Pushback to the Future: Predict Pushback Time at US Airports

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Abstract

As air traffic continues to grow, numerous airports have begun implementing optimization strategies for airport processes such as ground movement planning and runway sequencing. Effective solutions for optimizing these operations can result in significant reductions in fuel consumption and greenhouse gas emissions. At present, a major source of uncertainty is the aircraft's *pushback* time, which refers to the moment when the aircraft is pushed away from its parking position. Pushback marks the beginning of various airport procedures; therefore, predicting pushback time as accurately and as early as possible can enhance multiple airport processes, optimize flight schedules, and minimize delays. As part of a Machine Learning Applied To Climate Change course project, we participated in the public competition **Pushback to the Future**[1], hosted by the National Aeronautics and Space Administration (NASA) and the Federal Aviation Administration (FAA). The competition aimed to predict the *minutes until pushback* of a flight using public air traffic and weather data. We explored several heuristic-based and machine-learning methods for this task, discovering that machine learning-based methods marginally outperformed heuristic-based methods. Our submission to the competition based on XGBoost ranked 23rd out of 408 participants. We believe that further research is necessary to extract relevant features from raw data streams to enhance machine-learning methods' performance for this task.

1 Introduction

Transport accounted for about 23% of total energy-related CO2 emissions worldwide in 2014 (Masson-Delmotte et al., 2018), with passenger aviation being a significant contributor. With the global aviation industry projected to continue growing, the need for sustainable solutions has become imperative. A key strategy to mitigate the environmental impact of aviation is through the optimization of various airport processes, including ground movement planning and runway sequencing. Optimized airport operations can considerably reduce fuel consumption and associated emissions, thereby contributing to the global fight against climate change (Lee et al., 2015; Jacquillat and Odoni, 2018). Recently, machine learning techniques have been utilized to improve airport operation efficiency, providing promising solutions to these challenges (Brownlee et al., 2018; Yan et al., 2022).

A major source of uncertainty in airport operations is the pushback time of aircraft, which refers to the time at which an aircraft is pushed backward away from its parking position. Pushback is the starting point for several subsequent airport procedures, such as taxiing, takeoff, and departure sequencing. Mori (2019) demonstrated that the pushback time provided by airlines is not sufficiently accurate, which hinders the effectiveness of airport operations. Accurate and timely prediction of pushback times can not only streamline airport processes but also improve flight scheduling, reduce delays, and minimize fuel consumption and associated emissions.

Although pushback time prediction is of great significance to airport operations, it has not attracted considerable attention in research, possibly due to the lack of available training data. The complex interdependencies among various factors, such as aircraft type, airport layout, air traffic conditions, and weather patterns, pose a significant challenge in accurately predicting pushback times. However, machine learning techniques have the potential to model these intricate relationships and improve pushback prediction accuracy.

To address this research gap and promote the development of novel approaches to pushback time prediction, the National Aeronautics and Space

[1] drivendata.org/nasa-airport-pushback

Administration (NASA) and the Federal Aviation Administration (FAA) initiated the public competition, **Pushback to the Future: Predict Pushback Time at US Airports**[1]. The goal is to predict the *minutes until pushback* for a given flight based on publicly available air traffic and weather data.

In this paper, we explore and compare various heuristic-based and machine-learning methods for this problem. Our goal is to identify the most effective techniques for accurate pushback prediction and discuss their implications in the broader context of climate change mitigation.

The remainder of this paper is organized as follows: Section 2 presents a review of the relevant literature on pushback prediction and its connection to climate change. Section 3 offers a comprehensive description of the datasets utilized in this study. Section 4 outlines the methodology, including preprocessing steps, evaluation criteria, and the machine learning algorithms employed. Section 5 showcases the experimental results and compares the performance of the various approaches considered. Section 6 discusses the pathway to impact and identifies the stakeholders involved in the problem. Section 7 provides general considerations for implementing a model to address this issue, while Section 8 concludes the paper and offers suggestions for future research.

2 Related Work

Airport airside ground operations contribute significantly to airport-related emissions (Ekici et al., 2013; Winther et al., 2015). Various sub-problems exist within ground operations optimization, such as runway sequencing (Bennell et al., 2013), gate allocation (Bouras et al., 2014), and ground movement routing and scheduling (Atkin et al., 2010). The pushback process is crucial in many of these problems. (Stergianos et al., 2015) investigated the impact of the pushback process on the routing and scheduling of aircraft ground movement, finding that neglecting the pushback process could considerably underestimate taxi times for specific aircraft and consequently limit the benefits provided by a ground movement system.

A substantial body of research focuses on scheduling departure pushback times or Target Start-Up Approval Times (TSAT) to minimize waiting times at taxiway and runway queues, an area known as Departure Metering (DM; Brinton et al. 2011). Early DM methods employed basic rules to keep aircraft at gates when the total number of airside aircraft exceeded a certain threshold (Pujet, 1999). Burgain et al. (2012) modeled the task as a Markov Decision Process (MDP), demonstrating that incorporating airport surface surveillance information led to significant benefits over naive gate-holding policies, especially during adverse weather conditions. Simaiakis et al. (2014) integrated airside departure models into the MDP formulation and identified optimal DM policies using dynamic programming algorithms. Zhu et al. (2018) approached TSAT prediction as a multivariate linear regression problem, employing features such as the number of departure aircraft on taxiways and runway configurations. Ali et al. (2022) introduced a novel, model-free, and simulation-based approach to learn DM control policies by leveraging cutting-edge Deep Reinforcement Learning (DRL) techniques.

DM models depend on accurate *ready to pushback* times provided by airlines. However, Mori (2019) showed that the estimation accuracy of pushback times given by airlines is insufficient for implementing effective DM methods in ground movement optimization. To the best of our knowledge, predicting *ready to pushback* times has not been extensively explored, possibly due to the lack of available data. The competition addressed in this project provides a unique opportunity to study this aspect by offering publicly accessible air traffic and weather data.

3 Dataset Description

The dataset for this competition comprises approximately two years (2020-2021) of historical air traffic and weather data for ten US airports, spanning a diverse range of locations and conditions. This data has been compiled from various agencies, such as the Federal Aviation Administration (FAA), LAMP (Localized Aviation MOS (Model Output Statistics) Program), and airline operators, to facilitate the development and improvement of air traffic management tools.

3.1 Air Traffic Data

The air traffic data is sourced from Fuser, a data processing platform designed by NASA as part of the ATD-2 project, which processes the FAA's raw data stream and distributes real-time, cleaned data on individual flight statuses across the nation. The air traffic data includes:

- Actual departure and arrival times and runway codes for each flight
- Actual arrival and departure times to/from a gate
- Active runway configurations at different times for each airport
- First position timestamps for arriving flights
- Metadata of each flight such as engine class, aircraft type, airline carrier, etc

The estimated departure and arrival times are based on two FAA systems – TFM (traffic flow management) and TBFM (time-based flow management). The data consists of predictions at various timestamps leading up to the actual arrival.

3.2 Weather Data

The primary source of weather data is the Localized Aviation MOS (Model Output Statistics) Program (LAMP), operated by the National Weather Service. For each of the airport facilities, the data includes simple indicators such as temperature and humidity, as well as quantities that are particularly relevant to aviation, such as visibility, cloud ceiling, wind direction, wind speed, the likelihood of precipitation, and the likelihood of lightning. For a given timestamp, the weather data includes weather conditions *observed* in the past, as well as weather conditions *predicted* for the future by LAMP at that timestamp. Each prediction includes a forecast for the next 25 hours.

3.3 Data Usage Restrictions

The model developed for pushback prediction is intended to be compatible with other airport optimization services. In the context of the competition, the proposed solution will be part of NASA's Digital Information Platform (DIP), a platform designed to process torrents of raw data and provide service predictions to facilitate downstream air traffic management tools. To ensure successful integration, the competition rules impose certain restrictions on how raw data can be used to make pushback predictions at inference time.

- **Time:** Only data from the previous 30 hours up to the time of estimation will be available for use in generating predictions.
- **Location:** Only data from the airport where a flight is departing will be available for analysis.
- **Independence:** Each prediction should be treated as an independent observation, meaning that past predictions cannot be used as input for inference.

These restrictions guide feature selection and feature engineering for machine learning-based approaches to this problem (Section 4), ensuring that the developed models adhere to real-world constraints and maintain practical applicability.

Airport	**Train**	**Test**
KATL	3,194,032	303,836
KCLT	2,133,639	198,963
KDEN	2,848,350	281,311
KDFW	3,091,326	297,171
KJFK	1,236,903	99,604
KMEM	1,185,493	120,957
KMIA	1,404,563	125,964
KORD	2,933,510	295,604
KPHX	1,689,702	161,993
KSEA	1,647,433	157,320

Table 1: Number of examples in train and test splits of the dataset for each airport

The training labels for the task consist of the target variable `minute_until_pushback` from time of prediction for a given flight. The number of training and test labels for each airport is given in Table 1. The `minute_until_pushback` of the test set are hidden. We form a development set using a 15% ransom split from the training set.

3.4 Exploratory Data Analysis

We conducted preliminary exploratory data analysis, as illustrated in Figure 1 and Figure 2. Figure 1 depicts the average distribution of minutes until pushback across all airports. We observed that the trend is relatively consistent across all airports, with the average value being approximately 50. Figure 2 displays the average values of crucial weather data features - temperature, wind, and visibility - across five airports. We observed no anomalous ranges for any airport, and the trend remains somewhat constant for all three factors.

4 Experiment Setup

In this section, we describe the experiment setup, including the preprocessing steps, feature engineering, model details, and evaluation metrics used for our pushback prediction task.

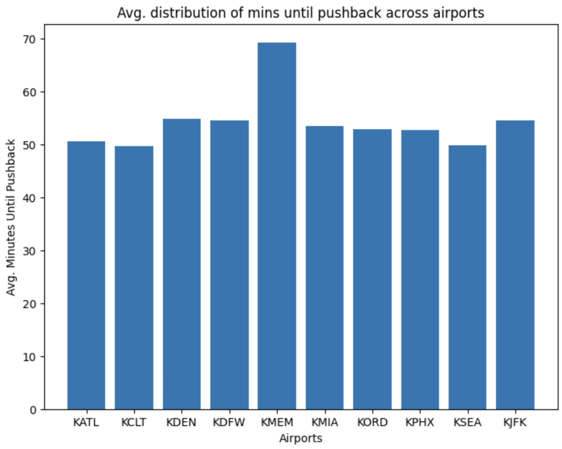

Figure 1: Average distribution of mins until pushback across all airports

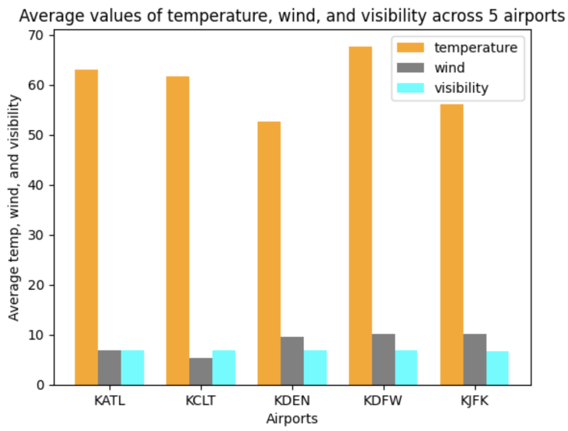

Figure 2: Average values of temperature, wind, and visibility across five airports

4.1 Data Preprocessing and Feature Engineering

The raw data streams from various sources needed to be filtered and transformed to create a meaningful and manageable dataset for our pushback prediction models. Due to the complexity and volume of the data, using all available data at a given timestamp is infeasible. For each timestamp and flight ID, we performed the following filtering and transformation steps:

- **ETD:** We selected the most recent expected time of departure prediction available at the given timestamp.
- **LAMP:** We considered the most recently observed weather conditions at the given timestamp.
- **Traffic:** We utilized TFM and TBMF data to estimate airport traffic by counting the number of unique flight IDs in the 30 hours preceding the given timestamp.
- **Runway:** We extracted the number of departure runways available at each airport at the given timestamp.
- **Metadata:** We included the metadata of the flight, such as aircraft type, airline carrier, and other relevant information.

After filtering and transforming the raw data, we performed feature engineering to create additional features that could improve the model's predictive performance. The engineered features included:

- **Timestamp Processing:** The dataset consists of two timestamps: the timestamp of making the prediction and the expected time of departure (ETD). For both timestamps, we extracted the year, month, day, hour, and minute. Additionally, we included the difference between these two timestamps as a feature (**Diff**).
- **Encoding:** We used binary, label, and one-hot encoding techniques for converting categorical features such as airport name, aircraft type, GUFI, etc. into numerical representations suitable for machine learning algorithms.

With the preprocessed and engineered features, our dataset was ready for model training and evaluation.

4.2 Evaluation

All the models are evaluated on Mean Absolute Error (MAE) metric. Given that y_i is the ground truth and $\hat{y}_i$ is the predicted value, MAE for N samples is calculated as:

$$MAE = \frac{1}{N}\sum_{i=0}^{N}|y_i - \hat{y}_i|$$

4.3 Modeling details

4.3.1 Heuristic Models

As a baseline, we implemented a couple of heuristic models that does not rely on machine learning techniques.

The intuition behind the first heuristic approach is that the pushback of an aircraft generally happens 10-20 minutes before the actual departure. To optimize this heuristic model's performance on the test set, we employed a trial-and-error approach. We iteratively evaluated the mean absolute error

(MAE) on the validation and test sets by selecting a time value in the range of 10-20 minutes and subtracting this value from the estimated time of departure (ETD) for a given timestamp for each aircraft. Through this iterative process, we identified the optimal pushback time for this task to be 15 minutes before the estimated time of departure. We refer to this heuristic model as **ETD–15**.

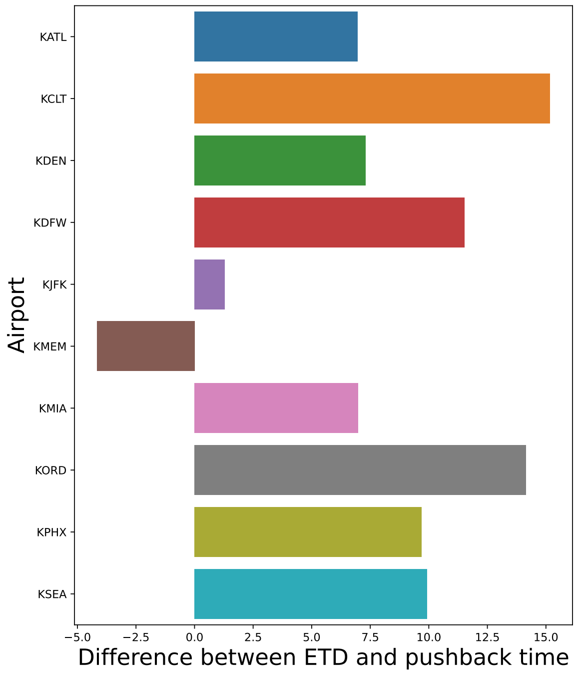

Figure 3

The next heuristic approach builds upon **ETD–15**. Rather than using the same time value for each airport, we find an optimal time value to subtract from the estimated time of departure for each airport by analyzing its training labels. In particular, we look at the average difference between the estimated time of departure (ETD) and the pushback time for each airport. These are visualized in Figure 3. We utilize these airport-specific values to subtract from the estimated time of departure to get the pushback time. We refer to this heuristic model as **ETD–X**.

4.3.2 Machine Learning Models

We developed various machine learning models to address this regression problem, including Linear Regression, Polynomial Regression, Random Forest Regressor, and XGBoost Regressor. A brief description of each model is provided below:

Linear Regression: A statistical method that models the relationship between a dependent variable and one or more independent variables. It is widely used for tasks such as prediction, forecasting, and determining the strength of relationships between variables. Linear Regression fits a line to the data that best represents the relationship between the variables.

Polynomial Regression: A regression technique that fits a polynomial function to the data instead of a straight line. This method is particularly useful when the relationship between variables is nonlinear and can be better approximated by a curve.

Random Forest Regressor: An ensemble learning method that constructs multiple decision trees and aggregates their predictions to achieve a more accurate and robust prediction. Random Forest is particularly effective for complex data with high dimensionality and nonlinear relationships between variables.

XGBoost Regressor: A gradient boosting-based method that combines decision trees to make highly accurate predictions. XGBoost Regressor excels at handling missing data, high dimensionality, and nonlinearity, making it a popular choice for predictive modeling across various fields.

We conducted randomized searches to select the best hyperparameters for each model and performed additional hyperparameter tuning when necessary. For Polynomial Regression, we experimented with different polynomial degrees, while for tree-based methods, we tuned hyperparameters such as `max_depth`, `n_estimators`, `minimum_sample_split`, and `minimum_sample _leaf`, in addition to testing default configurations.

Furthermore, for each machine learning approach, we experimented with separately training a model instance for each airport (**SEP**) and jointly training one model instance on datasets of all 10 airports (**ALL**).

5 Results and Discussion

In Table 2, we present the results of our experiments. Based on these findings, we address the following research questions:

How well do machine learning approaches perform compared to heuristic approaches?
As demonstrated in Table 2, the **ETD–15** heuristic baseline exhibits a strong performance with a mean absolute error (MAE) of 14.01 on the test set. Among the various model configurations, only one model configuration (XGBoost trained

Model	SEP/ALL	Features Used	Dev MAE	Test MAE
ETD–15	–	–	14.5	14.01
ETD–X	–	–	15.19	–
Random Forest	ALL	ETD+LAMP+Traffic+Runway+Metadata+Diff	12.43	20.27
Random Forest	SEP	Diff	14.16	13.84
XGBoost	ALL	ETD+LAMP+Traffic+Runway+Metadata+Diff	12.65	16.11
XGBoost	SEP	Diff	14.15	13.84
Linear Regression	ALL	Diff	14.46	14.39
Linear Regression	SEP	Diff	15.36	14.97
Polynomial Regression	ALL	Diff	14.64	14.31

Table 2: Performance of different models on the pushback prediction problem.

separately on all airports using only the Diff feature) surpasses the heuristic baseline. However, the performance difference is marginal (13.84 vs. 14.01). It is important to note that the **ETD–15** heuristic is not an ideal predictor, as an error of approximately 14 minutes in pushback time prediction can significantly hinder the optimization of other airport operations, which generally require more precise predictions with lower error margins.

Which features are crucial for solving the pushback prediction problem?

For both Random Forest and XGBoost models, we observed that incorporating all available features often leads to overfitting. This is evident from the lower dev MAE when compared to using only the Diff feature (12.65 vs 14.15 for Random Forest), but much higher test MAE (20.27 vs 13.84 for Random Forest). This finding indicates that the Diff feature (the difference in minutes between the time of making the prediction and the expected time of departure) is a valuable predictor for this problem. Further investigation is needed to identify and extract relevant features from other data streams.

Is it more effective to train a single model for all airports or separate models for each airport?

Although we have not conducted controlled experiments to validate this observation, in general, we found that models trained individually for each airport outperformed those trained on the complete dataset. This can be attributed to the fact that machine learning models typically exhibit better performance when trained on data specific to a particular domain or context, rather than on generalized data. By developing airport-specific models, we were able to incorporate domain-specific knowledge, leading to enhanced performance.

6 Pathways to Impact

Developing and implementing an effective system for predicting accurate pushback times at airports necessitates a comprehensive and collaborative approach, which includes active engagement from various stakeholders. The following stakeholders will be directly or indirectly influenced by the decision-making and policy implications of this project:

- **Civil Aviation Authority** - Overseeing safety, policy enforcement, and regulation for all aviation activities, including aircraft operations, air traffic services, and maintenance.
- **Ministry of Transport** - Tasked with the development of policies and infrastructure for different modes of transport, including aviation.
- **Air Traffic Controllers (ATCs)** - Responsible for issuing take-off, landing, and clearance instructions to pilots while monitoring air traffic and weather conditions to manage airspace congestion.
- **Ground Handlers** - Accountable for the safe and efficient provision of ground-level services for aircraft, such as towing, parking, marshaling, loading/unloading, and pushback.
- **Pilots** - Accurate pushback times can enable pilots to plan pre-departure flight checks more effectively, resulting in improved operational efficiency and safety.
- **Airport Management** - With precise pushback times, airport management can allocate airport resources more efficiently, considering aircraft parking positions, ground handling services, gate availability, and aircraft schedules.

- **Airlines** - Knowledge of accurate pushback times allows airlines to optimize flight schedules, manage aircraft turnaround times, reduce costs associated with delays, and ultimately provide a better customer experience.
- **Passengers** - As the end-users, passengers are directly affected by changes in flight departure times. Improved pushback time predictions can enhance the overall travel experience for passengers.

The initial step is to gain access to both historical and near real-time data from various airports through collaboration with different stakeholders. Subsequently, extensive research and development should be conducted on various predictive modeling techniques to determine accurate pushback times. To evaluate the system's performance on real-world data, it must be integrated with airport operations and continuously assessed for potential failures. Once a preliminary prototype proves successful, federated learning can be employed to access diversified data that would typically be unavailable due to privacy concerns. This approach can lead to better generalization, improved accuracy, and increased efficiency in data transfer and model training.

In the future, pushback time prediction will be integrated into NASA's Digital Information Platform (DIP) as one of its services. This new prediction capability can be employed for ground traffic prediction, delay mitigation, and flight trajectory optimization, which will help reduce excessive fuel consumption and related emissions while saving significant costs.

7 General Considerations

Predicting pushback time is an intricate task, as it depends on a multitude of factors. Several general considerations or challenges need to be addressed to develop an efficient machine learning system for this purpose:

- **Limited data access**: The current study utilizes publicly available data to predict pushback time. Since such sources may not be ideal for accurate pushback time prediction, access to more authentic and high-quality data directly from airlines or airports is necessary. Moreover, obtaining more recent data is crucial for enhancing pushback time prediction accuracy.
- **Limited predictability**: Even if a system can predict pushback time based on historical data and relevant features, there will always be unpredictable factors, such as delayed passengers, air traffic control delays, or mechanical issues, which cannot be anticipated in advance. These factors introduce challenges in accurately predicting pushback time.
- **Problem complexity**: Pushback time can be influenced by various factors, including aircraft type, gate availability, baggage loading delays, passenger boarding, weather conditions, air traffic control, and other operational aspects. Accurately modeling all these factors demands significant resources and domain expertise, making it a complex task.
- **Compliance with regulations**: The aviation industry is highly regulated; therefore, any machine learning system employed for pushback time prediction must adhere to the regulatory requirements of aircraft, airlines, and the aviation industry as a whole. Ensuring compliance with such rules and regulations guarantees passenger safety and security while meeting the basic standards set by aviation authorities.

8 Conclusion

In this research, we aimed to predict the minutes until pushback for a flight using publicly available air traffic and weather data. Through feature engineering and experimentation with complex models, we found that the best-performing model was remarkably simple. Employing a single feature and an XGBoost Regressor, we achieved the lowest MAE. This result aligns with Occam's razor principle, emphasizing the enhanced performance of simpler models in comparison to more complex alternatives. Furthermore, our analysis showed that creating separate models for each of the ten airports led to improved performance compared to using a single model. We ascribe this progress to the integration of domain-specific knowledge in the models, facilitated by developing airport-specific models. This strategy enabled more sophisticated modeling of each airport's unique data characteristics, resulting in a significant boost in model performance. Our submission to the competition based on XGBoost ranked 23rd out of 408 participants. Nonetheless, we recognize the need for further research to devise efficient predictive algorithms for this problem, which could help optimize additional airport operations, reduce greenhouse gas emissions, and improve overall air travel efficiency.

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