Overall (*Overall*). A weather impact feature flight set includes all flights with flight plan gate departure time during an hour when its airport has the given impact level defined for the given impact category. Weather impact feature flight sets $W_{c,l}$ were generated for all impact categories c in {*OPSNET*, *Apt*, *NearbyTS*, *EnrouteTS*, *Overall*} paired with the following permutations of impact level l: Minor (*Min*), Moderate (*Mod*), Severe (*Sev*), Minor or Moderate or Severe (*Min+*), Moderate or Severe (*Mod+*), and Minor or Moderate (*MinMod*). For example, $W_{NearTS,Mod+}$ is the set of flights with flight plan gate departure time during an hour when its airport has an impact level of Moderate or Severe for category Nearby Thunderstorms.

D. Feature Combination

Several combined feature flight sets were generated for inclusion in the ML model by taking the intersection or union of two or more of the feature flight sets discussed in the above subsections. A combined weather impact category $AnyTS = NearbyTS \cup EnrouteTS$ was paired with the same impact level permutations as the rest of the weather categories. Also, two intersections of delay savings and weather impact feature flights sets were generated: $W_{AnyTS,Min+} \cap S_{Off,l}$ for l in $\{0,15\}$. Following ML model development, additional combinations of feature flight sets (discussed in Section V) were generated to manually refine a feature for a Linear Regression model with which to compare ML model results and estimate delay benefits.

V. Prediction Model Development

The goal of the ML model is to predict the number of CDDR rerouted flights from the TRACON features developed. Because target data for model training is available only for D10, it is impossible to validate the extensibility of the D10 trained ML model to other TRACONs without actual field data. Also, it can be difficult to explain why the ML model finds some features more important than others. Therefore, a Linear Regression model was developed independently by manually refining a single feature flight set combining previously defined intuitively important feature flight sets to achieve higher linear correlation, to serve as a more explainable alternative to the ML model. Then the results for the ML and Linear Regression models applied to the top 10 TRACONs are compared.

A. D10 Targets

The prediction model is trained on D10 using Field Data as targets. There were several options for targets including numbers of Candidates, Submitted, and Approved, in addition to subdivisions of these categories into TMI and non-TMI. Table 2 shows the total number of flights and percentage of days and weeks with flights in each of these categories between May 1, 2022 and April 29, 2023. The number of Approved reroutes provides the most accurate number of CDDR rerouted flights. However, with a total of only 59 Approved CDDR reroutes occurring within only 8% of days, this dataset is too sparse to train a prediction model. CDDR reroutes are Submitted only about twice as often as Approved with 115 Submitted occurring within 12% of days. Number of Candidates offered the largest set of targets (1188 within 49% of days) on which to train a prediction model. Three outliers with extremely high number of Candidates (none of which were Approved) relative to other days were removed from the dataset.

Table 2 D10 Target Categories

	Total Number of Flights			Percent Days with Flights			Percent Weeks with Flights		
	TMI	**non-TMI**	**Total**	**TMI**	**non-TMI**	**Total**	**TMI**	**non-TMI**	**Total**
Candidate	922	266	1188	31%	35%	49%	85%	87%	90%
Submitted	70	45	115	7%	9%	12%	40%	46%	58%
Approved	32	27	59	5%	5%	8%	31%	25%	44%

As initial attempts to train a ML model on daily Candidate counts yielded poor results, the features and target data sets were aggregated weekly (after removing the 3 daily outliers) which improved the density of data points with target Candidates from 49% of days to 90% of weeks with Candidates.

B. Machine Learning Model

Features and targets were preprocessed by dividing each value by an appropriate total flight count or average resulting in fractional features and targets ranging between 0 and 1. Let T be the total set of TRACON departure flights extracted from ASPM Flight Level Data which is a superset of all other flight sets. All $n(F)$ features were divided by $n(T)$. All $d_c(F)$ features were divided by $d_c(T)$. Operations $d_{Air}(T)$ and $s_c(T)$ cannot be calculated because T as the superset of all fights cannot be a subset of R_{1+} which is required to compute Airborne Delay. Therefore, all $d_{Air}(F)$ and $s_c(F)$ features were divided by ($d_{Gate}(T) + d_{Taxi}(T) + d_{EDCT}(T)$). All targets (counts of TMI, non-TIM, and total Candidates) were divided by $n(R_{1+})$ as flights without route options cannot be considered for candidacy. Table 3 lists all the unitless features used to develop the ML model, totaling 63 features.

Table 3 Unitless Features for ML Model Development

Unitless Features	Permutations
$n(R_l)/n(T)$	$l \in \{0, 1, 1+, 2+\}$
$d_c(R_l)/d_c(T)$	$c \in \{Gate, Taxi, EDCT\}$ $l \in \{0, 1, 1+, 2+\}$
$d_{Air}(R_l)/(d_{Gate}(T)+d_{Taxi}(T)+d_{EDCT}(T))$	$l \in \{1, 1+, 2+\}$
$n(D_{c,15})/n(T)$	$c \in \{Gate, Off\}$
$n(S_{Off,l})/n(T)$	$l \in \{0,15\}$
$n(W_{c,l})/n(T)$	$c \in \{OPSNET, Apt, NearbyTS, EnrouteTS, AnyTS, Overall\}$ $l \in \{Min, Mod, MinMod, Min+, Mod+, Sev\}$
$n(W_{AnyTS,Min+} \cap S_{Off,l})/n(T)$	$l \in \{0,15\}$
$s_{Off}(W_{AnyTS,Min+} \cap S_{Off,l})/(d_{Gate}(T)+d_{Taxi}(T)+d_{EDCT}(T))$	$l \in \{0,15\}$

After experimenting with several ML model types, Gradient Boost was selected for consistently outperforming other models. Best results were achieved by training two separate ML models using weekly TMI and non-TMI Candidate flights as targets and then summing the results. For each target, ten-fold cross validation was performed. In each fold, a Gradient Boost model was generated using the training data and all 63 features from which the top 10 most important features were selected. Figure 6 identifies the most important features selected for the TMI and non-TMI Candidate models.

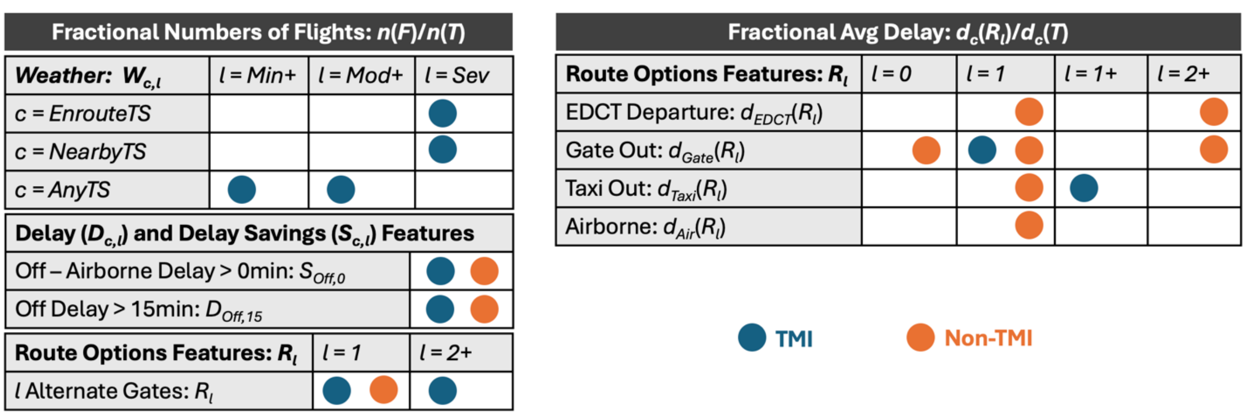

Figure 6 Most Important Features for TMI and non-TMI Candidate ML Models

Weather impact features were important only for the TMI model, whereas average delays were most important for the non-TMI model. This makes sense as most TMIs are initiated in response to weather events, making weather important to the TMI model. The non-TMI Candidates are identified more for efficiency rather than weather avoidance, making delays more important to the non-TMI model. Both models found counts of flights exceeding off delay and delay savings thresholds important. The delay threshold features $n(D)$ identify an inefficiency, whatever the cause, and the delay savings threshold features $n(S)$ ensure that a short enough reroute exists that can mitigate the inefficiency. Both models found counts of flights with route options important as there can be no candidates for reroutes without the existence of alternate routes.

Ten-fold cross validation was performed on models trained on the D10 field data for TMI and non-TMI candidates separately. At each fold of the cross validation, an initial Gradient Boost model was generated using the training data and all 63 features and basic hyperparameters. The top 10 most important features were selected based on that initial model. Hyperparameters for the Gradient Boost model were then tuned using a grid search function and the training set with only the top 10 features. The feature set was trimmed to speed up the process of tuning hyperparameters. The best model was selected and used to generate predictions for the D10 test set and saved to be applied to other TRACONs. Prediction values reported for D10 combine predictions of the hold out observations for each fold using the model built on the associated training set (not including the hold out observations). All ten models produced during cross validation were saved and applied to the other TRACONs. The weekly predictions for each of the other TRACONs were generated by averaging the individual predictions across all ten models for each weekly prediction. Finally, the TMI and non-TMI predictions were added together to get total predicted Candidates.

C. Linear Regression Model

Linear Regression model development focused on refining a single feature combining route options, delay savings, and weather impact correlating with total Candidate counts, regardless of whether they were TMI or non-TMI. A flight count feature rather than an average delay feature was desired as the target was also a flight count. Features and targets were aggregated daily rather than weekly, ignoring days with no D10 TOS Activity Reports.

Figure 7 shows the correlations of all $n(W)$ with Candidates. The highest correlating cross section of categories *NearbyTS* and *AnyTS* with impact levels *Min+*, *Mod+*, and *Sev* were selected for further consideration.

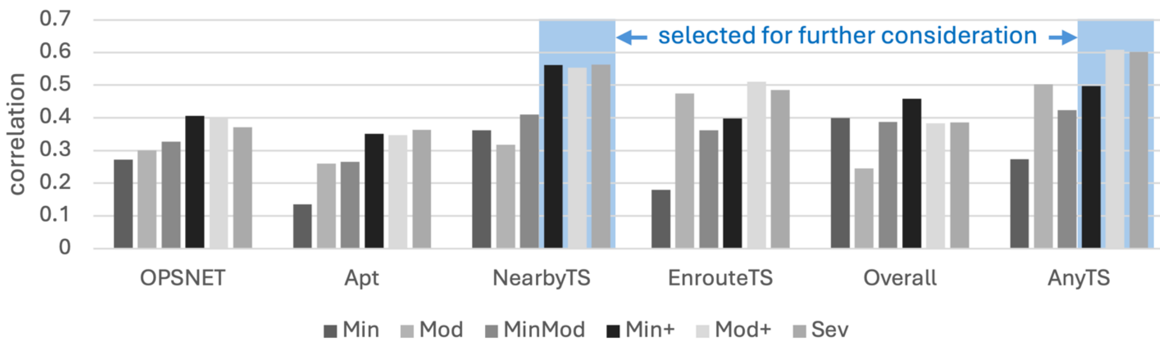

Figure 7 Weather Impact Feature Daily Flight Count Correlation with Candidates

Route option flight count features $n(R)$ did not correlate well with Candidates (all ~ -0.1). Of the average delay features $d(R)$, taxi delay $d_{Taxi}(R)$, features correlated by far the best (0.39-0.46). Because a flight count feature was desired, additional delay and delay savings threshold flight sets incorporating Taxi Delay, $D_{Taxi,l}$ and $S_{Taxi,l}$, and a finer range of thresholds, l in {0, 5, 10, 15},were explored. Figure 8 shows the correlations of all $n(D_{Off,l})$, $n(D_{Taxi,l})$, $n(S_{Off,l})$, and $n(S_{Taxi,l})$ with Candidates. The Delay and Delay Savings flight count correlations using Taxi Delay are consistently higher than those using Off Delay. Delay Savings features are preferred over Delay features as they incorporate aspects of route options by using Airborne Delay which can only be calculated for R_{1+}. Therefore, all Taxi Delay Savings $n(S_{Taxi,l})$ features were selected for further consideration.

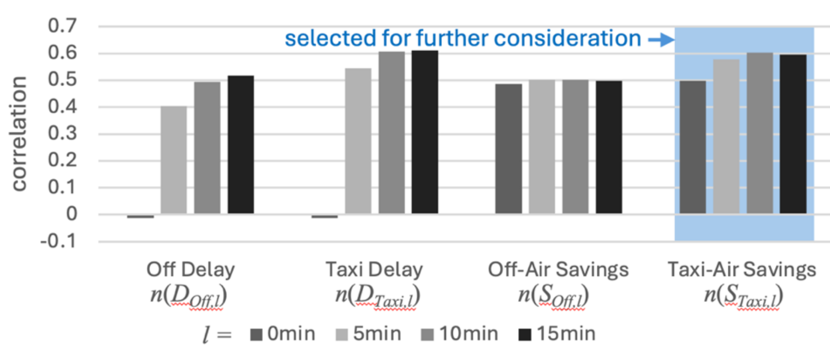

Figure 8 Delay and Delay Savings Feature Daily Flight Count Correlation with Candidates

Finally, all intersections between the selected Weather Impact features and Taxi Delay Savings features were compared to identify the highest correlating feature with Candidates. Figure 9 shows the correlations of the combined feature finalists with Candidates. The highest correlating flight count feature combines weather category *AnyTS* of impact level *Mod+* with Taxi Delay Savings > 0min. Let this Alpha feature flight set $A = W_{AnyTS,Mod+} \cap S_{Taxi,0}$.

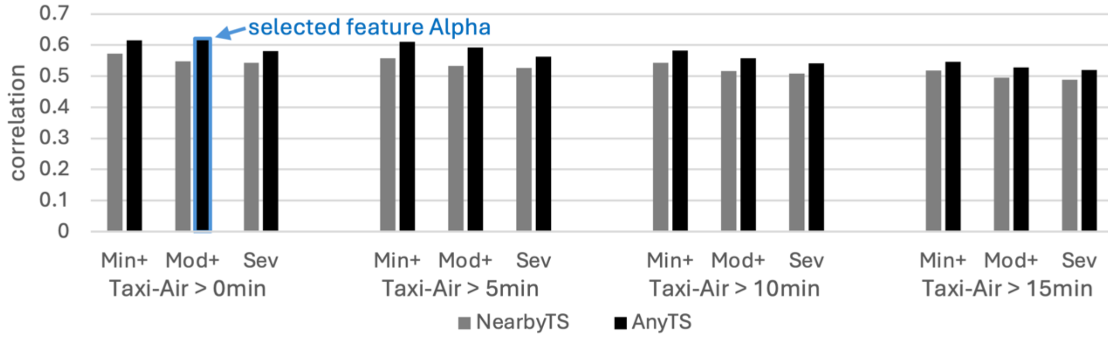

Figure 9 Combined Feature Daily Flight Count Correlations with Candidates

Figure 10 shows how the flight count is impacted at each stage of feature flight set refinement. Flight set R_{1+} is shown as the maximum set of flights that could reroute by virtue of having at least one route option available through an alternate Gate, of which $S_{taxi,0}$ is a subset. TRACONs are presented in order of OPSNET rank from Table 1 and the Total flight counts follow a similar trend with some small differences due to counting only departures and possibly accounting for different subsets of airports within each TRACON. However, the order of TRACON R_{1+} flight counts drastically changes. Most notably, SCT with 2nd highest Total, drops to the lowest R_{1+} count. Upon closer inspection of SCT CDRs, only flights to the East have alternate Gates, leaving flights to San Francisco and Seattle with only one route option. SCT also has one of the lowest Weather Impact flight counts. Therefore, it is not surprising that SCT's Alpha flight count is so low as to be almost invisible.

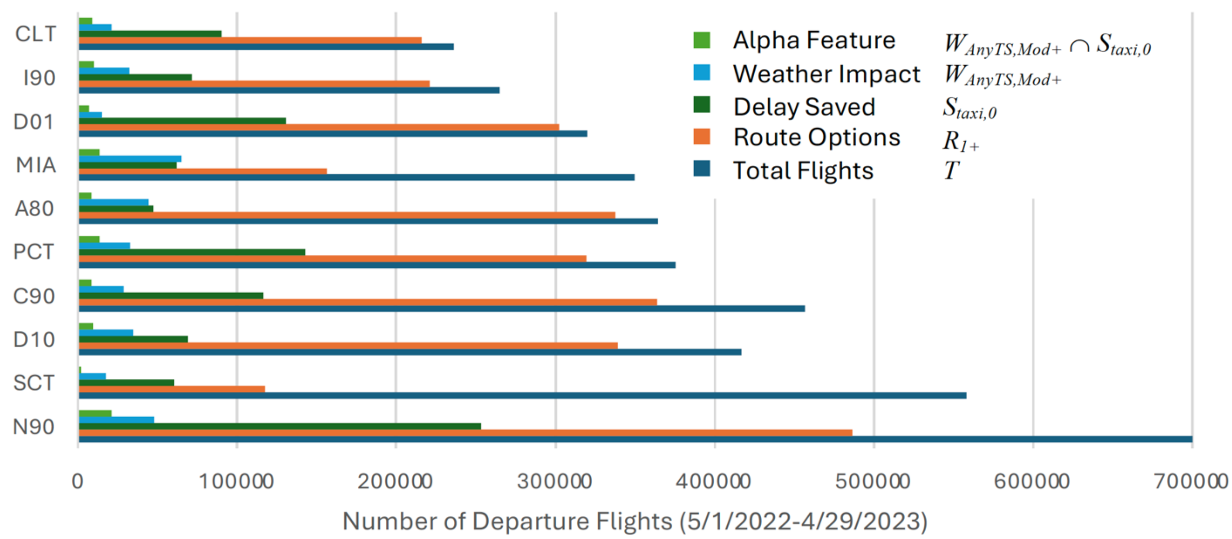

Figure 10 Feature Refinement Flight Count Comparison by TRACON

The zero-intercept linear regression between daily $n(A)$ and D10 Candidates generated a slope of 0.0829. The Linear prediction of candidates $0.0829n(A)$ results in a root mean squared error (RMSE) of 6.21 flights daily or 14.52 flights weekly when compared to D10 Candidates.

D. Model Comparison

Figure 11 compares the weekly Candidate prediction performance of the ML and Linear models. The ML model performs 11% better with a RSME of 12.97 weekly flights vs the Linear model's RSME of 14.51. Both models tend to underpredict more when Candidate counts are higher.

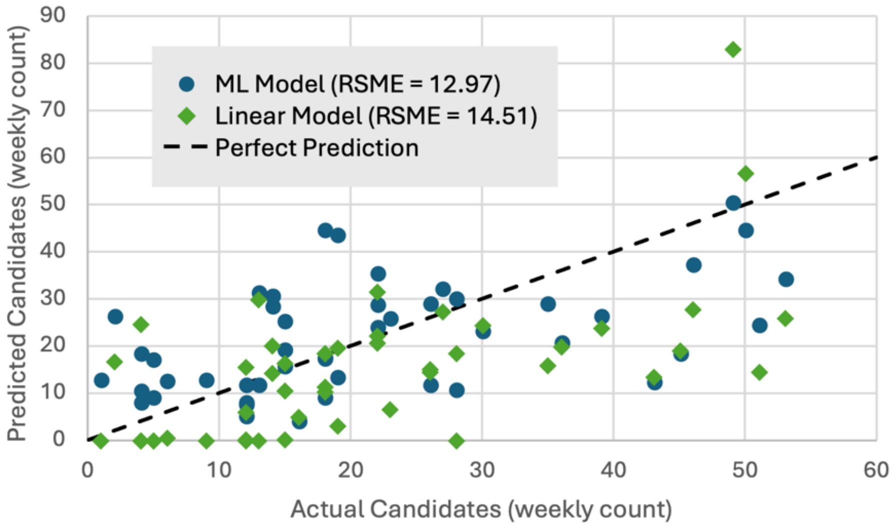

Figure 11 ML and Linear Model Precited vs Actual Weekly Candidates

The ML and Linear models were applied to all 10 TRACONs and predictions summed to get a yearly number of Candidates. Figure 12 compares the ML and Linear model predicted yearly Candidates by TRACONs. The total predicted yearly Candidates for all 10 TRACONs is shown on the right. In general, the two models follow similar trends between TRACONs with a total difference of about 20%. The ML model predicts about twice as many Candidates for C90 (Chicago), A80 (Atlanta), and D01 (Denver) and about half as many Candidates for MIA (Miami) as the Linear model. C90, A80, and D10 all have highly structured N-S-E-W spoked CDRs which may have been a factor in the ML model favoring these TRACONs. MIA stands out as having by far the greatest percentage of flights impacted by thunderstorms as can be seen by comparing the Weather Impact flight count in Figure 10. Perhaps the ML model places less emphasis on Weather Impact features than the Linear model imposes via the Alpha feature.

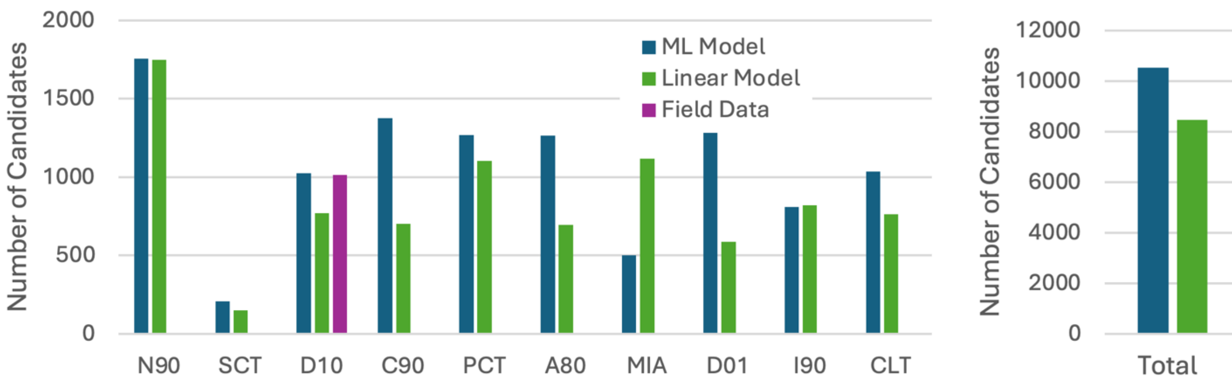

Figure 12 ML and Linear Model Precited Yearly Candidates by TRACON

The ML model's lower RSME suggests that this is the better model. The Linear model serves as a useful measuring stick to gauge the ML model validity in the absence of field data from multiple TRACONs.

VI. Estimating Benefits

CDDR benefits, including delay, cost, and fuel savings are derived from combinations of estimated Taxi Out Delay Savings, Airborne Delay Expense, and System Delay Savings per rerouted flight [8]. Taxi Out Delay Savings and Airborne Delay Expense (previously defined in Section IV.B.) per rerouted flight are estimated as 10% trimmed mean delays from the *A* feature flight set for the entire year (May 1, 2022– April 29, 2023), for each TRACON. These are compared to 10% trimmed mean Taxi Out Delay Savings and Airborne Delay Expense from the R_{1+} feature flight set and from D10 Field Data. In D10 TOS Activity Reports, Taxi Out Delay Savings and Airborne Delay Expense are logged as "Estimated TOS route (rte) OFF delay savings at OUT (min)" and "TOS rte notional additional (addl) flight time at OUT (min)", respectively.

System Delay Savings is notional surface delay saved by other flights in the system staying on their filed routes, that may benefit from the rerouted flight's new route and takeoff time. CDDR uses a surface prediction engine to estimate the impact of a proposed flight reroute to takeoff times for all flights with unimpeded takeoff time within 60 min after the flight proposed for reroute, the sum of which is the System Delay Savings due to the proposed reroute. In the absence of surface prediction engines for the other TRACONs, the 10% trimmed mean of D10 Filed Data System Delay Savings is used for all TRACONs. D10 TOS Activity Reports log the sum of Taxi Out Savings and System Delay Savings as Aggregated Delay Savings or "Agg OFF delay savings metroplex at OUT (min)." Therefore, System Delay Savings is calculated as "Agg OFF delay savings metroplex at OUT (min)" - "Estimated TOS rte OFF delay savings at OUT (min)."

A. Delay Comparison

Figure 13 compares the D10 10% trimmed mean delays between feature flight set *A* (Alpha) and R_{1+} (1+ Alt Gates), and Field Data Candidate, Submitted, and Approved target flight sets. The R_{1+} delays serve as a nominal operations baseline as this is the largest flight set for which Airborne Delay Expense can be calculated. Net Delay Savings is calculated as Taxi Out Delay Savings – Airborne Delay Expense. Note that R_{1+} Taxi Out Delay Savings is less than half its Airborne Delay Expense resulting in negative Net Delay Savings. The *A* set has lower Airborne Delay Expense and more than four times the Taxi Out Delay Savings, yielding positive Net Delay Savings suitable for CDDR candidacy. It is encouraging that *A* Taxi Out Delay Savings is almost identical to that of Field Candidates as Candidates are what the Linear model trained on *A* is trying to predict. However, Field Data Airborne Delay Expenses are much lower than that of *A*, with negative Candidate Airborne Delay Expense. This means that most field Candidates tended to propose a reroute that was shorter than the filed route. As the feature flight set filed routes are assumed to be the shortest, it is impossible for feature flight set Airborne Delay Expense to be negative. This discrepancy could be mitigated in future efforts by identifying the actual filed route of each flight rather than assuming the shortest. However, ASPM Flight Level Data does not include filed route and so another flight level data source including filed route, such as SWIM, would need to be used.

The Field Data delays show an interesting pattern of decreasing Taxi Out Delay Savings and Net Delay Savings and increasing Airborne Delay Expense as the flight reroutes progress from CDDR proposed Candidate to operator Submitted to controller Approved status. There are many potential reasons why only a small percentage of Candidate reroutes are Submitted (11.1%) and Approved (5.8%), with labor shortage and personnel workload capacity being chief among them. One potential operational reason why some Candidate reroutes are not Submitted is because although they consider local Fix closures and MITs, they neglect to consider downstream weather that may be impacting the proposed reroute. Many of the Candidate reroutes are for longer filed routes proposed to reroute to the nominally preferred route. It is possible that most of these routes are not Submitted because the preferred route is blocked by downstream weather, the reason for filing a non-preferred route to begin with. There is ongoing work to include the information about the downstream weather in determining the preferred alternate route(s) which will alleviate this limitation. As CDDR is improved, more potential Candidate routes may be filtered, increase the percent of Submitted, and perhaps converge to delay behavior closer to Submitted. Unlike Taxi Out Delay Savings and Airborne Delay Expense, System Delay Savings is quite similar between Field Data flight sets with Submitted and Approved being almost identical. As Candidate routes aspire to be more like Submitted, the D10 Submitted System Delay Savings was selected to apply to all other TRACONs for benefit extrapolation.

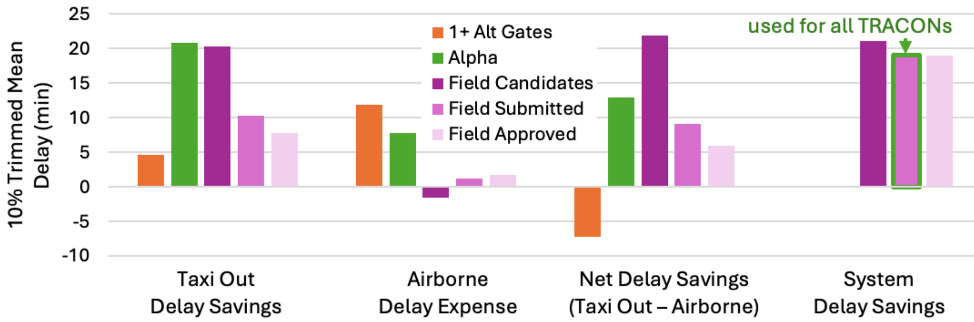

Figure 13 D10 Delays for Various Feature Flight Sets and Field Data

The *A* 10% trimmed mean Taxi Out, Airborne, and resulting Net Delays were selected to apply to all other TRACONs for benefit extrapolation. These are shown in Figure 14 for each TRACON ordered by OPSNET rank. The Net Delay of each TRACON follows a similar trend to the OPSNET rank, with the exception of SCT which has by far the lowest Net Delay with respect to its operational traffic volume.

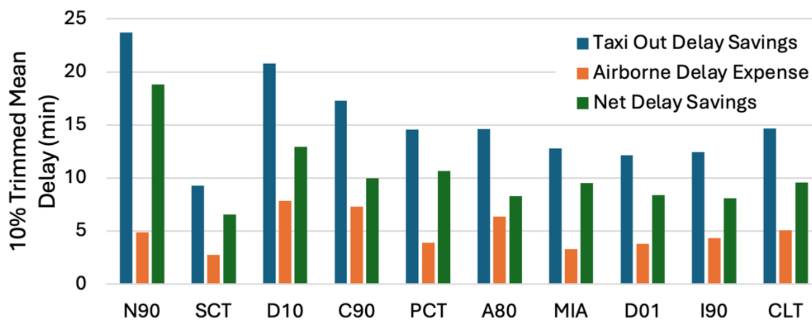

Figure 14 Alpha Flight Set Delays per Flight by TRACON

B. Benefit Calculation

The two main categories of benefits estimated are Delay Benefits and Fuel Benefits summarized in Table 4. Delay Benefits metrics include Net Delay Savings and Delay Cost Savings, which is the sum of Operational and Passenger Cost Savings, both linear functions of Net Delay Savings. According to the FAA Investment Planning and Analysis Group [9], Aircraft Direct Operating Costs (excluding fuel cost) FY2024 rates for average Air Transport aircraft (used for high level analysis) is $1,056 per hour of airborne or ground delay. Thus, Operational Cost Savings is Net Delay Savings (hours) multiplied by $1,056. From the same reference [9], the Passenger Value of Time FY2024 rate for all purposes is $61.20 per hour, the average air carrier passenger capacity is 154.8 per flight, and the average air carrier passenger load factor is 84.40%. Therefore, the average Passenger Value of Time per air carrier flight is $61.20 × 154.8 × 0.844 = $7,996 per hour. Thus, Passenger Cost Savings is Net Delay Savings (hours) multiplied by $7,996.

The fuel consumption calculation used to generate the D10 Field Data fuel savings estimations [8] is quite complex, accounting for different aircraft types and number of engines. Therefore, generalized surface and airborne fuel consumption rates were reverse engineered from D10 TOS Activity Reports. Individual observed surface fuel consumption rate is calculated as "TOS rte individual estimated surface fuel savings at OUT (kg)" / "Estimated TOS rte OFF delay savings at OUT (min)". Individual observed airborne fuel flow rate is calculated as "TOS rte notional airborne fuel savings at OUT (kg)" / "TOS rte notional addl flight time at OUT (min)". Let the generalized surface and airborne fuel consumption rates be the 10% trimmed means of the observed individual rates for all Candidates calculated as 11.72 kg/min (or 25.784 lb/min) and 38.91 kg/min (or 85.602 lb/min), respectively. Whereas, System Delay Savings is not included in Delay Benefits, it is included in the surface component of Fuel Benefits. Surface Fuel Savings is 25.784 × (Taxi Out Delay Savings + System Delay Savings) lb and Airborne Fuel Expense is 85.602 × Airborne Delay Expense lb. Then Net Fuel Savings is calculated as (Surface Fuel Savings – Airborne Fuel Expense) lb. According to the FAA Investment Planning and Analysis Group [9], the FY2024 fuel cost per gallon is $2.37. Using a conversion factor of 6.7lb/gal, $2.37/gal = $2.37 / 6.7 = $0.35/lb. Thus, Net Fuel Cost Savings is Net Fuel Savings (lb) multiplied by $0.35.

Table 4 Benefit Metrics Calculation

Benefit Metric	Calculation
Net Delay Savings (min or hour)	Taxi Out Delay Savings – Airborne Delay Expense
Ops Cost Savings ($)	Net Delay Savings × $1,056 [$ per hour]
Pax Cost Savings ($)	Net Delay Savings × $7,996 [$ per hour]
Delay Cost Savings ($)	Net Delay Savings × ($1,056 + $7,996) [$ per hour]
Surface Fuel Savings (lb)	(Taxi Out Delay Savings + System Delay Savings) × 25.784 [lb per min]
Airborne Fuel Expense (lb)	Airborne Delay Expense × 85.602 [lb per min]
Net Fuel Savings (lb)	Surface Fuel Savings - Airborne Fuel Expense
Net Fuel Cost Savings ($)	Net Fuel Savings × $0.35 [$ per lb]

C. Initial Benefit Results

Benefit metrics (Table 4) per flight are derived using Figure 14 Taxi Out Delay Savings and Airborne Delay Expense per flight per TRACON, and Figure 13 Field Submitted System Delay per flight for all TRACONs. Yearly benefits per TRACON are then calculate by multiplying the per flight benefit metrics by the predicted yearly number of Candidate (Figure 12), Submitted (11.1% of Candidates), or Approved (5.8% of Candidates) CDDR reroutes per year at each TRACON. Figure 15 shows the yearly Net Delay Savings and Net Fuel Savings at each TRACON based on predicted number of Submitted flights. D10 Field Data yearly benefits are also shown for comparison. The Net Delay Savings trends by TRACON hold for Delay Cost Savings and the Net Fuel Savings trends by TRACON hold for Net Fuel Cost Savings as these are zero intercept linear relationships. Whereas D10 Field Data Delay Benefits are comparable to both models, D10 Field Data Fuel Benefits are roughly double that of the models. This is due to the much smaller Airborne Delay Expense observed in field data. The effect on Net Fuel Savings is magnified because the observed airborne fuel consumption rate is more than three times the surface rate. This effect could be mitigated in future efforts by identifying the actual filed route of each flight rather than assuming the shortest to better estimate average Airborne Delay Expense for each TRACON.

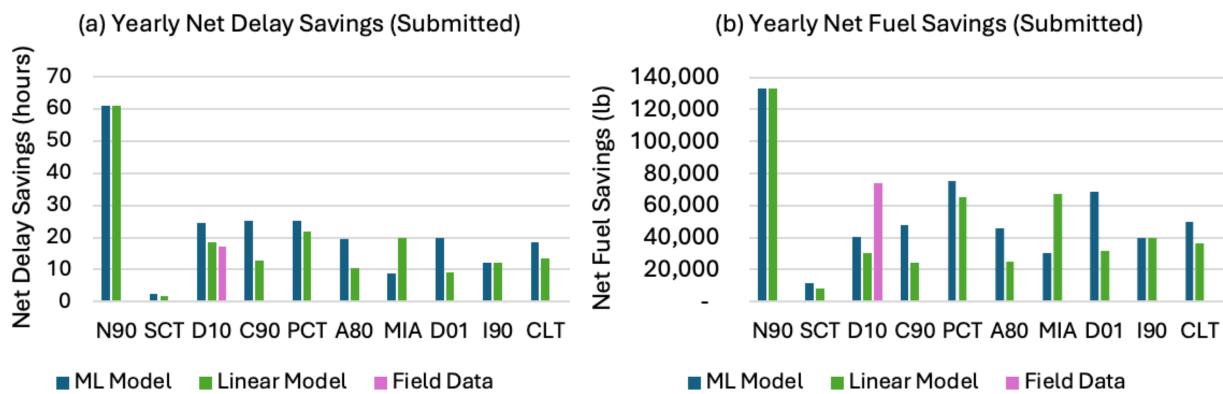

Figure 15 Yearly Delay Savings (a) and Fuel Savings (b) for Submitted Flights by TRACON

Table 5 summarizes total yearly benefit metrics for all 10 TRACONs for ML and Linear Model predictions of Candidate, Submitted, and Approved flights. The ML Submitted benefit metrics are selected as the best initial CDDR benefits extrapolation.

Table 5 Total Yearly Benefits for Top 10 TRACONs with CDRs

	Candidate		Submitted		Approved	
Model	**ML**	**Linear**	**ML**	**Linear**	**ML**	**Linear**
Flights	10,526	8,458	1,169	939	610	491
Net Delay Savings (hours)	1,956	1,632	217	181	113	95
Delay Cost Savings ($)	$17,709,322	$14,772,942	$1,965,735	$1,639,797	$1,027,141	$856,831
Net Fuel Savings (lb)	4,879,696	4,157,978	541,646	461,536	283,022	241,163
Fuel Cost Savings ($)	$1,707,894	$1,455,292	$189,576	$161,537	$99,058	$84,407

VII. Conclusions and Next Steps

A new method was developed for extrapolating the NAS-wide benefits of CDDR utilizing CDR and ASPM data and ML modeling. First, TRACON generic features were developed based on flight counts and average delays associated with sets of departure flights meeting criteria related to route options, delay, and weather impact. These features were then used to train an ML model to predict numbers of CDDR Candidate reroutes from D10 field data between May 1, 2022 and April 29, 2023. Concurrently, a single Alpha flight count feature combining route options, delay, and weather impact was refined manually and used to create a Linear Regression model also predicting numbers of CDDR Candidate reroutes. The ML Model outperformed the Linear Model with 11% lower weekly RMSE. When applied to the top 10 TRACONs in the US with CDRs, the ML and Linear models produced results with similar yearly count trends across TRACONs. Although the application of these models to TRACON's other than D10 cannot be validated without field data from other TRACONs, the similarity in trends across TRACONs builds some confidence. As CDDR is fielded at other TRACONs, those field data, such as I90, may be used to further validate the benefit extrapolation method. The 10% trimmed mean delays from the Alpha feature flight sets and D10 field data were used to estimate Taxi Out Delay Savings, Airborne Delay Expense, and System Delay Savings per predicted CDDR reroute at each TRACON. Delay and fuel savings benefits derived from these delays were then combined with model predicted counts of CDDR reroutes to extrapolate yearly benefits. When comparing delays and derived benefits between D10 field data and model prediction, Taxi Out Delay Savings were similar, whereas Airborne Delay Expense of utilizing an alternate reroute was much lower in field data. This is because the model always assumes the original filed route is the shortest CDR and therefore Airborne Delay Expense is positive. The actual filed route in the field is often longer than the CDDR reroute, greatly reducing the negative impact of Airborne Delay Expense on fuel savings benefits. The extrapolation method could be improved by utilizing flight level data sources including filed route which is absent from ASPM. The features presented focused on route options, delay, and weather impact. In the future, features related to departure gate throughputs derived from historic track data could be developed to improve the prediction model further.

Acknowledgments

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