Predicting Aircraft Landing Time in Extended-TMA Using Machine Learning Methods

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***Abstract*—Accurate prediction of aircraft arrival times is one of the fundamental elements for air traffic controllers to manage an optimal arrival and departure sequencing on the runway, reduce flight delays, and achieve a good collaboration with airports and airlines. In this work, we analyze the feature engineering problem to predict Aircraft Landing Time (LDT) in Extended-TMA with machine learning models. Two main contributions are highlighted in this work. First, the impact of different features in LDT prediction is investigated. Second, a machine learning prediction model is presented to predict LDT. Our case of study is the E-TMA of Singapore Changi Airport (WSSS) with a radius of 100NM. Firstly, data analysis is conducted to check the availability of different resource data, as well as cleaning the raw trajectory data. Then, feature construction and extraction are discussed in details, machine learning prediction models are proposed to address the LDT prediction. The experimental results show that 4 sets of features play a significant impact on LDT prediction for primary runway-in-use, they are: (1) Control intent: traffic demand, current traffic density, and adjacent flow; (2) Weather: surface wind; (3) Trajectory: the position of aircraft; (4) Seasonality: parts of a day and a week. Moreover, comparing three Machine Learning algorithms, in our study case, Extra-Trees is the best prediction algorithm compared with other machine learning models in terms of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). It is also found that Machine learning models perform much better than the current operational system. In summary, two main conclusions are drawn from the present work. First, predicting the aircraft LDT is strongly correlated with the TMA density at the flight operation time. Second, feature selection with domain knowledge and expert opinions is very important, and with good features, the model is less sensitive to the choice of machine learning algorithm.**

***Keywords*—Terminal Maneuvering Area, Trajectory prediction, Machine learning, Data mining, Aircraft Landing Time.**

I. Introduction

The increase of air traffic demand all over the world emphasizes the pressure around airports, yielding to a high congestion level on Terminal Maneuvering Area (TMA), which causes several air transportation problems, such as flight delays, the high workload for Air Traffic Controllers (ATCO), and non-optimal usage of ground resources [16].

Accurate knowledge of aircraft arrival times is one of the fundamental factors for ATCO to efficiently handle air traffic flows around the airport [13]. With more accurate information about arrival traffic, arrival manager systems, such as AMAN, will be more efficient in predicting the arrival sequencing, scheduled departure, and arrivals, then maintaining an orderly and safe flow in TMA (around 25 NM from the airport). These could lead to larger ground taxi times on airports and delays in the air. On the other hand, with an accurate prediction of arrival and departure times before reaching TMA, airport ground equipment and crews can be more effectively deployed in advance.

In this paper, we are going to propose a data-based approach to predict the Landing Time (LDT) of an aircraft in the Extended-TMA (E-TMA) airspace. With the available data, we will emphasize on the feature selection and extraction problem in Machine learning methods. Changi airport is considered as the case in our study to validate the proposed methodology.

The structure of this paper is organized as follows. First, section II presents an overview of the background, and a literature review summarizing the previous main works that belong to the scoop of our topic. Second, section III describes our proposed methodology, which is divided into two sub-sections: data preparation and data exploration. Then, section IV highlights the feature extraction and prediction model. Section V discusses the computational results. Finally, conclusions are drawn in section VI.

II. State of the art

A. Arrival management in TMA

The ATCO is responsible for guiding each arrival aircraft entering the TMA until reaching the runway. In reality, this process is performed as follows:

- ATCO assigns to each aircraft the STAR route, which represents a set of way-points to be flown.
- The Flight Management System (FMS) computes the optimal descent plan and transmits the Estimated Time of Arrival (ETA) and the feasible time window at the metering fix to the ATCO.
- ATCO assigns a Controlled Time of Arrival (CTA) within the feasible window.
- FMS computes the optimal descent plan complying with the CTA.
- FMS executes the descent plan and meets the CTA.

Furthermore, in order to meet the required level of safety and efficiency, ATCO relies on decision support tools, such as Arrival Manager System (AMAN) to compute the optimal

sequences and scheduling of landings flights at the runway. To this end, the AMAN systems apply prediction models to predict the time of arrival of the aircraft to the runway. The used prediction models heavily rely on mathematical approaches, which usually fail in accurately predicting flight arrival times due to its inefficiency in handling uncertainties. As a result, the arrival sequencing has to be updated constantly so as to provide precise information to ATCOs [14], [15]. An accurate prediction of aircraft LDT is a challenging task due to the non-deterministic nature of both environmental and air traffic factors which are summarized as follows:

- Uncertainty in the wind and temperature calculation: FMS uses a typical wind forecast generated by Numerical Weather Prediction (NWP) models, which is several hours before aircraft reaching the Top Of Descent (TOD).
- Inaccuracy in-flight parameter, such as weight and velocity.
- The trajectory assigned by the ATCO to the flight is unknown in advance.
- ATCO frequently vectors the aircraft from the STAR routes, either by elongating the trajectory or by shortening it. These reroutings are caused by many factors, such as meeting time constraints at the runway, maintaining separation with surrounding traffic, avoiding bad weather, or minimizing fuel consumption.

Those last-minute perturbations of flight sequencing yield to penalizing flight withholding time and trajectory deviations, which in turn cause delays and non-optimal flight sequencing.

B. Literature review

Predicting flight arrival times has attracted numerous attention from worldwide researchers in the past decades. Early works focused on LDT prediction by applying deterministic and probabilistic approaches that heavily rely on aircraft performance models, along with either parametric or physics-based trajectory models. The models are based on kinematic assumptions where parameters are determined based on aircraft performance, planned flight routes and predicted atmospheric conditions [5]–[7]. Despite the significant contributions of these aircraft performance models, their main issues are that they rely on ideal assumptions while overlooking the actual constraints and human behavior factors.

On the other hand, when dealing with uncertainty and prediction problems, machine learning approaches are powerful tools that have proved their efficiencies in many fields for several years. In the context of aviation, several methods from the field of artificial intelligence are used to cluster [24]–[27], detect anomalies [28], [29], [33], [34] and predict aircraft trajectories [35]–[37], predict and resolve conflicts [30], [31], develop dynamic airspace designs [38], [39], analyse runway and apron operations [32], [33], [40]–[42], determine airport performance including the impact of local weather events [43], [44], and for airport terminal operations (turnaround) [45]. More initiatives to leverage ADS-B open data in order to improve the state of the art are already commonplace, esp. in the field of aircraft modelling [46], [47].

In particular, predicting LDT using data-based approaches has been proposed as well. For example, Glina et al. [8] apply Quantile Regression Forests (QRF) to estimate aircraft landing times. Their model is validated with flight data from the Dallas/Fort Worth International Airport. Their findings consist of a short-term prediction (with a radius of prediction ranging between 20-30 NM) of flight arrival times with accuracy about 60 seconds for 68% of flights. In the same context, [10] presents a short-term trajectory prediction in TMA based on 4D trajectory prediction. Their model consists of data mining and Deep Neural Networks (DNNs) model. They predict the LDT at the TMA (within 25NM from the airport) with a MAE of 70 seconds. We believe that controllers need to have an accurate prediction not only in TMA, but also in larger areas. This will help in better handling the traffic for an optimal flight sequencing on the runway.

Furthermore, feature engineering is the process of transforming raw data into features that better represent the underlying problem to the predictive models, resulting in improved model accuracy on unseen data. In data-based LDT prediction researches, several researchers emphasize the importance of feature selection. For example, the work presented in [9] aimed at improving the Estimated Time of Arrival (ETA) predictions generated by the Federal Aviation Administration (FAA)'s Enhanced Traffic Management System (ETMS). In their work, intensive feature analysis was presented in order to understand the main feature influencing the prediction of ETA. By applying Random Forest (RF), they predicted ETA with 78.8% more accurately than the FAA's ETMS. In [9], they did not take trajectory shape into features, but in [11], [12], authors propose to cluster trajectories in feature engineering before applying the prediction model. Numerical experiments demonstrated that Neural Network (NN) with DBSCAN prepossessing performs best in terms of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). However, the aircraft trajectories with holding pattern are all considered as noise and not served as input for the prediction model. As inspired by Hong et al. [1], in our research, controllers intent will be considered as an important feature in our prediction model. We are trying to build up the features to reflect the controllers' decisions impact on the trajectory prediction. We would like to investigate the assumption that the LDT prediction model may achieve higher accuracy with more operational features.

Thus, given a set of historical flight data, our objective is to implement a data-based approach to predict the LDT for each arrival aircraft in E-TMA. The framework of concept is illustrated in Figure 1. We will address the following challenges:

- All features related to arrival time prediction are considered and discussed in detail. Especially, wind data and controllers' decision intent will be considered in feature engineering.
- Some deviations of the flight trajectories from the assigned STAR route are considered. Trajectories with normal holding are included in the experiments.

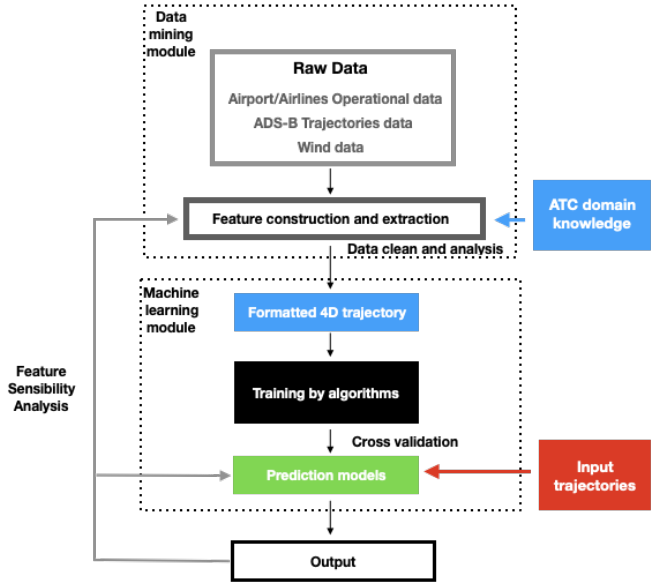


Fig. 1: Framework

III. Data Analysis

The performance of data-based algorithms is directly related to the quality of the data. A common problem affecting the quality of data is the presence of noise and outliers. Noise instances refer to unnecessary information with missing or invaluable attributes, while outliers refer to instances with exceptional values in comparison with the rest of the data. In this section, we describe the data we use in our model, as well as the techniques applied to remove both noise and outliers.

A. Data source

The data used in this work is related to arrival flights to Changi International Airport (ICAO: WSSS) in March and April of 2019. They are collected from the following sources:

1) TMA airspace data: WSSS has two parallel runways for domestic use, designated as $02L/20R$ and $02C/20C$.

2) Trajectory data: The trajectory data source of this study is Automatic Dependent Surveillance-Broadcast (ADS-B) flight data. The public availability of aircraft ADS-B messages has contributed to the development of online services that display the current air traffic in real-time with worldwide receiver networks (depending on the local coverage), such as The OpenSky Network [17] (see Figure 2) or Flightradar24 (flightradar24.com). However, aircraft that are not equipped with ADS-B transponder are not considered in the current study since we do not have their flight data. ADS-B is a co-operative surveillance technology, which provides situational awareness in the air traffic management system. Aircraft determine their position via satellite, inertial and radio navigation and periodically emit it (roughly one sample per second) with other relevant parameters to ground stations and other equipped aircraft. Signals are broadcast at 1090 MHz: a decent ADS-B receiver antenna can receive messages from cruising aircraft located up to 400 km far away, while the range is much lower for aircraft flying in low altitude or on the ground. For each flight trajectory, ADS-B data are recorded with unequal frequency. Thus, interpolation was performed on trajectory points in order to fix the time difference between 2 adjacent records as 5 seconds.

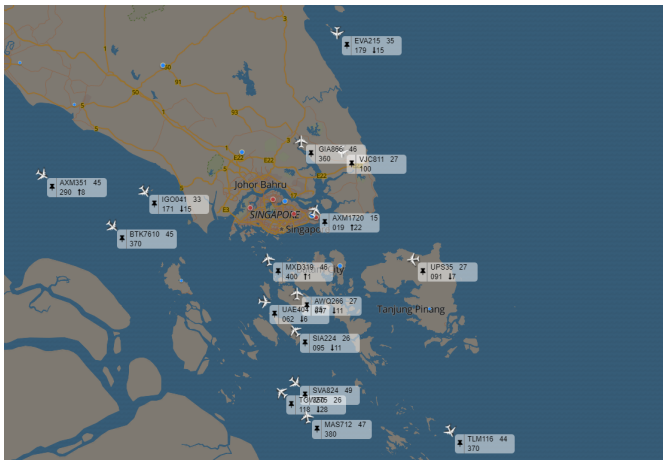


Fig. 2: ADS-B messages received from arriving and departing aircraft at Changi airport (https://opensky-network.org/)

3) Flight operational data: The flight operational data include Scheduled Time of Departure (STD), Actual Time of Departure (ATD), Scheduled Time of Arrival (STA), and Actual Time of Arrival (ATA) for each flight. Flight plan information (STD and STA) are provided by the website of Changi airport. Furthermore, ATA is calculated using a data-driven milestone approach [19], [42].

4) Meteorological data: The meteorological data comes from Singapore Changi airport station. This data contains surface wind information, including wind direction (relative to true north) and wind speed. Each record is stated as the measured or estimated mean value of each component over the 10 minutes prior to the issue time, unless there are significant variations during this period. This data updates every half-hour.

B. Data cleaning

1) Noise filtering: The following points are considered as noise data, which should be removed:

- Duplicated data;
- Trajectories with less than 30 recording points;
- Trajectories with missing points are retained and missing points are tuned by interpolation. However, if one of the flight or airport features are missing, this flight is not considered. Also, if STD, ATD, STA are missing, this flight is removed from the dataset.

2) Outliers removing: In statistics, an outlier is an observation point that is distant from other observations. To keep our data coherent in terms of remaining flight time (or travel time in E-TMA), flights with very long trajectories (generally the trajectory with very long holding time) should be removed.

For this reason, we apply the standard deviation method. This approach ensures that 85% of remaining flight time is within the standard deviation from the mean. As a result, trajectories with reasonable holding are still included in the experiments.

C. Data exploration

Data exploration aims to investigate the main characteristics of the dataset. Firstly, raw data contains 4985 flight trajectories in WSSS area. After removing outliers and missing data, the remaining dataset includes 3762 flight trajectories. Furthermore, it is found that runways 02L and 02C accommodate about 90% of the traffic (3376 flight). Thus, this research focus on runway 02L and runway 02C. All aircraft trajectories landing to North are illustrated in Figure 3. Furthermore, it is

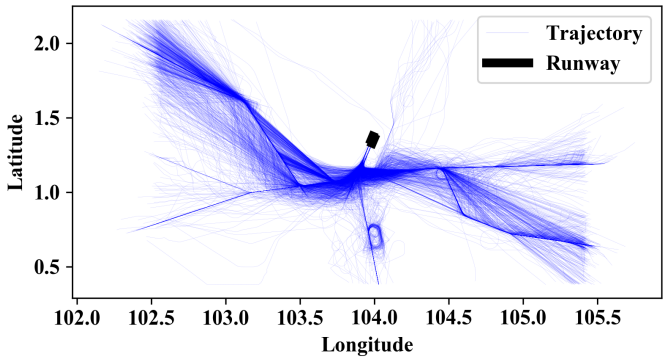


Fig. 3: Arrival trajectories with primary runway-in-use 02L and 02C at WSSS

of significance to explore the distribution of predicted value. The histogram and distribution of remaining flight time are shown in Figure 4. The distribution is estimated with the kernel density estimate. The mean is 25.17 min and the standard deviation is 2.25 min. The magnitude and variation of the predicted values provide another perspective on the difficulty of this prediction task.

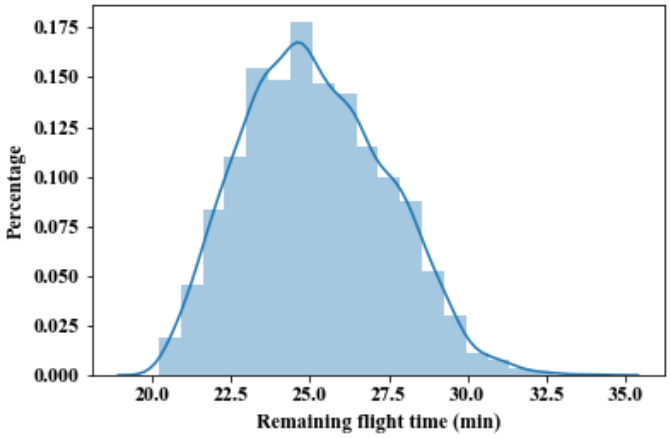


Fig. 4: Remaining flight time distribution

IV. Methodology

A. Feature construction and extraction

In ADS-B data, there are a list of features could be used to predict the LDT. However, based on the discussions with domain experts in Air Traffic Management (ATM), other factors may significantly influence the LDT prediction as well, they could be included as features in LDT prediction problem. Detailed discussions are listed as following:

- Entry zone: Figure 5 plotted the points 100NM away from the airport of trajectories in the training set. It can be seen that flights are coming from mainly 7 directions. we cluster the flights into different entry zones according to the angle with the runway. The entry zone of each flight then becomes a feature to specify the coming direction of flights.

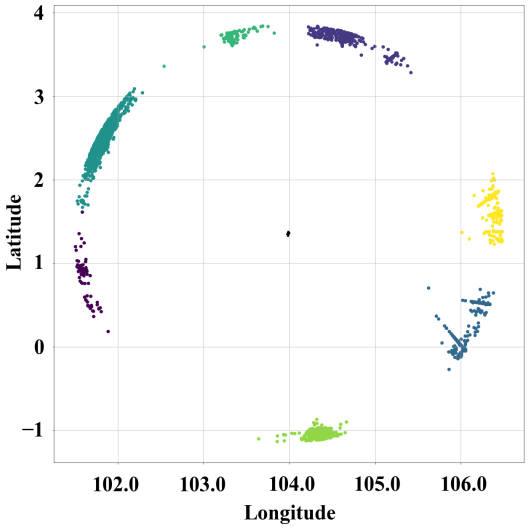


Fig. 5: Flight entry zone clusters

- Traffic density and capacity: generally, if the traffic density is lower, then the traffic demand may be lower than capacity; If the traffic density is super higher, then the traffic demand may be higher than capacity. The traffic demand, density, and flow conditions directly link the current or potential complexity of the airport. As a result, the flight trajectories more likely deviated from the STAR route and longer than normal. More seriously, even with holding and delay may happen. In order to measure this aspect, the following features are considered:
  - Number of flights entering the E-TMA in the past 15 minutes.
  - Number of flights expected to enter the E-TMA in the next 15 minutes.
  - Number of flights departing from WSSS in the past 15 minutes.
  - Number of flights departing from WSSS in the next 15 minutes.
  - Number of flights entering the E-TMA from the same flight entry zone in the past 15 minutes.

  - Number of flights expected to enter the E-TMA from the same flight entry zone in the next 15 minutes.
- Landing sequencing: deviation of trajectories is strongly related to the arrival sequencing on the runway. The flight trajectory could be elongated or shortened in order to satisfy an optimal and safe use of the runway. Therefore, based on First-Come-First-Serve (FCFS) arrival sequencing on the runway, we are considering to add the following features for each flight:
  - Decision intent: it can be either *elongation* if the flight is expected to shift its initial landing slot backward; or *nominal* if the flight is expected to keep its initial landing slot, or *short-cut* if the flight is expected to shift its initial landing slot forward.
  - Time shift: represents the time window needed in order to satisfy the optimal sequencing on the runway resulting from the FCFS algorithm. The time shift is positive in case of *elongation*, null in case of *nominal* and negative in case of *short-cut*.
- Seasonality: the chronological information is important to consider when tracking air traffic data. traffic flow in the airport can be affected by different seasonal factors, including the time of the day, holiday, etc. Limited by the size of the dataset, we only focus on the daily and weekly patterns. To avoid creating too many features (24 hours per day, 7 days per week), for each record, the hour is classified into the morning, afternoon, or dark by sunrise time, solar noon and sunset time. The date is classified into weekday or weekend. In the dark, the traffic demand, density, and flow become few. On the contrary, they are more likely dense in the morning and afternoon, but with opposite trends. The air traffic flow also links with days of the week.
- Wind: firstly, surface wind direction and speed will affect the runway-in-use for arrival flights, because generally, aircraft need to land in headwind condition. In exceptional tailwind conditions, the maximum tailwind limitation for a safe landing is normally 15 knots. Secondly, tailwind conditions at high altitudes will increase aircraft ground speed. Thus, if the remaining distance is fixed, then the required flight time will be shorter. In our case, if the traffic density in TMA is low, and there is no capacity limitation at airport, then a tailwind condition will definitely accelerate the aircraft to land at the airport; however, if there is already frequent delay happening at the airport, then the tailwind effect on aircraft landing time prediction could be ignored. In brief, tailwind conditions in high altitudes will benefit the aircraft with decision intent labeled by *short-cut*. Currently, we don't have the wind field data, as the wind energy will increase with the altitude in E-TMA airspace, so we will only use surface wind data in this paper.

B. Prediction models

Several machine learning models are used in this study, including Gradient Boosting Machine (GBM) [21], Random Forests (RF) [22] and Extra-Trees (ET) [23]. Deep learning techniques and linear models are not used, since deep learning is hard to be implemented with limited data, and linear models are not suitable for this task. GBM is a famous ensemble learning method and can be viewed as iterative functional gradient descent algorithms. RF are popular tree-based ensemble learning method. They are combinations of tree predictors such that each tree in the forest depends on the values of a random vector sampled independently and with the same distribution. With the combination of weak learners, a stronger learner will be generated. As an ideal candidate for bootstrap aggregating (bagging) algorithm, the idea in RF is to improve the variance reduction of bagging by reducing the correlation between the trees, without increasing the variance too much. ET are also a popular tree-based ensemble learning model. ET are very similar to RF, except for the sampling and split strategy.

V. Results

A. Feature discussion

All possible feature types are summarized in Table I. These features could be grouped into 6 types: aircraft-related features, airport-related features, trajectory related features, weather-related features, control intent related features and seasonality related features. All categorical features are encoded into dummy variables, namely one-hot encoding. The final feature set contains 244 features. Remark that the available data is not rich enough for training given such number of features. Besides, the large number of dummy variables make the feature set very sparse. Some of the features may be either redundant or irrelevant. Thus, feature selection should be performed.

To have an initial impression on the relationship between features and target variable, Pearson correlation coefficient is used as a measure of the linear correlation between variables. It's absolute value is between 0 and 1, 0 is no linear correlation and 1 is total linear correlation. Figure 6 highlights the 20

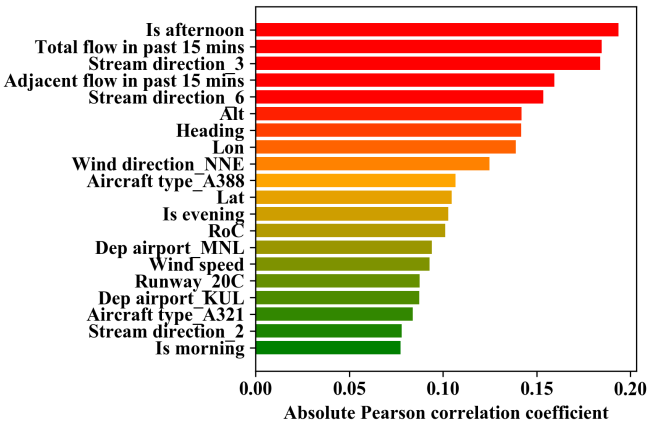


Fig. 6: Absolute Pearson correlation efficient between features and target variable

TABLE I: Summary of All Possible Features

Group	Feature	Description
Aircraft	Airline	Name of the airline
	Aircraft type	Type of the aircraft
Airport	Departure airport	Airport the flight departs from
	Destination airport	Airport the flight arrives to
	Runway	Runway the aircraft will be landing in
Trajectory	Latitude, longitude and altitude	3D position of the flight at each point
	Speed	Ground-speed of the aircraft at each position
	RoC	Rate of climb of the aircraft at each position
	Heading	Heading of the aircraft at each position
	STD	Scheduled Time of Departure at the runway
	ATD	Actual Time of departure at the runway
	STA	Scheduled Time of Arrival at the runway
	Entry zone	The zone that flight is coming from in E-TMA
Weather	Surface wind	Wind direction and speed
Control intent	Current traffic density	Number of arrival and departure aircraft in the last 15 minutes in E-TMA
	Traffic demand	Number of arrival and departure aircraft in the next 15 minutes in E-TMA
	Adjacent flow	Number of aircraft in the last and next 15 minutes in the same entry zone
	Landing sequencing decision	Elongation, Short-cut, or Nominal based on FCFS sequencing
	Sequencing time shift	The amount of shift time for safe sequencing and landing
Seasonality	Parts of a day	Morning, afternoon, or dark
	Parts of a week	weekday or weekend

highest Pearson correlation coefficients between the model features and the flight LDT. It can be seen that even the highest coefficient is less than 0.2, which indicates that there is no obvious linear correlation between features and LDT. The nonlinear relationship between the explanatory variable and the response variable illustrate again the great challenge of this study.

To select the features, permutation feature importance is introduced [20]. It is defined to be the decrease in a model score when a single feature value is randomly shuffled. Figure 7 illustrates the first 20 important features in the training set of three models. These features are selected as the input variables for each model. Each feature is permuted for 20 times. The overall permutation importance of each feature is illustrated by the box plot.

These feature ranking results give an insight into the impact of the model attributes on the prediction results. However, each model has a different view of features for the prediction. Therefore, the feature importance differs for different models. In RF, the traffic demand, current traffic density, parts of a day and surface wind are considered more important than other features. These features are also important in ET, but the parts of a day are more focused on. In terms of GBM, the case is overall similar to other models, but a certain aircraft type A388, the world's largest passenger airliner, is thought to be relevant to LDT. Among the three models, 4 groups of features play a significant impact on LDT prediction, they are:

1) Control intent: traffic demand, current traffic density and adjacent flow;
2) Weather: surface wind;
3) Trajectory: the position of aircraft;
4) Seasonality: parts of a day and a week;

The common important features provide a novel point of view of the artificial intelligence point of view on the factors that influence LDT.

B. Prediction results

The LDT prediction model evaluation is based on two metrics : Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), computed as follows:

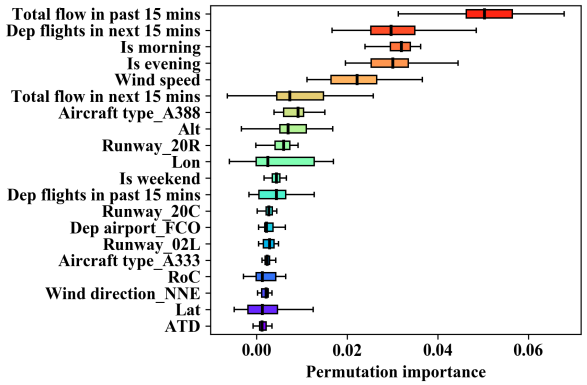
$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \tilde{y_i}| \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y_i})^2} \tag{2}$$

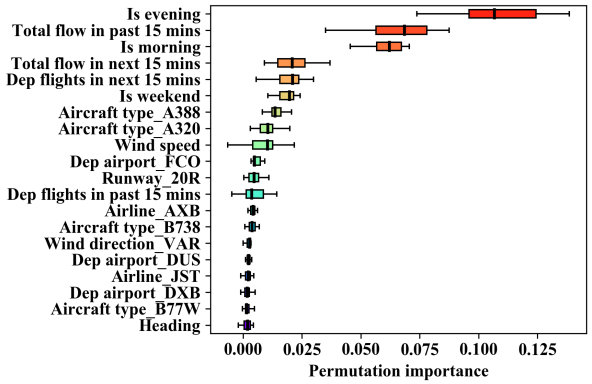
where n is the number of flights in the test flight set, $\tilde{y_i}$ is the LDT predicted value of the i-th flight and y_i is its true value.

The prediction results are shown in Table II. The performance of the three machine learning models is compared for the two runway in-use. By comparing the results of the three models we notice that our problem is less sensitive to the choice of the machine learning model. In fact, the MAE difference between the three models is less than 5 seconds for runway 02L, and 10 seconds for runway 02C. Nevertheless, in our model, ET provides better results than RF and GBM in terms of MAE and RMSE for the two runway-in-use.

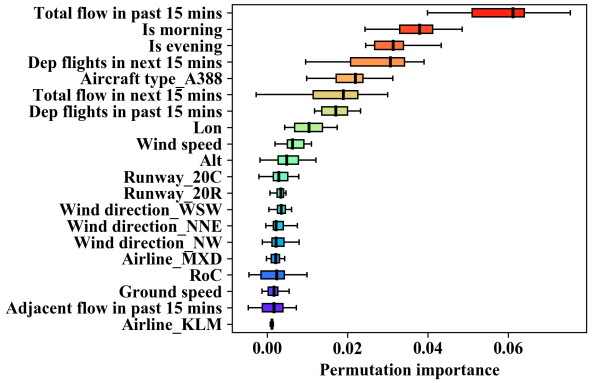
To further evaluate the prediction result of machine learning models, we demand the ETA data predicted by the current operations system in WSSS and the ATA data of these flights from the airport operations control center. The operations system is called baseline. For comparison, the best machine learning model reduces the MAE over 50 seconds and the RMSE nearly 150 seconds. In terms of runway 02L, MAE is reduced by over 30 seconds and RMSE is reduced by nearly 100 seconds. This result also reflects the prediction of LDT made by the current operations system is not stable, which contains very large errors. Machine learning models perform much better, which can be used to enhance the airport operations system.



(a) RF



(b) ET



(c) GBM

Fig. 7: Permutation importance of models

VI. Conclusions

In this work, a method to predict aircraft Landing Times (LDT) is presented. The proposed model includes data analysis in order to determine the most important features that have an impact on predicting the arrival times on runway. Then, 3 machine learning models are trained for the prediction.

In order to evaluate the performance of our models, computational results are conducted on real traffic data for Changi Extended TMA. Two important conclusions can be drawn.

TABLE II: Aircraft LDT Prediction Results

Models	02L		02C	
	MAE (s)	RMSE (s)	MAE (s)	RMSE (s)
Baseline	142.84	260.13	116.14	200.08
RF	101.92	125.94	94.19	115.2
ET	91.96	111.97	85.32	104.05
GBM	93.07	114.8	86.47	106.14

First, predicting the aircraft LDT is strongly correlated with the TMA density at the flight operation time. This is not surprising as in dense traffic controllers require more elongations to handle the traffic sequencing on the runway, while in less dense situations, short-cut trajectories are frequently proposed. Second, feature selection with domain knowledge and expert opinions is very important, and with good features, the model is less sensitive to the choice of machine learning algorithm.

In future works, we plan to include wind field data at the extended TMA, not only the runway surface wind. Furthermore, in our current model, we do not consider dynamic runway change. Thus, a classification model for runway prediction should be investigated.

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