Quantification of WAFS weather forecast uncertainties and its effect on fuel burn using historical flight data

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***Abstract*—Weather conditions directly influence flight operations. Although daily weather forecast data has been employed when forming optimal flight trajectory and fuel requirements, no forecast is without error. In this regard, studies that sought to improve our understanding of weather uncertainties and their effect on trajectory and fuel burn prediction have shined a spotlight on future air traffic control, flight planning and fuel-saving strategies. Though such studies are not new, their findings are often difficult to apply to real-world airline operations. Most of these studies do not consider the fact that airlines, in practice, use lower resolution weather forecasts that are distributed from the World Area Forecast System (WAFS). In this paper, we introduce several data handling techniques to understand the cause of WAFS weather forecast error and quantify its effect on the predictions of cruise stage fuel burn. Using historical data, we merged the second-by-second recorded flight data with the corresponding WAFS weather forecast; we also calculated the deviation of different forecasted weather parameters to the realized weather conditions. Fuel flow deviations and overall cruise stage fuel burn deviations due to weather uncertainties were then modeled using the fuel consumption model. In summary, our analysis found that weather forecast errors increase with time elapsed from departure; we also found that weather forecast errors are route-specific. High variance in wind direction forecast error is found at low-latitude of the trans-Pacific routes and at high-latitude of the southern-hemispheric routes. Furthermore, an overestimation in forecast temperature is found in two southern-hemispheric routes. Based on the comparison between the performance under the forecasted weather and actual weather, the southern-hemispheric routes tend to overestimate fuel consumption with a median of up to 223 kg. An underestimation in temperature along with an underprediction in cruise stage fuel consumption with a median up to 202 kg is found for trans-Pacific and Asia-pacific routes.**

Keywords-Fuel planning; World Area Forecast System (WAFS); Weather forecast uncertainty

I. INTRODUCTION

Airlines utilize weather forecast products from London and Washington's World Area Forecast Centers (WAFCs) to calculate the trajectory and fuel required for their mid- to long-haul flight operations. These meteorological forecast products generated from the two World Area Forecast Systems (WAFS) are deterministic and extrapolated from finer numerical weather prediction (NWP) model. This paper studies the effect of weather forecast uncertainty on fuel planning. Instead of using the information provided by ensemble weather forecasts (which are commonly used in literature), this paper uses forecasts generated from the WAFS, which, despite having a lower resolution, are used in practice by airlines. As such, this study aims to quantify the WAFS weather forecast inaccuracies and its effect on fuel burn.

Fuel is one of the major cost drivers in airline operations and establishing fuel-saving strategy is of paramount importance to operators. In this regard, it is necessary to understand fuel consumption characteristics. With advancing data collection capabilities from flight recorders and enhanced computational power, more information on fuel burn performance can now be extracted and studied than ever before. Today, there are new and novel methodologies that can now be applied to this area of research. We bridge the gap in the current literature by linking the weather forecast products currently in use by airlines and the available flight data to investigate aircraft fuel consumption variability attributed to weather, and we explore how this may affect fuel uplift planning.

Weather forecast parameters and forecast files, generated from NWP models and distributed from the two WAFCs, are used to facilitate flight and fuel planning. Yet, these NWP models are susceptible to initial input conditions, boundary layer conditions, time and geographical conditions, etc. An assessment carried out by Cole, Schwartz and Benjamin [1] showed that the errors in the forecasted wind fields increase at higher wind speeds. They also found that different types of weather can influence the accuracy of wind field forecasts. Due to the complexity of integrating weather uncertainty to flight operation analysis, many previous studies accounted for weather forecast errors by approximating a mean deviation value and/or applying a statistical distribution in simulation [2]. However, weather forecasts – by nature – are subject to seasonal changes, geographical locations, forecast time and accuracy of individual forecast centers. There is little research that matches weather forecast values with real flight data as measured from an aircraft's Flight Recorder (FR) or Quick

Access Recorder (QAR) [2]–[4]. There are even fewer studies that quantify weather forecast uncertainties and their effect on fuel uplift estimation [4], [5]. Even so, nowcast weather is typically used for those analysis and the effect of temperature is often omitted and delegated to future work. Weather parameters such as wind speed, wind direction and temperature have been shown to have a significant influence in fuel burn. As such, by comparing the forecast data with actual in-flight measurements from the flight data recorder, the impact of weather forecast uncertainty to fuel consumption can be quantified. In this paper, weather forecast data and modeled aircraft performance are compared with actual measured data obtained from flight data recorder to quantify the fuel burn deviation due to weather uncertainties.

The paper is organized as follows: Section II outlines the data used; Section III discusses the methodology and the merging of the weather forecasts and flight data; Section IV demonstrates the uncertainties of the weather forecast by comparing them with measurements obtained from historical flight data; Sections V to VII outline the effect of weather uncertainties on fuel burn; and the Section VIII concludes and proposes a research agenda.

II. Sources of Data

A. *Historical flight data*

Historical flight data used in this study was obtained from the aircrafts' quick access recorder (QAR). QAR data is measured from the aircraft's flight computer, sensors and other onboard instruments. The initial weight at the beginning of flight is inputted by the pilot based on estimated passenger weight, cargo, fuel weight and the aircraft's empty weight. Apart from the uncertainty of passenger weight, the other inputs are often reasonably accurate. The Aircraft Inertial Reference System (IRS) provides measurements for speed and the aircraft's position with respect to the ground. The air data computer calculates the Mach number, altitude and airspeed based on measured pressure and temperature from the pitot-static system and temperature sensor. The flight management computer then integrates this information from the air data computer and IRS to calculate the wind speed and direction, and hence, the headwind and aircraft route. These parameters are uploaded to the flight data recorder and QAR.

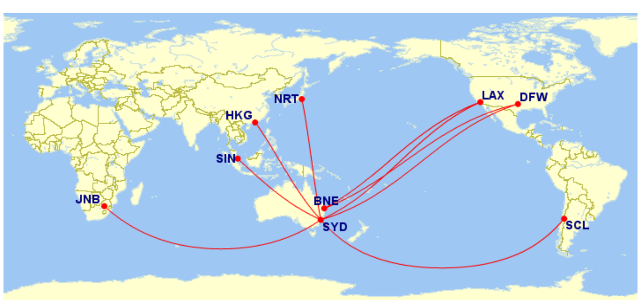

Figure 1. Flight data route map

The analysis in this paper considers uncertainties in wind speed, wind direction and temperature. By employing available flight data (one-year worth of data from a wide-body long-haul fleet, provided by a major Australian airline), the variability of aircraft fuel consumption due to weather uncertainties can be investigated. The routes analyzed are displayed in Fig. 1. It is noteworthy that the flight data are highly unbalanced from 3,000 to 100,000 sample points per route as shown in Table I.

TABLE I. The number of data points per route

Route	Number of observation
SYD-SCL	47196
SCL-SYD	39783
SYD-JNB	2999
JNB-SYD	64993
SYD-LAX	32659
LAX-SYD	51385
BNE-LAX	99140
LAX-BNE	69960
SYD-DFW	48167
DFW-BNE	56101
SYD-HKG	13204
HKG-SYD	20321
SYD-SIN	5570
SIN-SYD	7521
SYD-NRT	42852
NRT-SYD	33474

B. *Weather data*

NWP data generated in forecast centers are usually presented using a finer grid size than their products designated for aviation. Therefore, it is likely that forecast centers 'coarsen' their results to meet the World Meteorological Organization (WMO) and International Civil Aviation Organization (ICAO) forecast standards. However, when these products are distributed to airlines, the forecast is interpolated back to a finer grid size for flight planning and dispatch purposes. In the process of grid size scaling, errors can occur and accumulate. Note that different interpolation techniques can result in different levels of accuracy; and for computational efficiency, this paper will only adopt linear spatial and temporal interpolation. For more information on spatial and temporal interpolation errors, readers are suggested to see [6].

WAFS data is provided in a format of "Load Time + Forecast Hour", where load time represents the modeling time of the weather forecast system, and forecast hour refers to the number of hours the forecast is ahead of its load time. This data is stored in a gridded binary (GRIB) format. Depending on the temporal resolution, multiple forecast files are built for different forecast windows. The weather forecast inside the GRIB file is separated by specific geopotential height levels and gridded geographical locations. According to WMO and ICAO standards, forecast centers must produce forecast products at a standardized resolution. Forecast data are produced every six hours (00, 06, 12, 18Z) with a forecast window of 6 to 36 hours ahead (+06, +12…+36). Each forecast file (also known as a GRIB file) has a spatial resolution of 1.25º x 1.25º (which is approximately 100km x 100km, depending on the latitude) horizontally and is separated by 13 unequally spaced vertical layers. The 13 verticals layers are based on geopotential height, and are: 850hPa, 700hPa, 600hPa, 500hPa, 400hPa, 350hPa, 300hPa, 275hPa, 250hPa, 225hPa, 200hPa, 150hPa, 100hPa ranging from approximately 4,800 feet to 54,000 feet.

III. Linking WAFS forecast to flight data

We ensure a systematic and thorough process for extracting WAFS forecast and historical flight information so a comprehensive, and accurate, merge of the two datasets is achieved. This section outlines the flight and weather forecast data handling techniques used.

A. Flight data handling

Plenty of information is available from flight data recorders. With respect to this study, information regarding latitude, longitude, altitude, time, weight, measured wind speed, wind direction, temperature, fuel flow and fuel quantity values were extracted. Furthermore, flight data was recorded on a second-by-second basis. To reduce computation time, the record was shrunk to a minute-by-minute frequency by taking a snapshot of the first-second of each minute.

The flight data recorder stores information beyond the flight journey, such as data rolled over from the previous operation and/or after taxi-in. Such "excess" data are filtered for the purpose of this study. Start of the cruise stage, i.e. top of climb data, is extracted by locating the data point with an altitude greater than 25,000 ft and with a rate of change in altitude smaller than 1 ft/s.

Step climbs occasionally occur in mid- and long-haul flights. In order to isolate the effect of the cruise, and in a bid to reduce measurement error, data during step climbs are omitted. Similar to the process of identifying the top of climb data, the start and end of a step climb are detected by identifying a significant difference in the rate of change in altitude.

The departure time and top of climb weight are extracted explicitly for the fuel flow and fuel burn analysis carried out in Section VI.

B. Weather data handling

1) Temporal aligning

WAFS forecast data are provided to operators with four-hour intervals, which means the flight planning system, even with its most updated weather forecast, will have at least a four-hour lag. Table II presents the relationship between the lapsed weather forecast cycle/load time to the corresponding departure time.

TABLE II. FORECAST FILE LOAD TIME

Flight Time (Z)	Load Time (Z)	Flight Time (Z)	Load Time (Z)
0000	1800	1200	0600
0100	1800	1300	0600
0200	1800	1400	0600
0300	1800	1500	0600
0400	0000	1600	1200
0500	0000	1700	1200
0600	0000	1800	1200
0700	0000	1900	1200
0800	0000	2000	1200
0900	0000	2100	1200
1000	0600	2200	1800
1100	0600	2300	1800

a. Z refers to Zulu time, which is equivalent to UTC+0, and Greenwich Mean Time. This notation will be used throughout the paper.

2) Forecast weather handling at grid vertex

The wind speed forecast in WAFS is stored as zonal and meridional component wind. To facilitate our comparison, these wind components are transformed into a resultant wind speed and direction using (1) and (2).

$$Wind\ Speed = \sqrt{U_{wind}^2 + V_{wind}^2} \tag{1}$$

$$Wind\ Direction = \left(\frac{180}{\pi}\right)\tan^{-1}\left(\frac{U_{wind}}{V_{wind}}\right) + A \tag{2}$$

where $A = \begin{cases} 180 & V_{wind} \geq 0 \\ 0 & U_{wind} < 0;\ V_{wind} < 0 \\ 360 & U_{wind} > 0;\ V_{wind} < 0 \end{cases}$,

and U_{wind} is the forecast zonal wind speed, V_{wind} is the forecast meridional wind speed.

3) Forecast data interpolation

As mentioned in Section II.B, the weather forecast data has a horizontal resolution of 1.25° x 1.25°, a vertical resolution of either 50 to 100 hPa apart and a temporal resolution of three hours. While previous studies apply various interpolation techniques, it has been found that the trilinear spatial (horizontal and vertical) and linear temporal interpolations have achieved reasonable accuracy and computational efficiency [6].

C. Calculating weather forecast error

As the forecast error is defined in (3), the number of forecast errors available will equal to the number of observations available. Using a specific grouping method, the means and standard deviations of the forecast errors can be calculated for different flight routes, the time difference between the most recent forecast file and duration from departure.

$$\varepsilon = v_{obs} - v_{for} \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\varepsilon_i^2} \tag{4}$$

where ε is the forecast error, v_{obs} is the observed value, v_{for} is the forecast value

IV. WAFS FORECAST PERFORMANCE

In this section, several WAFS forecast error analyses are introduced. The weather forecast parameters that are taken into consideration include wind speed, wind direction and temperature.

Weather forecast values obtained from the GRIB files were compared with the measurements obtained from the historical flight data. The forecast error is defined according to (3). After omitting outliers from the sample, boxplots, means, and standard deviations of the forecast errors could be calculated and presented. Below we introduce three analyses to quantify forecast errors.

A. By flight route

We first divided the results by flight route. As shown in Fig. 2, the results in general follow a bell-shaped distribution with a median close to zero. Furthermore, based on Fig. 2, southern hemispheric routes consistently exhibit a negative median temperature forecast error and tend to have a higher variance in temperature forecast error. This suggests that the WAFS forecast tends to overpredict the temperature along those routes. This result aligns with Fig. 5 which shows a majority of negative mean temperature forecast errors along the analyzed routes geographically.

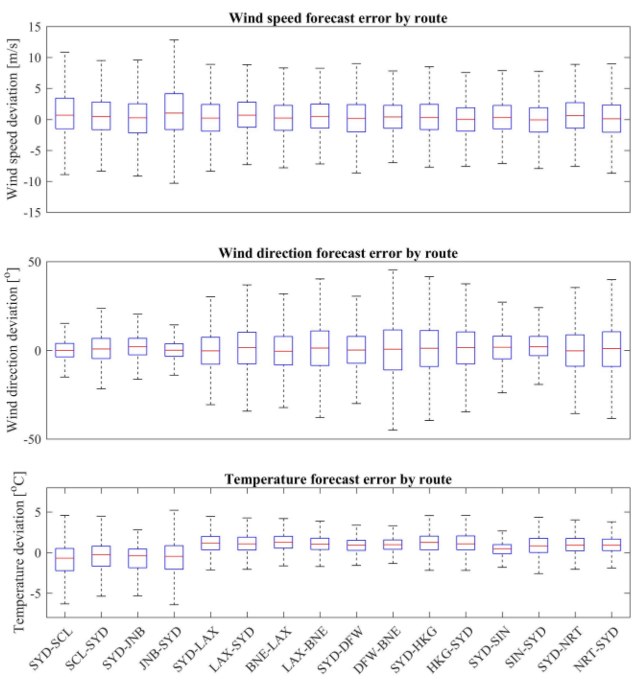

Figure 2. Boxplot of forecast error by flight route

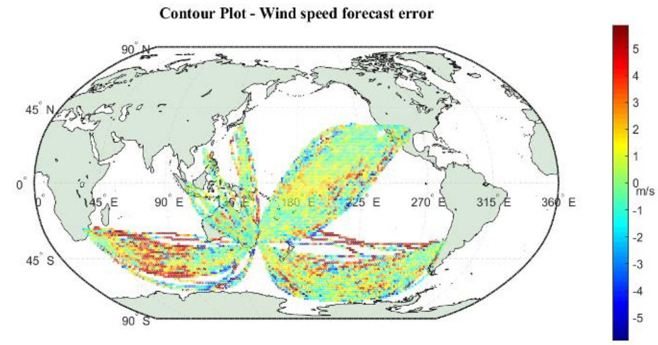

Figure 3. Map of mean wind speed forecast error

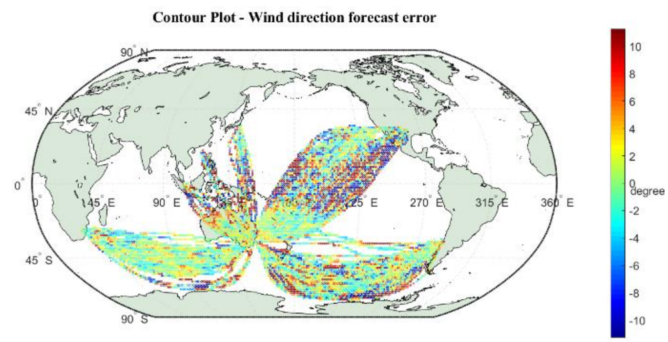

Figure 4. Map of mean wind direction forecast error

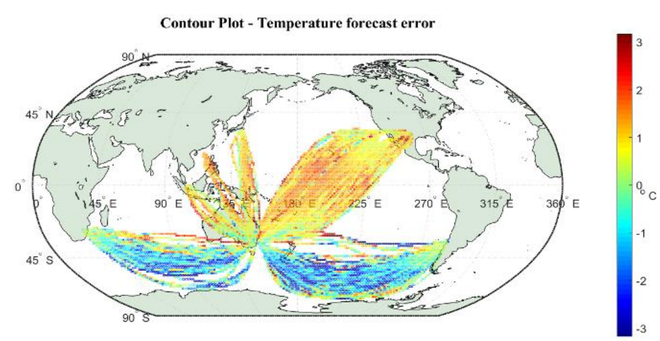

Figure 5. Map of mean temperature forecast error

It is noteworthy that each dot plotted in Fig. 3 to 5 represent the mean value of a collection of data points within a grid. The grid has the same spatial resolution horizontally as WAFS GRIB files (i.e. 1.25º x 1.25º) and the mean value of weather parameters' forecast error is subject to the number of data points available in the same grid. The effect of altitude is neglected when grouping the data, hence data within the same grid but with different altitudes are considered as the same group when the mean value is calculated.

While the standard deviation of the wind speed forecast error across different routes remains at approximately 2 to 3 m/s, the wind direction forecast error, demonstrated in Fig. 4, tends to exhibit a higher variance at low-latitude (30ºN – 30ºS) in the AU-US (trans-Pacific) and Asia-Pacific routes, and at high-latitude (60ºS – 90ºS) in the Southern-hemispheric routes.

Wind speed and direction forecast directly influence headwind prediction and temperature forecast plays an important role in defining the international standard atmosphere (ISA) deviation and the Mach number. The effect of these weather parameters on fuel burn prediction will be further discussed in subsequent sections.

B. By time from the most recent GRIB file

While the GRIB files are three-hours apart, instances between the two forecast files are temporally interpolated for flight planning purposes. We carried out the following analysis to quantify the effect of temporal interpolation between forecast files. The forecast error data was grouped into 10 bins, each with approximately 1200 seconds apart, up to the end of the three-hour window. From the results shown in Fig. 6, the forecast error standard deviation increases with the interpolation time.

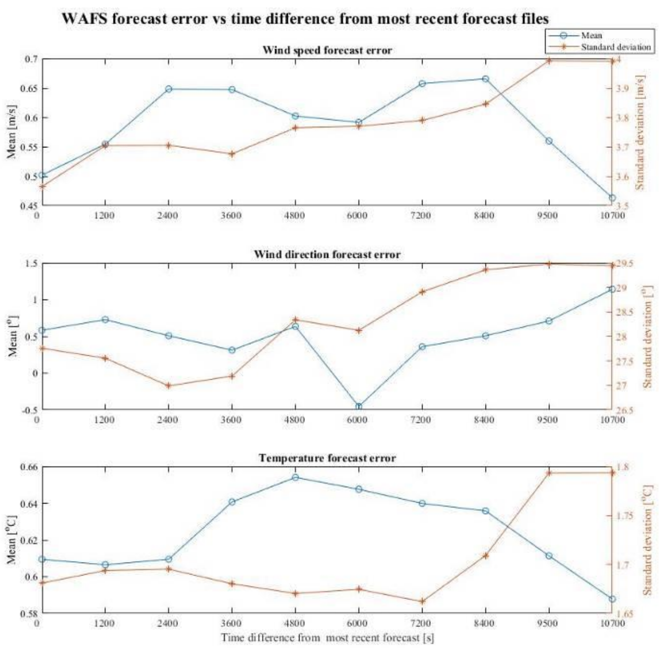

Figure 6. Forecast error by time difference from the most recent forecast

It is not surprising that the mean value does not increase with the standard deviation but instead begins to fluctuate. This is because the temporal interpolation could be an interpolation between +06 and +09 or it could also be an interpolation between +09 and +12 and so on. On one hand, this suggests that the results inform of how the forecast error varies between forecast files, rather than how the forecast error changes with the load time. On the other hand, based on the magnitude of errors, it demonstrates that the effect of the time from the most recent GRIB file is not as significant as the geographical effect on weather forecast errors.

C. By time from departure

Weather forecasts deteriorate as the forecast window increases. To visualize this in a quantitative manner, we temporally grouped the forecast errors with their time from departure. From the results shown in Fig. 7, the mean temperature forecast error increasingly deviates from zero (indicating no forecast error) as the time difference increases.

A dramatic drop in the standard deviation of the forecast error is found in the last group. This is likely due to insufficient data points as the flight is near the end of its cruise stage (top of decent). It is worth noting that this explanation also applies to the mean values. Despite a lack of data points at the end of cruise stage, mean temperature forecast error, as shown in Fig. 7, has demonstrated an increasing trend as the time difference since departure increases.

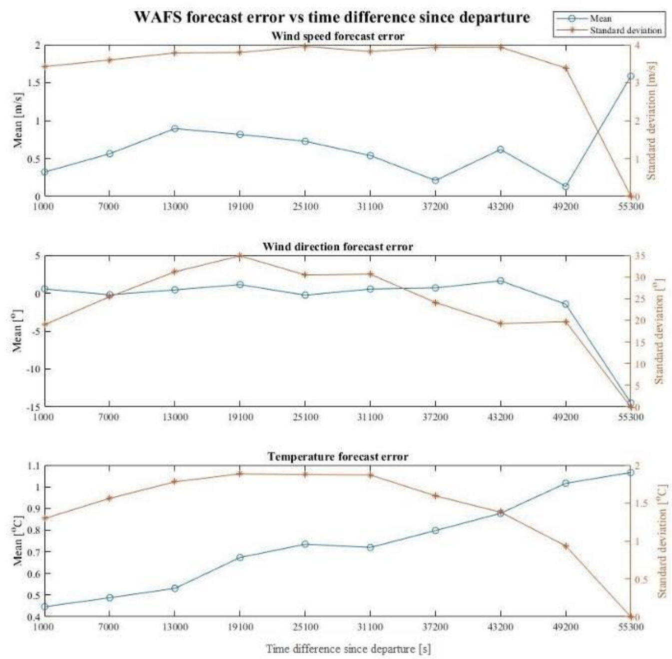

Figure 7. Forecast error by time difference since departure

The magnitude of forecast errors caused by increasing time from departure is similar to that caused by the time from the most recent forecast file. Comparing this with the forecast errors affected by flight routes (as shown in Section IV.A), it indicates that the temporal accuracy of WAFS products performs better than its spatial accuracy.

V. WEATHER AND FUEL CONSUMPTION

While in the previous section, WAFS forecast uncertainties were analyzed, this section demonstrates the effect of weather uncertainties on fuel consumption. Wind speed, wind direction and temperature forecasts are the primary variables considered during flight and fuel planning. The wind properties directly affect the aircraft's track direction and ground speed, as shown in (7). Deviations in wind speed and direction can cause along-track errors and flight range deviations with the relationship shown in (8).

$$a = \sqrt{kRT} \tag{5}$$

$$V_{TAS} = Ma \tag{6}$$

$$V_g = V_{TAS}\cos(\theta_{HDG} - \theta_{TRK}) + V_w \cos(\theta_{TRK} - \theta_w) \tag{7}$$

$$R = \sum_i V_i \Delta t_i \tag{8}$$

where a is the speed of sound, k is the adiabatic constant, T is the temperature, M is the Mach number, V_{TAS} is the true airspeed, V_g is the ground speed, V_W is the wind speed, θ_{HDG} is the aircraft heading, θ_{TRK} is the aircraft track, θ_W is the wind direction, i is the time between segments/iterations; R is the cruise range and t is the time.

These errors and deviations, in turn, may result in the aircraft flying in suboptimal flight and fuel conditions. Early work considering wind uncertainties in flight planning quantified wind uncertainties as a sum of three spatial and temporal correlated terms: the error of representativeness, the prediction error and the large-scale error; and propagated these uncertainties to a trajectory planning model using Monte Carlo simulations [3]. Tino and Ren [7] conducted an extended study of wind uncertainties on trajectory prediction by comparing the results with flight data. Later, with the development of Ensemble Prediction System by European Centre of Medium-Range Weather Forecasts (ECMWF), wind uncertainties are better quantified and more accessible for subsequent studies. Arribas et al. [8] developed an algorithm using pseudo-spectral methods and ensemble weather forecasts to find a wind-optimal route and measure the impact of wind forecast uncertainties on optimal flight paths. Cheung et al. [9] utilized ensemble wind forecast to develop an ensemble trajectory prediction model. Franco, Rivas and Valenzuela [10]–[12], on the other hand, developed a probabilistic trajectory prediction model that propagated the ensemble wind forecast uncertainties using a generalized polynomial chaos method (previously used in [13]).

As for temperature, although the Mach number has little fluctuation during the cruise stage, the speed of sound changes with air temperature according to (5) and (6). In this regard, true airspeed, ground speed, and flight time are affected due to temperature deviations; and temperature deviations are closely related to altitude due to atmospheric conditions. Despite its influence on flight and fuel planning, most researchers have focused on the quantification and propagation of wind forecast while ignoring temperature. In practice, the effect of temperature deviations cannot be disregarded and treated separately as they directly and dynamically affect fuel predictions, aircraft weight predictions and aircraft performance along the flight.

VI. ANALYSIS OF FUEL CONSUMPTION DUE TO WEATHER UNCERTAINTIES

In order to find the effect of weather uncertainties on fuel consumption deviation, we compared the modeled performance under actual weather conditions with forecasted weather conditions during cruise. The actual flight route and the same starting weight value was inputted into the model to isolate the effect of position and initial mass errors. This process ensures the evaluated fuel burn deviation is solely attributed to weather forecast deviations.

A. *Fuel consumption model*

While the fuel burn model used in our study was coupled with high quality aircraft performance reference data generated from manufacturers' performance engineering programs [14], theoretically, fuel consumption is relative to equations of motion and thrust. Equation (9) – (14) are presented in differing formats across several aerodynamic textbooks. Here, we simplified and reproduced them for convenience in demonstrating the concept and dependency of variables.

$$L = \frac{1}{2}\rho V_{TAS}^2 S C_L \tag{9}$$

$$L = W \tag{10}$$

$$F_T = D \tag{11}$$

$$D = \frac{1}{2}\rho V_{TAS}^2 S C_D \tag{12}$$

$$\dot{m}_f = TSFC \times F_T \tag{13}$$

$$Total\ Fuel\ Burn = \sum_i (\dot{m}_{f_i} \Delta t_i) \tag{14}$$

where L is the lift force, ρ is the air density, V_{TAS} is the true airspeed, S is the aircraft wing area, C_L is the coefficient of lift, W is the weight of the aircraft, F_T is the thrust, D is the drag force, C_D is the coefficient of drag, $\dot{m}_f$ is the fuel flow rate, *TSFC* is the thrust specific fuel coefficient for turbojet aircraft, Δt is the time step, i is the step size.

Based on (13), it can be seen that the fuel flow rate is directly influenced by TSFC provided by manufacturers and the thrust required as per operators' speed setting which, in turn, according to (11) and (12), is determined by weight, air density, the square of aircraft's true airspeed, wing area and coefficient of lift. While air density changes with temperature and altitude, the true airspeed is determined by the operators' cost index (CI) setting which we obtained from historical flight plans. CI, with the definition shown in (15), is the relationship between fuel-related and time-related (e.g. maintenance, crew scheduling etc.) costs. It is a value carefully selected by operators that allows them to achieve an optimal trip cost based on their trade-off between operating costs per hour and incremental fuel burn [15]. We can simplify the fuel flow equation with the expression shown in (17).

$$Cost\ Index\ (CI) = \frac{Cost\ of\ time}{Cost\ of\ fuel} = \frac{C_T}{C_F} \quad (15)$$

$$M = f(W, alt, isaDev, H/W, CI) \quad (16)$$

$$FF = f(W, alt, isaDev, M) \quad (17)$$

where *M* is Mach number; *W* is weight; alt is altitude; *isaDev* is the international standard atmosphere (ISA) deviation; *H/W* is headwind; *CI* is cost index

While aerodynamic coefficients are known and remain more or less constant during the cruise stage, TSFC varies with speed and altitude. Based on (16) and (17), it could be seen that fuel consumption dynamically varies with changes in weight, altitude, speed, temperature and wind.

B. Assumption and model setting

Several boundary conditions and constraints were applied. Time and weight at the top of climb position in the aircraft data were used to start the analysis. Forecast weather data was updated with respect to model time. Aircraft position obtained from historical flight data was used to ensure that the modeled performance was using the same route as the actual flight.

VII. FUEL BURN DEVIATION DUE TO WEATHER UNCERTAINTIES

From Section IV.A, we have briefly mentioned the effect of wind speed and direction on headwind and the effect of temperature on ISA deviation; and from Section VI.A, we defined fuel flow rate as a function of weight, altitude, headwind, CI and ISA deviation. In this section, we quantify the combined effect of all WAFS parameters' forecast errors on fuel flow and the cruise stage fuel burn by modeling and comparing the fuel burn under actual and forecasted weather conditions.

The fuel flow rate modeled from actual weather is compared with the fuel flow rate modeled from the forecast weather. The results, by route, are presented in Fig. 8. From the results of the four southern-hemispheric flights, the root mean squared errors are higher than those of the AU-US and Asia-pacific routes. This is likely the result of the southern jet stream and the deviations of forecasted temperatures as demonstrated in Section IV.A. The drop for SYD-JNB route is likely due to a lack of data as previously discussed in Section II.A.

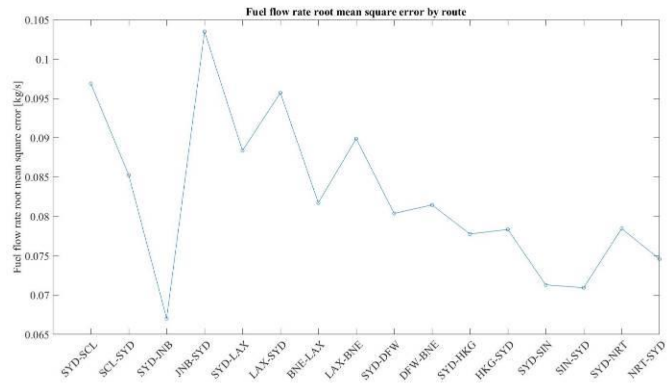

Figure 8. Fuel flow rate root mean squared error by route

While Eulerian analyses were conducted in the previous sections, we use a Lagrangian analysis to find the cruise stage fuel consumption variability due to weather uncertainties. Modeled performance under actual weather condition and modeled performance under forecast weather condition during cruise stage were compared. The fuel consumption based on actual and forecast weather were modeled separately under the same route configuration to carry out a fair comparison and isolate the effect of model and position deviation. This approach allows us to find the fuel burn deviation solely due to weather forecast deviation. The effect of WAFS forecast error was accumulated by modeling the entire flight based on WAFS forecasts.

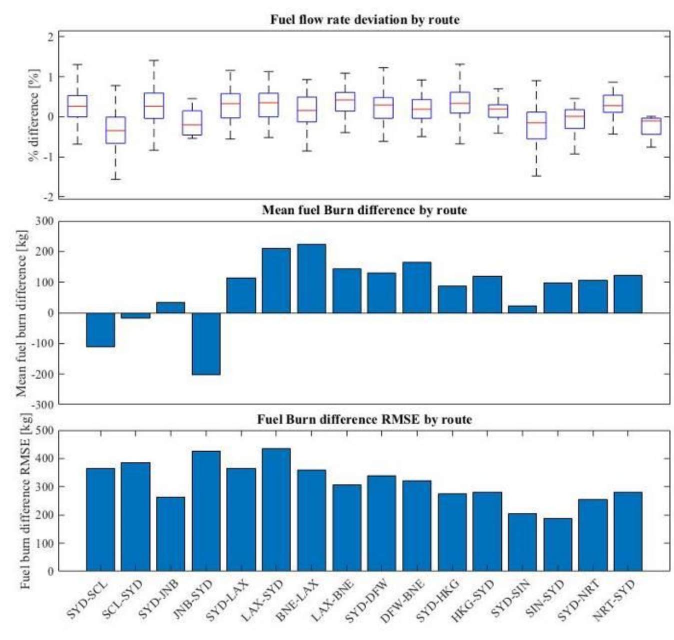

Figure 9. Percentage difference in cruise stage fuel burn deviation

The initial weight and model set-up are defined in Section VI.B. The percentage difference in cruise stage fuel burn is quantified and displayed in Fig. 9 and the fuel burn percentage difference is defined according to (18).

$$\Delta FB\% = \frac{\left(FB_a - FB_f\right) \times 100\%}{FB_f} \quad (18)$$

where *ΔFB%* is the fuel burn percentage difference; FB_a is the fuel burn due to actual weather; FB_f is the fuel burn due to forecast weather.

Based on (18), a positive percentage difference indicates that more fuel is burnt under actual conditions than those forecasted, and vice versa. The results quantify the deviation in fuel consumption between actual and forecasted weather conditions. Routes where fuel-saving strategies can be improved are identified. Based on the results shown in Fig. 9, southern hemispherical routes tend to produce negative values and the AU-US and Asia-pacific routes tend to produce positive values. This result suggests that fuel-saving strategies can be applied to southern-hemispheric flight routes using weather uncertainty analysis.

VIII. Conclusion

In this paper, we introduce several WAFS forecast uncertainty analyses and a technique to quantify its effect on cruise stage fuel burn predictions. These tools assist in identifying the cause of weather forecast errors and their effect on fuel consumption. Temporal and horizontal spatial effect to WAFS weather forecast errors were conducted in our current study and a robust framework in WAFS products forecast error quantification has been built. To further understand the cause of weather forecast errors, many other factors such as the spatial interpolation of weather forecasts, interpolation methods etc. have not been considered in this paper. However, with increasing data collection, we anticipate future study to be extended to three and four-dimensional weather forecast uncertainties analysis on these WAFS products using similar techniques. We hope this paper serves as a starting point in understanding the causes and characteristics of weather forecast errors as well as developing future fuel-saving strategies via greater confidence in weather uncertainty. With flight and weather data available but not being analyzed, this paper also unlocks the possibility of enhancing operation efficiency by utilizing these data. Similar techniques could be applied in future studies to quantify the effect of other sources of en-route uncertainties to fuel consumption. With a better grasp of the effect of en-route uncertainties and the help of machine learning and statistical technique such as regression analysis, the current arbitrary fuel (especially contingency fuel) loading requirement could be better quantified; and this direction aligns with the increasing emphasis of performance-based approach in civil aviation authorities.

Acknowledgment

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