International Civil Aviation Organization

INFORMATION PAPER

Tenth Meeting of the Asia/Pacific Meteorological Requirements Working Group (MET/R WG/10)

Virtual Meeting (Online), 24 – 28 May 2021

Agenda Item 5: **Coordination between MET and ATM services**

UTILIZING WEATHER INFORMATION IN IMPROVING ARRIVAL FLIGHT TIME PREDICTION IN THE TERMINAL AREA

(Presented by Hong Kong, China)

SUMMARY

This paper presents a study on improving the arrival flight time prediction under significant weather over the terminal area of HKIA by constructing a machine learning model.

1. INTRODUCTION

1.1 Flight arrival delay could bring significant impact to air traffic and airline operations as it would affect the fuel planning, ground operations, turnover of planes, and other unnecessary operations. One of the key factors contributing to flight delays is significant convective weather conditions. This study attempts to examine the relationship between flight arrival time, fuel consumption and weather condition over the Hong Kong International Airport (HKIA) and the Hong Kong Flight Information Region (HKFIR).

1.2 The dataset utilized in the study includes:

(a) Over 60,000 sets of data of the arrival flights of Cathay Pacific Airlines (CPA) arriving HKIA in 2019. The information contained in the dataset includes landing time, departure airport, aircraft type, landing runway, planned entry waypoint, A150 figures, etc. The A150 figures are the planned and actual fuel used, time used, and the distance an aircraft travelled after entering the range of 150 nautical miles (around 280 km) from HKIA. This is approximately the distance around where pilots would start execute the descent procedures.

(b) METAR/SPECI and TAF prepared by the Airport Meteorological Office at HKIA.

(c) Tailored Meteorological Services for Terminal Area (MSTA) product, namely the Significant Convection monitoring and forecast (SIGConv) (Figure 1). It contains convection forecasts for the next 6/12 hours over 13 key air traffic control areas, 3 holding points and 20 nm of approach. Three colour coded forecasts (green/yellow/red) indicating different levels of chance (low/medium/high) of significant convection predicted to affect the above areas and points were used. Further details about SIGCov can be found in MET/R TF/3 WP/07.

1.3 A machine learning model was then constructed using the above dataset for predicting the arrival time for CPA flights descent towards HKIA (para 2.3-2.5).

2. DISCUSSION

Weather correlation study

2.1 Significant convective weather associated with showery or thunderstorms in the vicinity of the aerodrome are one of the key factors that could affect air traffic significantly. Parameters related to significant convective weather (i.e. SHRA/TSRA) in TAF issued 12 hours before the landing time of flight were used to classify the significant weather which might have affected the arrival aircraft into different scenarios, namely, Nil/Before/Experiencing/After/Between. Under various weather scenarios, the mean of time and fuel deviation were calculated, where time deviation is defined as (actual time used – planned time) while fuel deviation is defined as (actual fuel used - planned fuel)/ (planned fuel). Table 1 shows that when flights landing in the "Between" significant weather scenario, both the time and fuel deviation are highest. Meanwhile, higher time and fuel deviation for "Experiencing" and "After" scenarios are also observed. This demonstrates that showers and thunderstorms forecasts in TAF are good indicators for additional flight time over its planned values.

2.2 The MSTA SIGConv contains hourly significant convective weather forecasts over the 3 holding points and 20 nm of approach in the next 6 hours. In this analysis, forecasts with lead time of 2 hours before the landing time were utilized. Table 2 shows a notable increase in flight time when the number of holding areas with yellow/red increased in comparison with the planned value.

Predicting flight time using machine learning model

2.3 The prediction model would first focus on predicting the A150 flight time for short-haul flights with flight time of less than 4 hours considering the availability of nowcasting data. As fuel planning would normally be made 2 hours before the flight departs, the input weather data used in the prediction model would be 6 hours before the flight landing time.

2.4 A total of 45 aircraft and meteorological features spanning from flight data, meteorological observations to weather forecasts were selected for training the machine learning model. The flight data used include the landing time, entry way points, aircraft type and CPA planned time. Meteorological observations used include METAR/SPECI, TAF, and SIGConv over the areas/points mentioned in para. 1.2(c) above.

2.5 The prediction model utilized in this study is built based on the eXtreme Gradient Boosting (XGBoost) Regressor library. The dataset was then split randomly into 80% for model training and 20% of data for model testing. The cost function adapted in the training process was the mean squared error.

Results and discussions

2.6 Table 3 shows the performance of CPA plan time and the XGBoost model predicted time compared against the actual A150 time. The evaluation metrics were the root mean squared error (RMSE), RMSE for flights delayed longer than 20 minutes (RMSE_g20) and the 85th percentile; the latter two were introduced to evaluate the performance of the model in predicting cases with large time deviation (i.e. higher impact to operations). The result shows that the XGBoost model performed better than the CPA plan time. The CPA plan time had a RMSE of over 8 minutes while the XGBoost model was generally less than 5 minutes. The figure for the higher impact cases even dropped significantly from 11-12 minutes to 4-5 minutes. Analysis on the feature value contributions suggested that apart from landing time or weekday, the entry waypoint, the prediction of convective weather from TAF and SIGConv forecasts over the holding points had high contributions to the improved flight time prediction. This suggested that weather forecast information played a significant role in improving the time and fuel prediction for arrival flights.

2.7 This paper showcases the initial use of Artificial Intelligence (AI), i.e., a machine learning model, for studying weather impact, viz. flight time prediction for arrival flights to HKIA. Though there were some limitations of the study, including: lack of information on the air traffic condition, flight restriction imposed over the area, etc., the study results showed that by utilizing the meteorological information (METAR, TAF, and MSTA SIGConv in this case), it was feasible to construct an impact-based forecasting product using AI technology to help predict the arrival time and consequentially improve airline operations such as flight time prediction or fuel planning that may better serve the airline users.

3. ACTION BY THE MEETING

3.1 The meeting is invited to note the information contained in this paper.

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Figure 1 Integrated display of the MSTA: SigConv includes the panel specified in E) 6hour convection forecast around HKIA and significant waypoints; and G) 12hour significant convection forecast time series over key ATC areas

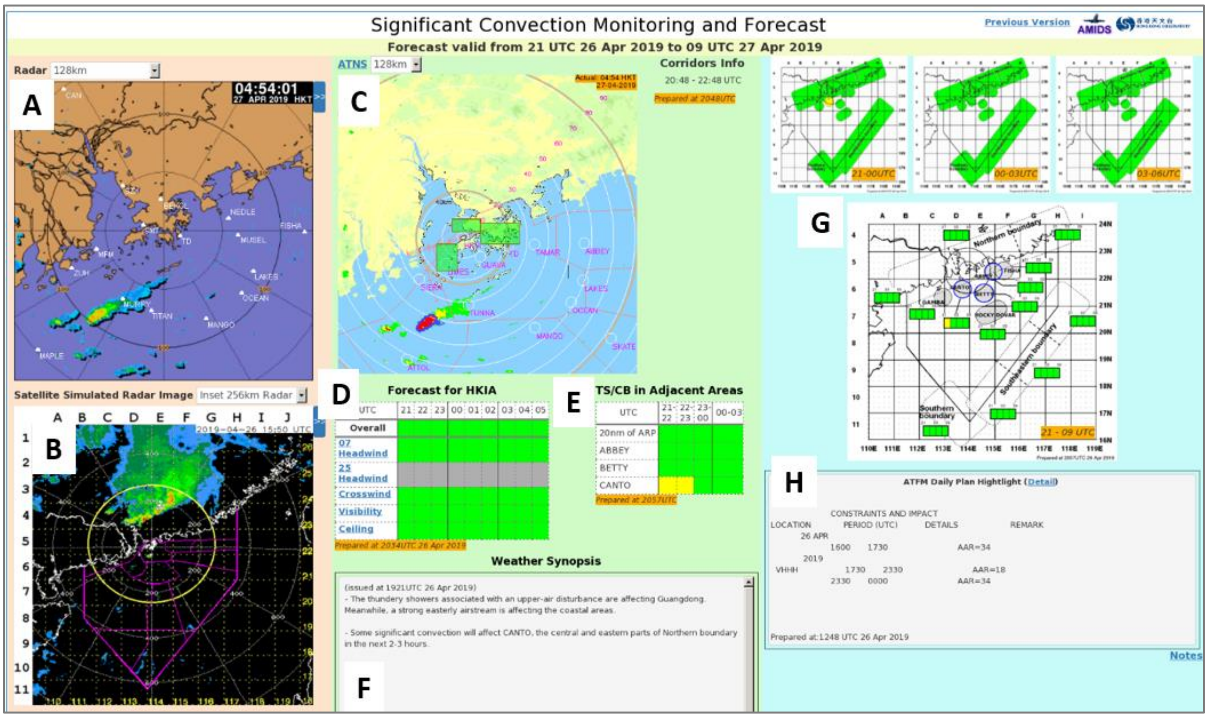

Table 1 Mean of Time and fuel deviation of flights classified into weather scenarios by TAF forecasts (Top). The classification of weather scenarios (Bottom).

TAF	No. of flights	Time deviation (mins)	Fuel deviation (%)
Nil	4520	3.22	30.26
Before	1117	3.03	33.81
Experiencing	3344	5.62	44.64
After	679	5.85	46.4
Between	848	6.93	53.6

Lead-lag time classification for each flight		
Nil		The flight experienced no weather
Before	B	The flight landed at most 12hr before weather
Experiencing	C	The flight landed during weather
After	D	The flight landed at most 6hr after weather and there is no weather within 12hr after the weather
Between	E	The flight landed between two weather

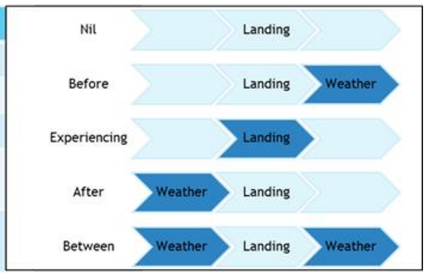

Table 2 Mean of time and fuel deviation of flights grouped by MSTA SIGConv forecast states

No. of area having Yellow or Red signal	No. of flights	Time deviation (mins)	Fuel deviation (%)
0	9090	3.72	34.32
1	508	7.55	54.69
2	426	10.59	72.22
3	158	12.92	78.39
4	94	15.99	98.99

Table 3 Performance of flight time prediction by CPA and XGBoost model as compared with the actual A150 time

	RMSE (mins)	RMSE_g20 (mins)	85 Percentile (mins)
CPA Plan Time	8.85	28.02	11.76
XGBoost model	4.6	10.72	4.42