Pushback to the Future: Predict Pushback Time at US Airports

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Abstract

With the growth in air traffic, several airports now employ optimization methods for airport processes such as ground movement planning, runway sequencing, etc. Effective solutions to optimizing these operations can lead to a considerable reduction in fuel consumption and emissions. Currently, a significant source of uncertainty is the *pushback* time of the aircraft – how long until the plane departs from the airport gate. Pushback is at the start of multiple airport procedures, hence, predicting pushback with as much lead time and certainty as possible will help to further improve a multitude of airport procedures, optimize flight schedules, and reduce delays. As part of the course project on Machine Learning Applied To Climate Change, we are participating in an ongoing competition[1] hosted by the National Aeronautics and Space Administration (NASA) and Federal Aviation Administration (FAA) to predict pushback time of a flight, based on public air traffic and weather data. To solve this real-time estimation task, we plan to implement and compare several Machine Learning and Deep Learning algorithms such as Regression Analysis, Random Forest (RF), Support Vector Regression, and Artificial Neural Networks.

1 Introduction

Greenhouse Gas (GHG) emissions are a major contributor to climate change, and aerospace industry operations are no exception. During the pushback process, aircraft engines are typically running, which can emit carbon dioxide (CO2), nitrogen oxides (NOx), and other GHGs into the atmosphere. These emissions can contribute to climate change, which has a range of negative effects, including rising global temperatures, sea level rise, frequent heat waves, etc.

The United Nations' International Civil Aviation Organization has set a goal of reaching net-zero carbon emissions by 2050 (ICAO). To mitigate the impact of GHG emissions from pushback, airlines can take several steps. One potential solution is to implement pushback control at airports. This involves regulating the timing of the pushback process, so that planes do not remain idling on the tarmac for prolonged periods before takeoff. Airlines can also use more environmentally friendly fuels, such as biofuels or synthetic fuels, which produce fewer emissions compared to traditional jet fuel.

Various approaches to predicting pushback time have been proposed using machine-learning techniques that depend on various factors, including Aircraft size and weight, Number of passengers and cargo, Weather conditions, etc. We discuss them in the related work section and mention details on the dataset and proposed methodology in the subsequent sections.

2 Related Work

Airside ground operations of an airport contribute to a significant proportion of airport-related emissions (Ekici et al., 2013; Winther et al., 2015). There are various sub-problems within ground operations optimization, including the sequencing of runways (Bennell et al., 2013), the allocation of gates (Bouras et al., 2014), and the routing and scheduling of ground movement (Atkin et al., 2010). Pushback process plays a key role in many such problems. (Stergianos et al., 2015) studied the impact of the pushback process on routing and scheduling of ground movement of aircraft. They found that neglecting the pushback process could result in a significant underestimation of taxi times for certain aircraft, thereby reducing the potential advantages offered by a ground movement system to a considerable extent.

A significant proportion of research has been

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

devoted to scheduling the departure pushback time or Target Start Up Approval Time (TSAT) such that waiting times at the taxiway and runway queues are reduced. In literature, this is known as Departure Metering (DM; Brinton et al. 2011).

Initial methods for DM involved basic rules to maintain aircraft at gates when the total number of aircraft present on the airside surpasses a particular limit. (Pujet, 1999). Burgain et al. (2012) modeled the task as a Markov Decision Process (MDP). They demonstrated that compared to a naive gate-holding policy, incorporating airport surface surveillance information yields significant benefits, especially under adverse weather conditions. Simaiakis et al. (2014) incorporated airside departure models in MDP formulation and found optimal DM policy using dynamic programming algorithms. Zhu et al. (2018) cast TSAT prediction as a multivariate linear regression problem, using features such as the number of departure aircraft in taxiways, the configuration of runways, etc. Ali et al. (2022) presents a novel approach to learn DM control policy, which is model-free and simulation-based, by utilizing the latest Deep Reinforcement Learning (DRL) techniques.

DM models rely on accurate *ready to pushback* time provided by airlines. However, Mori (2019) demonstrate that in practice, the estimation accuracy of pushback time provided by airlines is insufficient to introduce effective DM methods for ground movement optimization. In this project, we focus on predicting *ready to pushback* time based on public air traffic and weather data.

3 Dataset and Evaluation

In this project, we will be working with public air traffic and weather data from 10 US airports over approximately two years. This data is compiled and released by NASA as part of their competition **Pushback to the Future**. The data has been compiled from various agencies such as 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.

The feature data included in this competition can be categorized into two parts: (1) air traffic data and (2) weather conditions data.

Air Traffic data: For each flight, the dataset consists of runway information (runway code and departure/arrival time) and estimated arrival time as predicted by two FAA systems – TFM (traffic flow management) and TBFM (time-based flow management) at various timestamps leading up to the actual arrival. The dataset also consists of the runway configuration of the airports at different times, i.e. which runways will be used for arrival and departure and the flow directions of those runways. Finally, the metadata of each flight such as engine class, aircraft type, etc is also provided.

Weather data: The weather data for this competition is provided by LAMP, a weather forecast service 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.

The goal of this project is to develop a machine-learning model that will predict *minutes until pushback* – an integer value representing the number of minutes from the time of prediction (timestamp) until the actual pushback time. The model will be 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 Proposed Methodology

In order to calculate the time until pushback, we will use regression-based predictive models to train on the given data of Air Traffic and Weather for US airports. To begin with, we aim to clean and preprocess the dataset to generate relevant and important features for input to the model. We propose to use the following set of methods - 1) Support Vector Regression (SVR): It uses the concept of Support Vectors to generate the hyperplane also called the regression line. This method is robust as it is less sensitive to outliers and also helps to deal with non-linear regression problems. 2) Random

Forest Regression: The basic idea of Random Forest Regression is to build multiple decision trees on random subsets of the data, and then average their predictions to make a final prediction. This technique is advantageous in dealing with large datasets having many features (as in this case) and is also less prone to overfitting. 3) Artificial Neural Network (ANN): ANNs are prominently used for their ability to map non-linear relationships between the features and the target. These contain an input layer, hidden layers, and an output layer and they use forward and backward propagation to calculate and update the weights. The final outcome of all these algorithms will be a numerical value that will denote the time until pushback and the results will be further evaluated using Mean Absolute Error (MAE).

5 Pathways to Impact

Pushback prediction will be one of the services that will be integrated with the Digital Information Platform (DIP) of NASA in the future. This will provide a new prediction that could be used for ground traffic prediction, delay mitigation, and flight trajectory optimization, and will help in reducing excessive fuel burning and its related emissions, while also saving millions of dollars. Moreover, the accurate prediction of pushback time contributes well in the prediction of airport configuration, runway assignment, taxi time, etc that can finally help flight operators, airlines, and the aviation industry.

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