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Abstract

Meteorological observations are very important for weather forecasting; one potential source of observations is commercial aircraft. Commercial aircraft transmit Mode Selective Enhanced Surveillance (Mode-S) reports, which include data about the aircraft's ground speed and magnetic heading, but the reports do not include temperature readings. Instead, the Mach number and airspeed can be used to derive the temperature. However, to transmit the Mode-S report the precision in the Mach number and airspeed is reduced from 16 bits to 10 bits. This reduction in precision creates errors in the Mach number and airspeed, which in turn translate to errors between 4–7 K and 3–5 K respectively, in the derived temperature. These large errors may limit the use of these observations for weather forecasting. This paper investigates if optimal interpolation, a type of data assimilation, can be used to combine aircraft data with atmospheric model data to provide a better estimate of the temperature-derived observations. We find that optimal interpolation can reduce the standard deviation of the derived temperature observations to 1.12 K; however, this is too large to be used with numerical weather prediction where a standard deviation of 1.0K is required.

Keywords: Mode-S EHS, data assimilation, optimal interpolation, improving temperature-derived observations, numerical weather prediction.

Introduction

Meteorological observations are very important for numerical weather prediction (NWP) as they help keep mathematical models of the atmosphere on track. Observations at all heights in the atmosphere are needed as ground observations are not sufficient to improve predictions of the entire atmosphere. Current observation sources such as radiosondes that provide temperature profiles are infrequent. A potential source of frequent observations is commercial aircraft; they can provide observations from the ground to approximately 11 km in the atmosphere. Collecting observations from aircraft for meteorological purposes is not a new concept; it has been around since the First World War (Moninger et al., 2003: 203). The number of observations collected has grown ever since, and NWP centres routinely use data from the global Aircraft Meteorological Data Relay (AMDAR) programme (Stickland and Grooters, 2005). Currently, there are around 13,000–16,000 aircraft in the air around the world at any time (Morris, 2017) that could transmit valuable meteorological data.

Most commercial aircraft transmit Mode Selective Enhanced Surveillance (Mode-S EHS) reports, which are a potential source of frequent data. The Mode-S EHS data can be used to derive temperature and horizontal wind observations and these have been successfully used in weather forecasting (de Hann and Stoffelen, 2012: 927). However, Mode-S EHS reports send data with reduced precision. This truncation produces errors in the derived temperature (Mirza et al., 2016: 2965) which makes the observations in the atmospheric boundary layer, typically the lowest kilometre in the atmosphere, of limited use in NWP.

In this article we will consider if optimal interpolation (OI), a type of data assimilation, can be used to improve temperature observations derived from Mode-S EHS data. Data assimilation is the process of finding the best combination of the observation and model information which gives an optimal solution (Lahoz, 2010: 7). This process will be used to combine data from the aircraft and the Met Office UK Variable resolution (UKV) NWP model (Tang et al., 2013: 419) to give a better estimated temperature. The performance of the data assimilation will be assessed by comparing results to independent temperature measurements.

The paper is organised as follows: we will first look at the observation data and how it can be used to obtain the derived temperature. We will then describe data assimilation and OI. Next, we describe the background and observation data along with specifics of each assimilation experiment in the experimental design section. We then discuss our findings in the results section before summarising in the conclusions section.

Observation data

Mode-S EHS data

Commercial aircraft transmit a Mode-S EHS report every 4–12 seconds to air traffic control, but the report can be collected by third parties using an inexpensive receiver (Mirza et al., 2016: 2949). This means that receivers can be placed throughout different locations and used to collect data from commercial aircraft. These reports contain data about the aircraft, such as the selected altitude, roll angle, true airspeed, ground speed, magnetic heading, Mach number and the vertical rate (climb/descent rate) (de Haan, 2011: 2). The precision of data is reduced from 16 bits down to 10 bits during processing prior to sending the Mode-S EHS report, this introduces a quantisation error into the data. Quantisation error is the difference between the real, analogue signal and the digital representation of that real signal. In this manuscript, the estimated uncertainty in the Mach number is $0.004/\sqrt{12}$ and in the airspeed the estimated uncertainty is $2/\sqrt{12}$ knots (Mirza et al., 2016: 2957).

Derived temperature observations

The derived temperature observation (T_A) is obtained from:

$$T_A = \frac{T_0}{A_0^2}\left(\frac{V_A}{M}\right)^2, (1)$$

where the reported Mach number is M and the reported true airspeed is V_A (the speed of the aircraft relative to the air mass the aircraft is flying in). The ambient temperature (T_0=288.15K) and the speed of sound (A_0=340.294 ms^{-1}) are both constants defined at mean-sea-level pressure under standard atmospheric conditions (Authority of the Secretary General of the International Civil Aviation Organization, 1993: E–viii, E–xi).

The quantisation error in the Mach number and airspeed can have a significant impact on the derived temperature observation. The Mach number increments with a minimum of 0.004. When the airspeed is constant and when the Mach number changes by 0.004, then the temperature-derived observation changes by between 4 and 7 Kelvin. Similarly, when the Mach number is constant and the airspeed changes by approximately 1 ms^{-1}, the temperature-derived observation changes by between 3 and 5 Kelvin. These large errors in the derived temperature can make the data in its current form unusable for NWP (Mirza et al., 2016: 2965) as the data must have an uncertainty no greater than 1K (World Meteorological Organisation, 2018).

Data assimilation

The process of combining observational data with model data weighted by their errors is known as data assimilation (Lahoz, 2010: 7–8). The model data typically comes from a numerical model of the system of interest. The result of the data assimilation is called the analysis, which is the best estimate of the true state of the system. In our case, the observational data is the Mach number and the true airspeed while the model data, which we refer to as the background, is the temperature from the UKV NWP model. Data assimilation is a very useful tool to derive meaningful information when observations are too infrequent to use, or when the background or measurement has large associated errors.

Many different methods for data assimilation exist, such as the Kalman filter (Kalman, 1960) and 3D-Var (Courtier et al., 1998). In this paper, optimal interpolation will be used, which is an extension of a best linear unbiased estimator (BLUE). BLUE is described below:

- An estimator is a rule used to calculate an estimate of parameter(s) of a population by taking samples.
- Unbiased, meaning the expected value is the true value of the parameter being estimated.
- Linear, meaning that the value is being estimated through a linear function.
- Best, meaning the estimator gives the lowest variance of an estimated value than any other estimator; in this case, BLUE gives the lowest variance of any linear unbiased estimator.

Optimal interpolation

In optimal interpolation, the analysis is found using (Kalnay, 2003: 150-57):

$$x_a = x_b + W[y_o - \mathbf{H}(x_b)], (2)$$

where x_b is the model estimate, which we call the prior or background and y_o is the observed value. **H** is a transform operator that maps model space into observational space. The optimal weight is calculated by the following equation:

$$W = \mathbf{B}H^T(\mathbf{R} + H\mathbf{B}H^T)^{-1}, (3)$$

where W is the optimal weight matrix, *H* is the linear observational forward operator, **B** is the background error covariance and **R** is the observational error covariance. OI works by finding the difference between the observed value and the estimate, inside the square brackets in equation (2). This is then amplified or dampened by the weight matrix, which is dependent on the ratio of the errors in the background and observed data. Then the prior estimate is summed with the weighted difference. Assuming the errors are Gaussian, the new estimate will have an error no larger than the input data, but the error can be smaller. In this article, we will consider if OI can be used to improve temperature observations derived from Mode-S EHS data.

Experimental design

Observation Data

The reference and observation data used in this study were obtained from the Facility for Atmospheric Airborne Measurements (FAAM). We utilised data such as pressure altitude, temperature, Mach number, true airspeed, location. However, the aircraft does not have a Mode-S EHS transmitter on board, so the Mode-S reports were simulated (Mirza et al., 2016: 2950). The aircraft also recorded the local ambient temperature, which has a very high accuracy of ±0.3K. This independent data will be used to verify the derived temperatures and will be labelled as the reference throughout this paper.

For accurate measurements to be made, the aircraft must have a roll angle of less than 1.5° and an airspeed greater than 25m/s (Mirza et al., 2016: 2956). Thus there are gaps in the observation data.

We have two flights from the FAAM aircraft that will be investigated; flight 11 July 2013 and flight 28 July 2013. The weather conditions and flight details during July 2013 were as follows (Eden, 2013: i; Mirza, 2017: 58):

Flight 11 July 2013
It was a very warm, dry and sunny day as there was an anticyclonic spell. The FAAM aircraft departed Exeter airport and flew north to the Bristol Channel. It then performed east–west trajectories over the Irish Sea and to the north of Cornwall.

Flight 28 July 2013
The weather was unsettled with cooler temperatures than on 11 July 2013. The FAAM aircraft departed from Exeter airport and headed towards central Cornwall, in the region between Truro, Bodmin and St Austell. On arrival, it executed north–south, east–west trajectories.

Background data

The background data used in the paper was the temperature from the UK variable resolution numerical weather prediction model (UKV) which is a version of the Unified Model over the UK run by the Met Office (Tang et al., 2013: 417). Across the UK, the grid length is set to 1.5 km; the horizontal grid length is gradually changed to 4 km over a buffer zone near the lateral boundaries of the domain. The initial conditions of UKV are set using 3D-Var and the latent heat nudging of radar rainfall data, which are then used to produce forecasts every six hours (Ballard et al., 2016: 473–74).

The standard deviation of the temperature predictions varies with the height of the prediction and ranges between approximately 0.37 K and 0.58 K (Ballard et al., 2016: 479).

The background data is in temperature space, but it needs to be in Mach number space to be used in the optimal interpolation. To convert the background temperature, T_B, to background Mach number, M_B, we rearrange equation (1) as follows:

$$M_B = \frac{V_A}{A_0}\sqrt{\frac{T_0}{T_B}} = \mathbf{H}, \; (4)$$

H has been used in a non-standard way, as it maps T_B to M_B using observed information. The use of the observation data in the observation operator (**H**) has an effect on the background Mach number which, in turn will affect the derived-temperature produced from the data assimilation. This can be seen particularly in equation (1) where the reciprocal of the Mach number is squared.

Assimilation

There were three different approaches taken to calculate the analysis; temperature assimilation with fixed background errors, Mach number assimilation with fixed background errors and Mach number assimilation with variable background errors. We will compare these approaches to determine which performs better to reduce the uncertainty in the analysed temperature.

Temperature assimilation (T1)
For the temperature assimilation, the analysed variable in equation (1), X_a is temperature, X_b is the background temperature. The observations are the Mach numbers. To map the model to the observation space, we will use the observation operator defined in equation (4). The linear forward operator (**H**) is required to calculate the optimal weight using equation (3) and is the Jacobian of equation (4). The Jacobian function gives the local linear scaling for a given point (Lahoz, 2010: 50). Differentiating equation (4) with respect to T_B gives:

$$H = \frac{\partial}{\partial\, T_B}\left(\frac{V_A}{A_0}\sqrt{\frac{T_0}{T_B}}\right) = \frac{-V_A}{2A_0\; T_0}\left(\frac{T_B}{T_0}\right)^{-\frac{3}{2}}.(5)$$

The Jacobian is evaluated for T_B. It should also be noted that the error in airspeed was not taken into account in the temperature assimilation. The impact of omitting this error can be seen in the results section.

To calculate a value for the background uncertainty, an average was taken from (Ballard et al., 2016: 479). This gave the result of 0.475 K. The observation error is $0.004/\sqrt{12}$ as mentioned earlier in the observation section. Both the background and observation errors used are static and scalar, so they can be squared to give **B** and **R**, which in this case are the background and observation variances respectively.

Mach number assimilation (M1)

For the Mach number assimilation, X_a is Mach number, X_b is the background Mach number calculated prior to the assimilation using equation (4). Since both background and the observations are all Mach numbers, the linear (H) and non-linear (***H***) forward operator are set to one.

The background temperature has an error associated with it. When the temperature is converted into a Mach number, the error gets changed too. We use error propagation (Taylor, 1982: 75) to convert the background temperature error into a background Mach number error. The error variance of the background Mach number is given as:

$$\sigma^2_{Mb} = \left(\frac{\partial\ M}{\partial\ T_B}\ \times\ dT_B\right)^2\ +\ \left(\frac{\partial\ M}{\partial\ V_A}\ \times\ dV_A\right)^2.(6)$$

where σ^2_{Mb} is the variance in the background Mach number, where $\frac{\partial\ M}{\partial\ T_B}$ is equation (4) differentiated with respect to the background temperature (equation (5)). dT_B is the error in the background temperature. dV_A is the error in the true airspeed and $\frac{\partial\ M}{\partial\ V_A}$ is equation (4) differentiated with respect to the true airspeed, which gives:

$$M = \frac{d}{dV_A}\left(\frac{V_A}{A_0\sqrt{\frac{T_B}{T_0}}}\right) = \frac{1}{A_0\sqrt{\frac{T_B}{T_0}}}.\ (7)$$

Then, substituting the partial differentials gives:

$$\sigma^2_{Mb} = \left(\frac{-V_A}{2A_o\ T_o}\left(\frac{T_B}{T_o}\right)^{-\frac{3}{2}}\ \times\ dT_B\right)^2\ +\ \left(\frac{1}{A_0\sqrt{\frac{T_B}{T_0}}}\ \times\ dV_A\right)^2.(8)$$

An average of $\sigma^2_{Mb}\ =\ 9.107\ \times\ 10^{-7}$ was calculated using the mean values of the true airspeed and background temperature of the whole flight period in 11 July 2013. In general, we would be considering live flight data and not individual flights; therefore it would be necessary to provide a pre-determined estimate of the error. Therefore, the stated background error is used for both the 11 July 2013 and the 28 July 2013 flights.

Mach number assimilation: changing background errors with height (M2)
This assimilation is the same as M1, except that the background error varies with height in order to be consistent with the UKV errors (Ballard et al., 2016: 479). Using this along with the error propagation equation (equation (8)), the propagated background error can be calculated for different heights. The background error varies the most near the surface; therefore it was decided to split the heights into five sections with smaller height ranges near to the surface. Table 2 shows height intervals and the propagated background error. We note that the background is in Mach number, which is a dimensionless quantity.

Height (km)	**Background error variance (x10^{-4})**
4 < H ≤ 10	9.449
3 < H ≤ 4	9.648
2 < H ≤ 3	9.788
1 < H ≤ 2	9.703
H ≤ 1	9.940

Table 2: Varying the background error with height.

Data assimilation diagnostics
To understand the data assimilation performance across the entire flight period, we calculate the mean and the root mean square for the quantities given in Table 3. The mean is denoted using an overbar and calculated using $\bar{X} = Mean(X) = \frac{1}{N}\ \sum_{n=1}^{N}\ X_n$. The root mean square is denoted using σ and calculated using $\sigma_X = RMS(X) = \sqrt{\frac{1}{N}\ \sum_{n=1}^{N}\ |X_n|^2}$, where N is the number of samples and X is a general case for the differences in Table 3.

Statistic:	**Description:**
σ_A	the error in the analysis and is found using the following equation: $\sigma_A = \sqrt{(1 - WH)B}$. The result will be either in temperature or Mach number space.
ϵ_{RA}	The difference between the reference and analysis temperature.

Statistic:	Description:
ϵ_{RB}	The difference between the reference and background temperature.
ϵ_{RO}	The difference between the reference and observed temperature.
ϵ_{OA}	The difference between the observed and analysis temperature.
ϵ_{OB}	The difference between the observed and background temperature.

Table 3: A table showing the quantities used in this paper and their meaning. These are used to evaluate the performance of the data assimilation experiments.

Results

Temperature assimilation (T1)

The first results consider the FAAM flight on 11 June 2013. The background and observation errors are $B = 0.475\ K$ and $R = 0.004/\sqrt{12}$ respectively. We present the data assimilation diagnostics in Table 4, under the experiment ID: T1. Note that any quantity without defined units are in Mach number space, the Mach number is a dimensionless quantity.

Experiment ID	T1	M1	M2.1	M2.2
Flight Data	11/07/2013	11/07/2013	11/07/2013	28/07/2013
Assimilation Space	Temperature	Mach Number	Mach Number	Mach Number
Background Error	$0.475K$	9.543×10^{-4}	9.941×10^{-4} to 9.449×10^{-4}	9.941×10^{-4} to 9.449×10^{-4}
Observation Error (K)	1.155×10^{-3}	1.155×10^{-3}	1.155×10^{-3}	1.155×10^{-3}
$\bar{\sigma}_{OA}$	$0.453K$	0.001	0.001	0.001
$\bar{\epsilon}_{RA}$ (K)	-0.887	-0.626	-0.605	0.317
$\bar{\epsilon}_{RB}$ (K)	-1.005	-1.005	-1.005	0.525
$\bar{\epsilon}_{RO}$ (K)	-0.025	-0.025	-0.025	0.018
$\bar{\epsilon}_{OA}$ (K)	-0.862	-0.600	-0.580	0.299
$\bar{\epsilon}_{OB}$ (K)	-0.980	-0.980	-0.980	0.507
σ_{RA} (K)	1.412	1.256	1.268	1.121
σ_{RB} (K)	1.571	1.571	1.571	1.195
σ_{RO} (K)	2.059	2.059	2.059	2.156
σ_{OA} (K)	2.344	1.584	1.515	1.460
σ_{OB} (K)	2.575	2.575	2.575	2.488

Table 4: Summary of experimental data

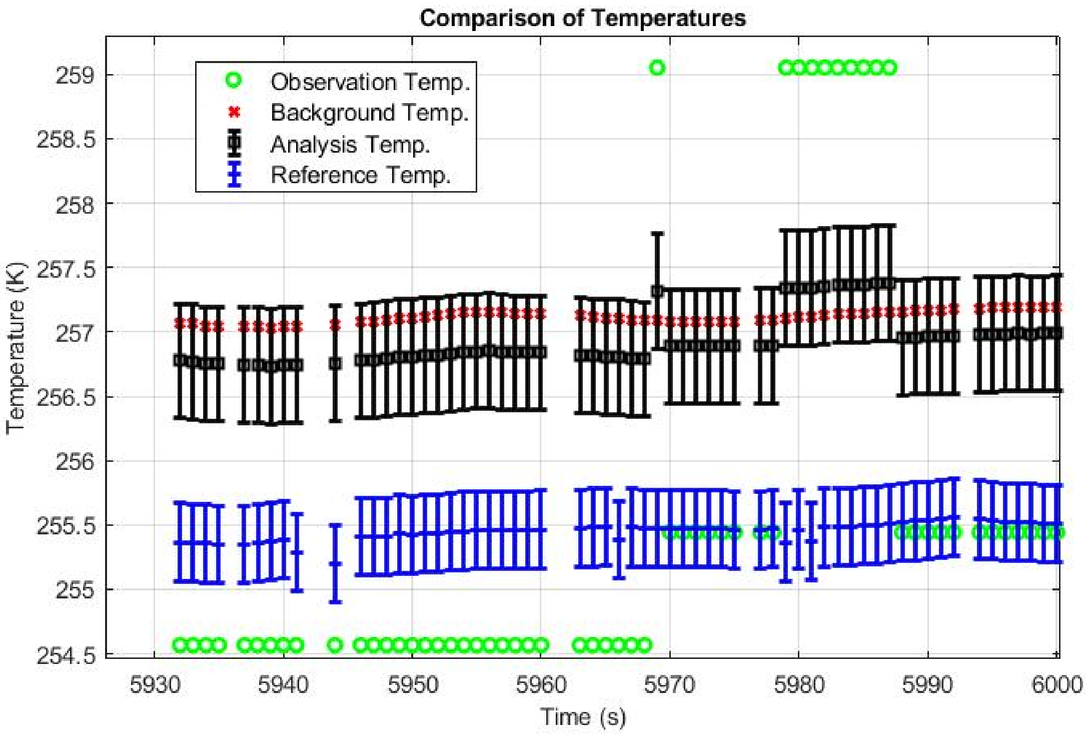

Figure 1: How the observation-derived (Mode-S EHS processed), background, analysis and reference (actual reading from onboard temperature sensors) varies between 5930–6000 seconds for experiment T1. The bars on the analysis and reference temperatures represent the uncertainty.

Figure 1 shows an indicative period of the entire flight; the analysis follows the background closely. From Table 4 we see that the analysis has an error variance of 0.453K. The reference temperature uncertainty is ±0.3K. Throughout the flight, neither uncertainties overlap very often, suggesting that the analysis is still far from the truth. As previously discussed, in this experiment the error in the airspeed is not accounted for. Accounting for the error in the airspeed may help improve the assimilation as it will allow the uncertainty in the observation operator to be accounted for.

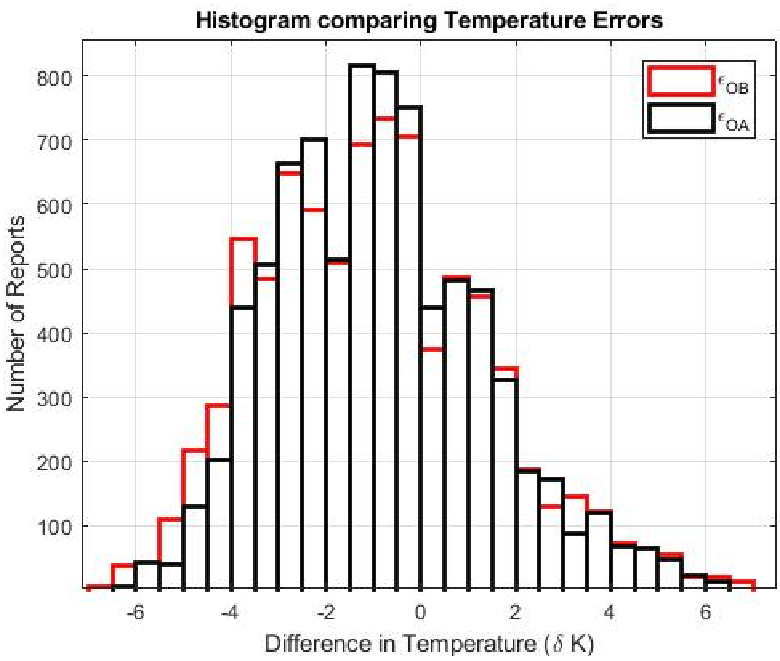

Figure 2a: Experiment T1.

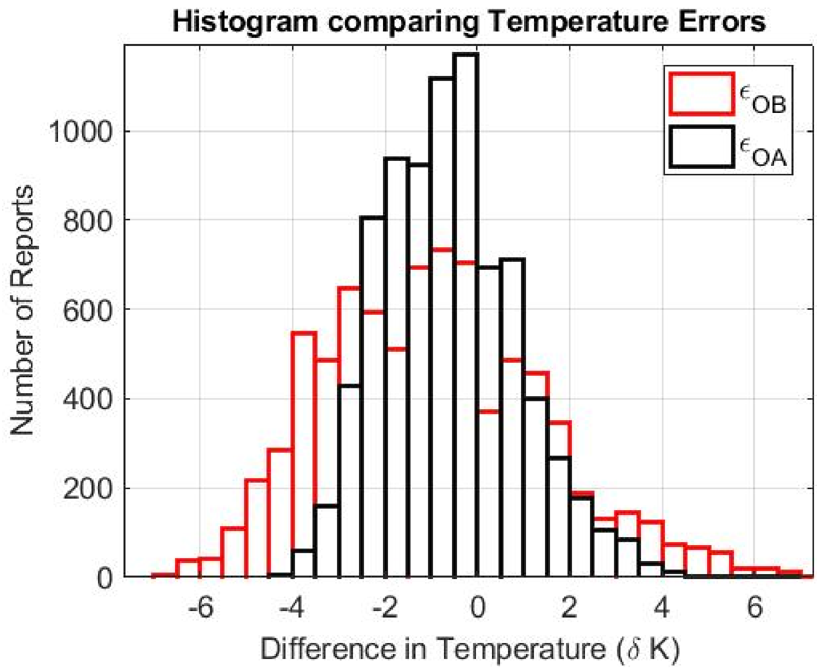

Figure 2b: Experiment M1.

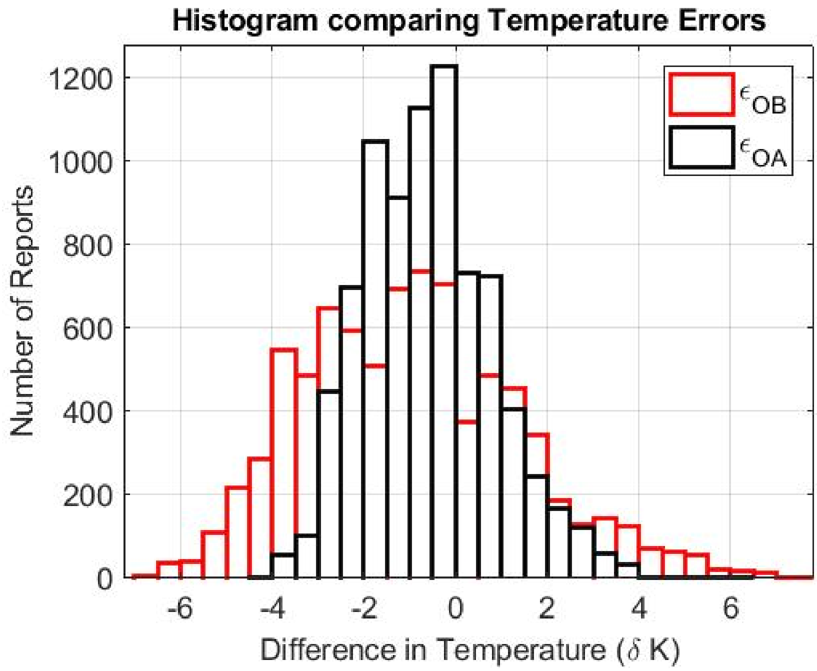

Figure 2c: Experiment M2.1.

Figure 2: Histogram of the observation-derived temperature minus background and observation-derived temperature minus the analysis.

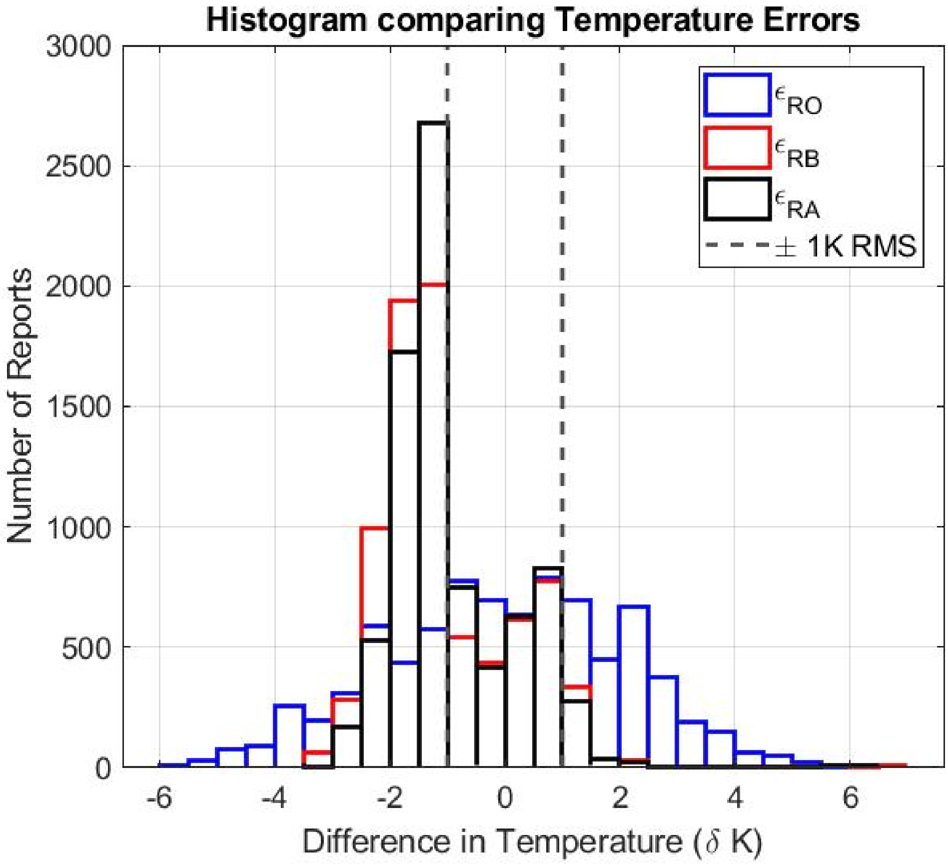

Figure 3a: Experiment T1.

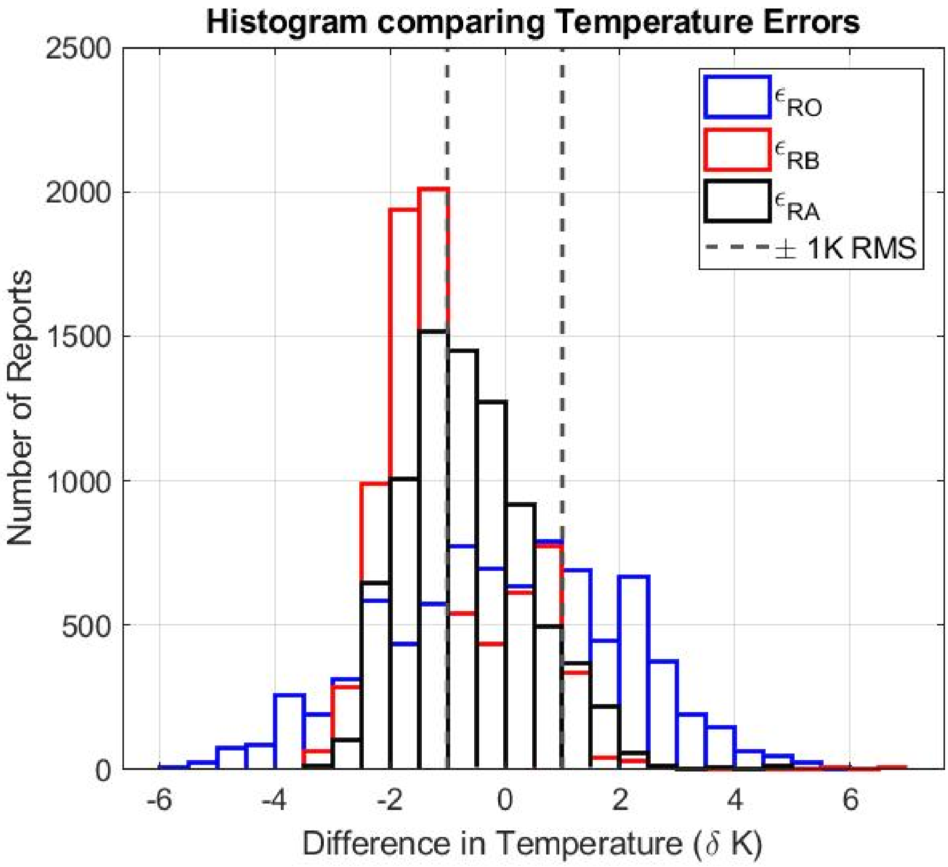

Figure 3b: Experiment M1.

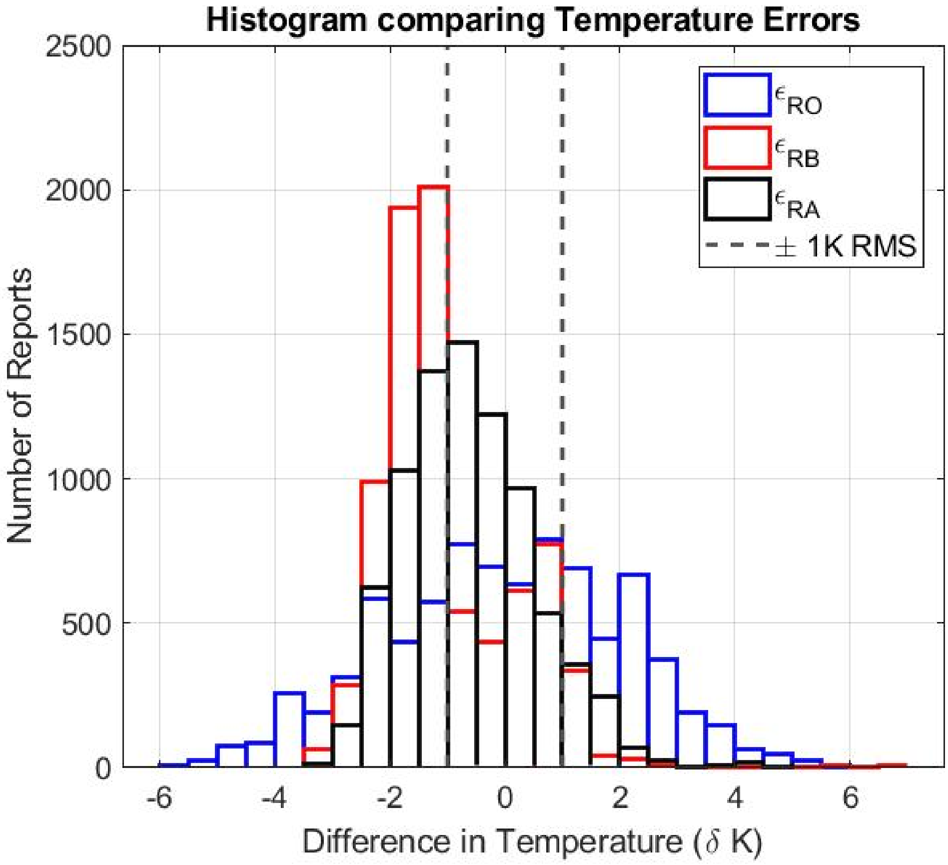

Figure 3c: Experiment M2.1.

Figure 3: Distribution of differences: reference-observed (blue), reference – background (red) and reference – analysis (black).

When comparing $\bar{\epsilon}_{OA} = -0.862K$ and $\bar{\epsilon}_{OB} = -0.98K$ from Table 4, we see that the mean error is only improved by approximately 0.12 K. This suggests that the bias in the background is not removed in the analysis. Figure 2a shows the distribution of ϵ_{OB} and ϵ_{OA}, this can be used to evaluate the performance of the OI by investigating where the majority of the data is. Ideally, ϵ_{OA} should be centred around 0 K, be more peaked and narrower than ϵ_{OB} . The assimilation made minor improvements but the spread in ϵ_{OB} and ϵ_{OA} are very similar. Comparing σ_{OA} and σ_{OB} in Table 4 confirms that the assimilation does not have a large impact since σ_{OA} is not significantly smaller than σ_{OB}.

Figure 3a shows a histogram of ϵ_{RA}, ϵ_{RB} and ϵ_{RO}. The largest spread is seen for ϵ_{RO}, but it is the set of data that resembles a normal distribution the closest and is almost unbiased ($\bar{\epsilon}_{RO} = -0.025\ K$). ϵ_{RB} has a large negative bias ($\bar{\epsilon}_{RB} = -1.005\ K$); however, we consider only a single flight, so the background bias may not be significant as it could vary daily. The large bias in ϵ_{RB} has a significant effect on the analysis since the analysis follows the background; from Table 4 it can be seen that $\sigma_{RA} = 1.412\ K$ and $\sigma_{RB} = 1.571\ K$ are quite similar, while $\sigma_{RO} = 2.059\ K$ is significantly larger. This may be a result of neglecting the airspeed error in the observation operator.

As the background error varies with height it was decided to consider the effects of varying both the background and observation uncertainties. Nine tests were conducted with a combination of background error values (0.38 K, 0.475 K and 0.57 K) and observation error values ($0.001/\sqrt{12}$, $0.004/\sqrt{12}$ and 0.002). As expected, we find that if the background error is small, the analysis fits closer to the background data. However, if the background error is large, the analysis fits closer to the observation data. This is because the accuracy in assimilation is sensitive to the background and observation errors being specified correctly (Houtekamer and Mitchell, 2005: 3273). We found that when different values were set for the background error, the analysis was more accurate at different heights (results not shown); this is because the background error varies with height, as shown in Figure 4 (b) of Ballard et al. (Ballard et al., 2016: 479).

Mach number assimilation (M1)

The derived observations in temperature space are of poor quality because the precision in the Mach number has been reduced. Hence, we now consider if we can obtain improved temperature estimates by performing the assimilation in Mach number space. $\mathrm{R} = 0.004/\sqrt{12}$ and $\mathbf{B} = 9.107 \times 10^{-7}$ were used as shown in Table 4 under the experiment ID: M1.

Figure 2b shows the distributions of ϵ_{OB} and ϵ_{OA}. From Table 4, we see a significant improvement; the analysis fits the observations better with the root mean square error being reduced to $\sigma_{OA} = 1.584\ K$ from $\sigma_{OB} = 2.575\ K$. The assimilation in experiment M1 is improved compared to experiment T1. When comparing $\bar{\epsilon}_{OA}$ for T1 and M1, it can be seen that M1 has a bias 0.26 K smaller than T1. When comparing σ_{OA} for T1 and M1, it can be seen that the spread of errors in M1 is reduced by 0.76K compared to T1. This shows that the assimilation in Mach number space provides a significantly smaller RMS but does not significantly effect the bias.

Figure 3b shows a histogram of ϵ_{RA}, ϵ_{RB} and ϵ_{RO}. There is a significant improvement in the analysis but there is still a slight negative bias due to the background data. The spread of the error in the analysis is greatly reduced and it is almost in the form of a normal distribution. In Table 4, when comparing $\sigma_{RA} = 1.256\ K$, $\sigma_{RB} = 1.571\ K$ and $\sigma_{RO} = 2.059\ K$, we see that σ_{RA} is significantly smaller which further shows the improvements that OI is making. However, these errors in the analysis is are still too large to use NWP because σ_{RA} is not within the desired 1 K.

Mach number assimilation: changing background errors with height (M2)

We continue to consider if we can obtain improved temperature estimates by performing the assimilation in Mach space. However, instead of just focusing on the basic assimilation itself, we will now look at the effects of varying the background error dependent on the height of the background data.

Flight 11 July 2013 (M2.1)

Figure 2c shows histogram of ϵ_{OB} and ϵ_{OA}. The improvement that the optimal interpolation makes can really be seen here; the spread in data is reduced from approximately ±7K to ±4K. This is further shown when comparing $\sigma_{OA} = 1.515\ K$ and $\sigma_{OB} = 2.575\ K$ from Table 4, σ_{OA} is over 1 Kelvin smaller. When comparing M1's $\bar{\epsilon}_{OA}$ and M2.1's $\bar{\epsilon}_{OA}$, the analysis bias that comes from the background is reduced by only 0.02 K. This suggests that varying the background error with height reduces the spread in the analysis but has little effect on the bias. However, while the improvement of M2 over M1 is marginal, M2 still improves over T1 by 0.14 K when comparing σ_{OA}.

Figure 3c shows the distribution of the background, observation and analysis errors. As expected, we see that the analysis distribution is between the observation and background distributions. From Table 4, when comparing $\bar{\epsilon}_{RA}$ and $\bar{\epsilon}_{RB}$ it can be seen that the bias is reduced from approximately -1K to approximately -0.6K.

In general, there is an improvement in the estimated temperature, however, the error in the analysis has quite a large spread ($3.4 - 4.6\ \delta\ K$). OI cannot overcome the large errors in the Mach number and in the airspeed.

Flight 28 July 2013 (M2.2)

The Mach assimilation (changing background error with height) is now repeated with another flight (28 July 2013) and we find that the results are qualitatively similar to the previous flight (11 July 2013). No histograms have been shown for this flight, as they are qualitatively similar to the plots provided in M2.1; however, the statistical information for this flight can be seen in Table 4.

When comparing the σ_{RB} of M2.2 to M2.1 (1.195 K and 1.571 K respectively), the background is more reliable as shown in Table 4; the spread of the background was smaller by approximately 0.38 K. This resulted in the analysis being improved too, when comparing σ_{RA} and the $\bar{\epsilon}_{RA}$ of M2.2 to M2.1. The $\bar{\epsilon}_{RA}$ is approximately half and positive; from -0.605 K to 0.317 K, indicating that the analysis is less biased. The σ_{RA} has reduced too; from 1.268 K to 1.121 K, it is now only 0.12 K larger than the required 1 K RMS required for NWP.

When comparing $\sigma_{RA} = 1.121\ K$ with $\sigma_{RB} = 1.195\ K$ in Table 4, there is not a great reduction, meaning that the OI might not be improving on the background significantly. However, when comparing $\sigma_{OA} = 1.460\ K$ with $\sigma_{OB} = 2.488\ K$ and $\bar{\epsilon}_{OA} = 0.299\ K$ with $\bar{\epsilon}_{OB} = 0.507\ K$, the improvement that the optimal interpolation makes can be seen. From Figure 2c, the spread of the analysis is reduced from (-7 K to 9 K) to (-4 K to 5 K).

Summary and conclusion

A large number of aeroplanes are in the sky at any time; this could provide valuable meteorological data at a high frequency which can be used to improve weather forecasting. The only cost is to buy and maintain receivers to collect the data. The aim of the paper was to combine aircraft data with UKV (a numerical weather prediction model) data to provide an accurate analysis of temperature that could be used in NWP.

The data from the aircraft and the UKV model was combined using OI data assimilation. Three novel approaches with the optimal interpolation were taken; the first using temperature, the second using Mach number, both with static errors, and the third using Mach number with the background error varying with height.

In both the temperature and Mach number assimilation, the analysis was more accurate than the derived observations, but the Mach number assimilation gave better results than the temperature assimilation by approximately 0.14K RMS. However, the airspeed error was not taken into account in the temperature assimilation, but it was taken into account in the Mach number assimilation which may be why the Mach number assimilation performed better. We also find that M1/M2 improves significantly over T1 because the precision in the Mach number effects the temperature assimilation more than the Mach number assimilations.

The analysis error (reference temperature – analysis temperature) was very large in all experiments; most of the analysis was with in ±2 K of the reference temperature, but there were still errors that were over 4 K. The main reason for this may be due to the reduced precision in the Mach number sent in the Mode-S EHS report. Our results show that the data assimilation produced an analysis that was closer to the reference temperature than either the derived observations or the background, the improvement was not significant enough to make the data suitable for use in numerical weather prediction. For the data to be suitable, it must be within 1 K RMS. The σ_{RA} still needs to be improved by 0.12 K to be suitable for NWP. Therefore, getting more precise Mach number reports or just having temperature reports included in the Mode-S EHS reports would be preferred to use for NWP.

One potential idea for further work is to smooth the observations so that when they are converted from Mach to temperature, there are no large changes in observation-derived temperatures and hence closer to the reference data.

Notes

[1] Jeremy Holzke has just completed his year in industry with Keysight Technologies and is now going into the final year of his Robotics degree at the University of Reading.

[2] Joanne Waller is a postdoctoral researcher at the University of Reading. Her research focuses on improving the use of observations in data assimilation.

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To cite this paper please use the following details: Holzke J. and Waller J.A. (2018), 'Improving Aircraft-Derived Temperature Observations Using Data Assimilation', *Reinvention: an International Journal of Undergraduate Research*, Volume 11, Issue 2, http://www.warwick.ac.uk/reinventionjournal/issues/volume11issue2/holzke. Date accessed [insert date]. If you cite this article or use it in any teaching or other related activities please let us know by e-mailing us at Reinventionjournal@warwick.ac.uk.

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