Abstract

Health monitoring during flight tests provides a means of data validation in flight. It is possible to design a data acquisition system such that the available instruments incorporate redundancy through analytic relationships. This analytic redundancy may be exploited in order to assess individual sensor system health and to validate accuracy claims. A practical example is presented in which an air data set is compared with GPS in order to isolate failures in the pressure and temperature transducers.
INTRODUCTION
Flight test data validation is becoming more difficult as the number of collected parameters per flight test increases dramatically while the human resources previously used to decode, process, analyze, and react to artifacts in the data are reduced. Automated methods are required to perform data reduction, analysis, and report artifacts to an engineer for investigation. Fault detection methods typically require redundancy in instrumentation or information in order to detect statistical anomalies in the data set. Rather than relying on hardware redundancy, redundancy may be achieved through analytic methods which require judicious instrumentation selection and processing the data using fault detection methods either during or after the flight test.

Analytic redundancy methods are defined as the process of using analytic relationships to compare two dis-similar instruments in order to detect possible failures or anomalies in the data set. Combining the different instrument measurements through algorithms referred to as fault detection filters can allow the user to batch process flight test results. Anomalies can be automatically detected, isolated, and even removed from flight test data. The user is provided with an output consisting of the data, the uncertainty in the data, and the probability that a failure exists.

This paper presents a method for performing fault detection on a set of common instruments typical in most flight test. First, a fault detection filter structure is defined as a means of comparing the different instruments. Then a residual processors used for detecting and isolating the failures is defined. Finally, the methodology is applied to the problem of detecting failures in an instrumentation system utilizing a GPS receiver to detect failures in a static and dynamic pressure sensor as well as a static temperature sensor. Flight test results are presented.

LINEAR ERROR MODELS
Error modeling for simple, linear systems is straightforward. The Guide to Expression of Uncertainty [1] defines the method for determining the error based on assumed uncertainty models. A nonlinear measurement model may be of the form in Eq. (1). The measurement \( y \) is a function of certain parameters \( x \). In this case, the noise term \( v \) has been included in anticipation of the development.

\[
y = f(x,v)
\]  

Using a first order Taylor’s series expansion of (1), the error in any measurement \( y \) is given by Eq. (2) in which the values for \( \bar{x} \) and \( \bar{v} \) are assumed known from calibration or other information and the partials of the function \( f(\ ) \) are evaluated at \( \bar{x} \) and \( \bar{v} \).

\[
y = f(\bar{x}, \bar{v}) + \frac{\partial f}{\partial x} \bigg|_{\bar{x},\bar{v}} (x-\bar{x}) + \frac{\partial f}{\partial v} \bigg|_{\bar{x},\bar{v}} (v-\bar{v})
\]  

If it is assumed that \( x \) and \( v \) are both Gaussians with mean \( \bar{x} \) and \( \bar{v} \) as well as each having a covariance \( M = E[(x-\bar{x})(x-\bar{x})^T] \) and \( V = E[(v-\bar{v})(v-\bar{v})^T] \) with
independent statistics such that \( E[(x - \bar{x})(v - \bar{v})^T] = 0 \), then the mean and covariance of the measurement \( y \) is expected to be as shown in Eq. (3) and (4) with the sensitivity matrix \( C \) defined in Eq. (5).

\[
\begin{align*}
\bar{y} &= f(\bar{x}, \bar{v}) \\
Y &= E[(y - \bar{y})(y - \bar{y})^T] = C \begin{bmatrix} M & 0 \\ 0 & V \end{bmatrix} C^T
\end{align*}
\]

\( C = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix}^T \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix} \)  

Calculation of the uncertainty in \( y \) is straightforward assuming knowledge of \( \bar{x}, \bar{v}, M, V \), and the function \( f \). The GUM standard includes suggestions for picking Gaussian statistics which over-bound error sources which are non-Gaussian [1].

Suppose that there are three parameters affecting the output of the measurement: the actual signal which we will refer to as \( x \), the measurement bias \( b \) and a measurement scale factor error \( S \). This typical model is utilized for most simple transducers such as pressure transducers, temperature sensors, or even single axis accelerometers. The nonlinear measurement models is defined in Eq. (6). The model is nonlinear because the scale factor error multiplies the actual measurement to be estimated.

\[
y = (1 + S)x + b + v
\]

A first order Taylor’s series expansion of Eq. (6) about calibrated values of \( \bar{x}, \bar{b} \), and \( \bar{S} \) is given by Eq. (7), where it is assumed that the noise term \( v \) has zero mean and the perturbations are defined by \( \delta x = x - \bar{x}, \delta S = S - \bar{S} \), and \( \delta b = b - \bar{b} \) represent the error in the calibrations or the error and the sensitivity matrix \( C \) is defined in Eq. (8).

\[
y = (1 + \bar{S})\bar{x} + \bar{b} + C \begin{bmatrix} \delta S \\ \delta b \end{bmatrix} + v + (1 + \bar{S})\delta x
\]

\[
C = \begin{bmatrix} (1 + \bar{x}) & I \end{bmatrix}
\]

The expected mean error in the measurement is then given in Eq. (9). Assuming that all of the uncertain perturbations (\( \delta x, \delta S, \delta b \)) are zero mean, Gaussian random variables, then the value for \( \bar{x} \) is determined in Eq (10) which is simply the measurement corrected for the calibrated bias and scale factor error according to the measurement model.

\[
E[y] = (1 + \bar{S})\bar{x} + \bar{b}
\]

\[
\bar{x} = \frac{y - \bar{b}}{1 + \bar{S}}
\]

Substituting Eq. (10) back into Eq. (7) allows us to solve for the uncertainty in the estimate \( \delta x \) as shown in Eq.(11).

\[
\delta x = \frac{1}{1 + \bar{S}} \begin{bmatrix} (1 + \bar{x}) & I \end{bmatrix} \begin{bmatrix} \delta S \\ \delta b \end{bmatrix} + \frac{v}{1 + \bar{S}}
\]
The covariance is calculated in Eq. (12) assuming that each of the elements have mean given by \( \bar{x} \), \( \bar{b} \), and \( \bar{S} \) and each has a covariance defined by \( M_x = E[\delta x \delta x^T] \), \( M_s = E[\delta S \delta S^T] \), \( M_b = E[\delta b \delta b^T] \), and \( V = E[\nu \nu^T] \). It is assumed that the bias, scale factor, and random noise are all defined by independent Gaussian random variables. However, it is trivial to add in cross-correlations into this formulation as necessary and if defined.

\[
M_x = E[\delta x \delta x^T] = \left( \frac{1}{1 + S} \right)^2 \begin{bmatrix} M_s & 0 \\ 0 & M_b \end{bmatrix} C^T + V \tag{12}
\]

**AIR DATA UNCERTAINTY USING CHAIN ERRORS**

More complex error models may be built sequentially from the simple error models. Error models such as the linear analysis previously presented can be utilized to determine a mean value and an over-bounding covariance for the uncertainties specified. The output from multiple of these simple models may be utilized as inputs to more complex systems to determine the uncertainty in a sensor fusion process. Given a measurement \( y \) is a function of \( N \) parameters \( x_i \). A nonlinear model describes the relationship between \( x_i \) and \( y \) in Eq. (13).

\[
y = f(x_1, x_2, ..., x_N) \tag{13}
\]

Each of the \( x_i \) variables has known mean \( \bar{x} \) and covariance \( M_{ui} \) determined by another process. Using a first order Taylor’s series expansion of (13), the mean value of the output is calculated from the known mean values of each of the parameters as shown in Eq. (14).

\[
E[y] = \bar{y} = f(\bar{x}_1, \bar{x}_2, ..., \bar{x}_N) \tag{14}
\]

A first order Taylor’s series is utilized to describe the effect of uncertainty \( \delta x_i \) in each of the input parameters on the output error \( \delta y \) as shown in Eq. (15). The covariance is then calculated in Eq. where \( M_{ui} = E[\delta x_i \delta x_i^T] \). In this case it is assumed that all of the \( \delta x_i \) are independent from each other such that \( E[\delta x_i \delta x_j^T] = 0 \) for every \( i \neq j \) which is reasonable if it is assumed that each of the input parameters \( x_i \) are derived from separate instruments.

\[
y - \bar{y} = \delta y = \sum_{i=1}^{N} \left. \frac{\delta f}{\delta x_i} \right|_{\bar{x}} \delta x_i \tag{15}
\]

\[
E[\delta y \delta y^T] = C' M_x C \tag{16}
\]

The values for the sensitivity matrix \( C \) are given in Eq. (17) while the covariance \( M_x \) is specified in Eq. (18).

\[
C' = \begin{bmatrix} \left( \frac{\delta f}{\delta x_1} \right)^T & \left( \frac{\delta f}{\delta x_2} \right)^T & \cdots & \left( \frac{\delta f}{\delta x_N} \right)^T \end{bmatrix} \tag{17}
\]
True airspeed can be thought of as a compound system. True airspeed requires three sensor measurements: static pressure $\bar{p}_0$, dynamic pressure $\bar{p}$, and static temperature $\bar{T}_0$.

The definition of true airspeed for subsonic flight including compressibility effects is given in Eq. (19) \[2\] where the true airspeed $V_{\text{true}}$ is a function of the sonic speed $c$ multiplied by the Mach number $M$.

$$V_{\text{true}} = cM = \sqrt{kRT_0} \left[ \frac{2}{k-1} \left( \frac{\bar{p}}{\bar{p}_0} \right)^{\frac{k-1}{k}} \right]^{-1}$$  \[(19)\]

In Eq. (19) the constant $k = 1.4$ for air and $R = 287.053 \frac{Nm}{kgK}$. If each of the three measurements of dynamic pressure, static pressure, and static temperature has known mean $\bar{p}$, $\bar{p}_0$, and $\bar{T}_0$ and known covariance $M_p$, $M_{p0}$, and $M_{T0}$ respectively, then the uncertainty in true airspeed may be calculated as shown in Eq. (20) using the first order Taylor’s series expansion of Mach number and sonic speed around the mean values of Mach number (Eq. (21)) and sonic speed (Eq. (22)).

$$V_{\text{true}} - \bar{V}_{\text{true}} = \left[ \frac{\bar{p}_0}{kM\bar{p}_0^2} \left( \frac{\bar{p}}{\bar{p}_0} \right)^{\gamma_k} - \frac{k-M}{k-1} \left( \frac{\bar{p}}{\bar{p}_0} \right)^{\gamma_k} \frac{\bar{M}}{2c} \right] \begin{bmatrix} \delta p \\ \delta p_0 \\ \delta T_0 \end{bmatrix}$$ \[(20)\]

$$\bar{M} = \sqrt{ \frac{2}{k-1} \left( \frac{\bar{p}}{\bar{p}_0} \right)^{\gamma_k} - 1 }$$ \[(21)\]

$$\bar{c} = \sqrt{kRT_0}$$ \[(22)\]

Of course, the mean value of true airspeed is calculated as in Eq. (23).

$$\bar{V}_{\text{true}} = \bar{c}\bar{M} = \sqrt{kRT_0} \left[ \frac{2}{k-1} \left( \frac{\bar{p}}{\bar{p}_0} \right)^{\gamma_k} - 1 \right]$$ \[(23)\]

The covariance in the output of airspeed is then given in Eq. (24) with sensitivity matrix $C_{\text{true}}$ defined in Eq.

$$E\left[ (V_{\text{true}} - \bar{V}_{\text{true}})(V_{\text{true}} - \bar{V}_{\text{true}}) \right] = C_{\text{true}} \begin{bmatrix} M_p & 0 & 0 \\ 0 & M_{p0} & 0 \\ 0 & 0 & M_{T0} \end{bmatrix}$$ \[(24)\]
Therefore, given a simple transducer model with scale factor and bias of the kind defined in Eq. (6) it is possible to define a mean and covariance estimate for each of the measurements. Then using this mean and covariance it is possible to calculate the true air speed mean and covariance.

A simpler problem utilizes the static pressure to calculate the altitude and error in the estimate of the altitude. For simplicity, the 1976 standard atmosphere [3] will be utilized in the region limited from sea level to 11 kilometers. The methodology presented works for the other regions as well. The altitude as a function of static pressure is defined in Eq. (26) in kilometers using coefficients defined in the model along with the assumed static pressure at sea level \( p_{0_{\text{sl}}}, 1.0 \text{ atmospheres} \). This analysis will only examine errors in the static pressure measurement at altitude.

\[
\begin{align*}
\bar{h}_p &= \frac{T_{\text{osl}}}{-L} \left( 1 - \left( \frac{\bar{p}_0}{p_{\text{osl}}} \right)^{-\frac{L R_{\text{gas}}}{g W_{\text{mol}}}} \right) \\
\end{align*}
\]

Using the process defined, the mean value of the altitude estimate would be defined in Eq. (27) using the mean value of the static pressure \( \bar{p}_0 \) and the error between the true altitude and mean value of altitude is defined in Eq. (27) where the sea level temperature \( T_{\text{osl}} \) is 288.15 K, gravity \( g \) is 9.0865 \( \text{m/s}^2 \), \( R_{\text{gas}} = 8.31432 \) is the gas constant, \( W_{\text{mol}} = 28.9644 \) is the molecular weight of air, and the coefficient for the gradient of temperature in the region prescribed is \( L = -6.5 \).

\[
\begin{align*}
\bar{h}_p &= \frac{T_{\text{osl}}}{-L} \left( 1 - \left( \frac{\bar{p}_0}{p_{\text{osl}}} \right)^{-\frac{L R_{\text{gas}}}{g W_{\text{mol}}}} \right) \\
\end{align*}
\]

\[
\begin{align*}
\delta h_p - \bar{h}_p &= \delta h_p \bigg|_{\bar{p}_0} \delta p_0 = -\frac{T_{\text{osl}}}{L \bar{p}_{\text{osl}}} \left( \frac{L (R_{\text{gas}})}{g (W_{\text{mol}})} \right) \left( \frac{\bar{p}_0}{p_{\text{osl}}} \right)^{-\frac{L (R_{\text{gas}})}{g (W_{\text{mol}})}} \delta p_0 \\
\end{align*}
\]

Eq. (28) may be re-written in terms of the error in the air data measurements as shown in Eq.

\[
\begin{align*}
\delta h_p = C_h \begin{bmatrix} \delta p \\ \delta p_0 \\ \delta T_0 \end{bmatrix} \\
\end{align*}
\]
Further, it is important to note that static temperature should change linearly with altitude within the region less than 11 km as defined in the standard [2]. Therefore a second measurement of altitude is available from measuring static temperature. The standard states that the relationship between altitude and temperature is given in Eq. (31)

$$h_r = \frac{1}{L}(T_0 - T_{0\text{sl}})$$

The error model therefore for the altitude as a result of temperature may be shown to be:

$$\tilde{h}_r = h_r + \frac{1}{L}\delta T_0 + C_{ht}\begin{bmatrix} \delta p \\ \delta p_0 \end{bmatrix}$$  (32)

$$\bar{h}_r = \frac{1}{L}(\bar{T}_0 - T_{0\text{sl}})$$  (33)

$$C_{ht} = \begin{bmatrix} 0 & 0 & \frac{1}{L} \end{bmatrix}$$  (34)

A total error model for the true airspeed and altitude measurements as a function of the sensor uncertainty is provided in Eq. (35). The assumed covariance of the three measurements is calculated in Eq. (36).

$$Y_{air} = E\left[ \begin{bmatrix} \tilde{V}_{TAS} \\ \tilde{h}_p \\ \tilde{h}_r \end{bmatrix} - \begin{bmatrix} \bar{V}_{TAS} \\ \bar{h}_p \\ \bar{h}_r \end{bmatrix} \right] = \begin{bmatrix} C_{True} & C_h & C_{ht} \end{bmatrix} \begin{bmatrix} M_{p} & 0 & 0 \\ 0 & M_{p0} & 0 \\ 0 & 0 & M_{T0} \end{bmatrix} \begin{bmatrix} C_{True} \end{bmatrix}^T$$  (36)

**FAULT DETECTION THROUGH COMPARISON WITH GPS**

Since it is now possible to estimate the true airspeed and altitude as well as the associated uncertainty in each derived parameter, one goal should be to implement automated health monitoring. For this case, we choose to compare the air data suite with a convenient sensor that produces all or nearly all of the same values. In this case, we utilize the Global Positioning System (GPS) receiver to provide a reference in the altitude and velocity. A simple measurement model is provided in Eq. (37) in which the velocity magnitude measurement $\tilde{V}_{GPS}$ is a function of the true velocity magnitude $V_{GPS}$ with additive, zero mean Gaussian noise $v_{VG}$ with covariance $V_{VG}$.
Likewise in Eq. (37), the altitude measurement $\tilde{h}_{GPS}$ is a function of the true altitude $h_{GPS}$ plus additive zero mean Gaussian noise $v_{hG}$ with associated covariance $V_{hG}$. The GPS measurements in Eq. (37) may be differenced with the airspeed measurements in Eq. (35) to form a residual which will be tested for failures as shown in Eq. (38).

$$
\begin{bmatrix}
\tilde{V}_{GPS} \\
\tilde{h}_{GPS}
\end{bmatrix} =
\begin{bmatrix}
V_{GPS} \\
h_{GPS}
\end{bmatrix} +
\begin{bmatrix}
v_{VG} \\
v_{hG}
\end{bmatrix}
$$

(37)

$$
\begin{bmatrix}
\tilde{V}_{TAS} \\
\tilde{h}_p \\
\tilde{h}_T
\end{bmatrix} -
\begin{bmatrix}
1 & 0 \\
0 & 1 \\
0 & 1
\end{bmatrix}
\begin{bmatrix}
\tilde{V}_{GPS} \\
h_{GPS}
\end{bmatrix} =
\begin{bmatrix}
C_{True} & \delta p
\\
C_h & \delta p_0
\\
C_{hT} & \delta T_0
\end{bmatrix}
\begin{bmatrix}
1 & 0
\\
0 & 1
\\
0 & 1
\end{bmatrix}
\begin{bmatrix}
v_{VG} \\
v_{hG}
\end{bmatrix}
+ E \mu
$$

(38)

Of course, Eq. (38) is only an approximation and assumes that the wind disturbances are relatively small. This assumption is reasonable for aircraft flying on calm days for flight tests in which the goal is to perform parameter estimation on the aircraft. A fault signal $\mu$ is introduced into Eq. (38). This signal is unknown and may enter into the static pressure, dynamic pressure, or temperature through the matrix $E$. For simplicity, no faults are assumed in the GPS receiver. For a dynamic pressure sensor fault $E$ is defined as shown in Eq. (39). For a static pressure or static temperature fault $E$ is defined as in Eq. (40) or (41), respectively. The matrix $E$ is a three by one vector for each case.

$$
E_p =
\begin{bmatrix}
C_{True} \\
C_h \\
C_{hT}
\end{bmatrix}
$$

(39)

$$
E_{p0} =
\begin{bmatrix}
C_{True} \\
C_h \\
C_{hT}
\end{bmatrix}
$$

(40)

$$
E_{r0} =
\begin{bmatrix}
C_{True} \\
C_h \\
C_{hT}
\end{bmatrix}
$$

(41)

Note that by inspection, a dynamic pressure failure only affects the airspeed measurement. However, both the static temperature and static pressure measurement failures affect both altitude and airspeed. For the no fault case, the covariance $Q$ of the residual in Eq. (38) will be as shown in Eq. (42) where the independence of the GPS altitude and velocity magnitude is assumed for convenience. The air data sensor errors are assumed independent of the GPS receiver errors.

$$
Q = E[rr^T] = Y_{air} -
\begin{bmatrix}
1 & 0 \\
0 & 1
\end{bmatrix}
\begin{bmatrix}
V_{VG} & 0 \\
0 & V_{hG}
\end{bmatrix}
\begin{bmatrix}
1 & 0 \\
0 & 1
\end{bmatrix}^T
$$

(42)

Fault detection methods are well defined and understood. Previous work in the field of least squares fault detection filters have been applied to GPS receivers [4] and is applied here. An annihilator $H$ is constructed for each failure mode such that each annihilator
removes the effect of one of the faults from the residual process, or \( HE = 0 \). The dynamic pressure annihilator \( H_p \) is constructed as shown in Eq. (43) with similar definitions for the annihilator for the static pressure and temperature.

\[
H_p = I - E_p \left( E_p^T E_p \right)^{-1} E_p^T
\]  

(43)

Three test residuals are constructed for each failure mode and tested separately as shown in Eq. (44)-(46). Each of the residuals will remain zero mean in the presence of the particular fault annihilated, but will be susceptible to another fault.

\[
r_p = H_p r = H_p \begin{bmatrix} C_{true} \\ C_h \\ C_{hT} \end{bmatrix} \begin{bmatrix} \delta p \\ \delta p_0 \\ \delta T_0 \end{bmatrix} - \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} v_{pG} \\ v_{hG} \end{bmatrix}
\]

(44)

\[
r_{p0} = H_{p0} r = H_{p0} \begin{bmatrix} C_{true} \\ C_h \\ C_{hT} \end{bmatrix} \begin{bmatrix} \delta p \\ \delta p_0 \\ \delta T_0 \end{bmatrix} - \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} v_{pG} \\ v_{hG} \end{bmatrix}
\]

(45)

\[
r_{T0} = H_{T0} r = H_{T0} \begin{bmatrix} C_{true} \\ C_h \\ C_{hT} \end{bmatrix} \begin{bmatrix} \delta p \\ \delta p_0 \\ \delta T_0 \end{bmatrix} - \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} v_{pG} \\ v_{hG} \end{bmatrix}
\]

(46)

The covariance in the residuals projected residual in Eq. (44) is calculated for the dynamic pressure as shown in Eq. (47) and represented by \( Q_p \) and similar definitions hold for the covariance of the static pressure residual \( Q_{p0} \) and static pressure residual covariance \( Q_{T0} \).

\[
Q_p = H_p Q_h H_p^T
\]

(47)

The weighted residuals are calculated for each of the three residuals tests as shown in Eq. (48)-(50). If any of the tests exceed a threshold value (typically greater than 1.0) then a failure is declared. The failure is isolated if two of the test statistics exceed the prescribed threshold. The test designed to annihilate a particular failure which remains below the prescribed threshold is identified as the failed instrument since that test residual is immune to the particular failure.

\[
u_p = r_p^T Q_p^{-1} r_p
\]

(48)

\[
u_{p0} = r_{p0}^T Q_{p0}^{-1} r_{p0}
\]

(49)

\[
u_{T0} = r_{T0}^T Q_{T0}^{-1} r_{T0}
\]

(50)

Alternatively, more sophisticated residual testing such as the Multiple Hypothesis Shirayev Sequential Probability Ratio Test (MHSSPRT) may be applied for improved performance such as in Speyer[5]. These tests improve responsiveness to small failures and detect and isolate failures in minimum time, but are not utilized here for brevity.

**FLIGHT TEST RESULTS**
An aircraft was flown at low altitude and low speed. Data was collected from the air data system and the GPS receiver. The data was recorded and played back through the algorithm described. The pressure and temperature data were combined to form estimates of airspeed and two altitude estimates. The aircraft flew at about 60 meters per second at an altitude of about 3000 meters. The vehicle performed simple parameter identification maneuvers in clean air. Data was collected and processed at 500 Hz.

Estimating the uncertainty in a GPS is beyond the scope of this paper. In fact, many references have been written which provide discussions on proper estimation given flight conditions such as Parkinson[6] or Hoffman Wellenhoff[7] to name a few. However, sometimes, on low budget experiments, all of the information from a GPS receiver is not available and the user is limited to a subset of information and must estimate the uncertainty. For instance if satellite geometry is unknown, a proper calculation of HDOP is not available for estimation of errors. For the present case, we will assume that the altitude has a 5 meter standard deviation and that the velocity magnitude estimated from the GPS has a standard deviation of 0.25 m/s. A fifty second portion of data is processed.

For the instruments, we assume that the combined total uncertainty for the Temperature sensor (the uncertainty including scale factor and bias errors) has a 1.0 degree C standard deviation. Each of the pressure sensors is assumed to have a 0.01 Psi standard deviation overbound (including bias and scale factor).

![Figure 1: Residual Difference with Error Bounds Between Air Data and GPS](image-url)
Figure 1 shows the residuals between the GPS estimates of velocity and altitude and the air data system as calculated in Eq. (38) with uncertainty bounds as calculated in Eq. (42). The residuals show that the temperature is within bounds but both the dynamic and static pressure are outside or right at the limit of the respective 1 sigma bound.

Three separate annihilated residuals are created and processed using Eq. (44)-(46) with uncertainty bounds for each computed as described. The results are shown in Figures 2-4. These results show that the residuals designed to be intolerant to a dynamic pressure failure and a static temperature failure do not remain zero mean and exceed the error bounds. However, Figure shows the test residuals which are immune to a static pressure fault. All three of the residuals are zero mean and within the error bounds. From these results a simple voting scheme or advanced MHSSPRT could be employed to calculate the probability of a failure automatically.

![Residual With Dynamic Pressure Fault Removed](image1.png)

![PO Alt Resid (m)](image2.png)

![TO Alt Resid (m)](image3.png)

**Figure 2: Test Residual Immune to a Dynamic Pressure Fault**
The results show an error in the static pressure sensor. The residual set that is immune to that failure remains zero mean and within the error bounds while the other residuals immune to different faults show susceptibility to the static pressure failure fault which causes the residuals to exceed the error bounds.

It was revealed to the author that in fact a failure did occur and the static pressure sensor was not operating properly in this data set. The failure went unnoticed during several flight tests which impaired the ability of the engineers to utilize this data to characterize the flight qualities of the aircraft. This system clearly identifies the problem and provides a means of automating the search for failures in the air data system utilizing a GPS receiver.
CONCLUSIONS

An example of multi-sensor fusion fault detection has been presented. The error models for pressure and temperature transducers using a bias and scale factor are presented. A method for utilizing the uncertainties in each instrument in order to calculate the uncertainty in altitude and airspeed is also presented. Calculating error in airspeed and altitude with the output of a GPS receiver provides an estimate of the air data system health which may be utilized to detect failures in any of the three sensors.

The results presented showed a real flight test with a large sensor error in the static pressure. The error is almost immediately recognizable once the air speed and altitude residuals are plotted with error bounds. Without calculating the difference between the altitude and airspeed with respect to the GPS, the engineer would not know that there was a faulted condition. Even plotting the error is not enough since the plot without the error bounds does not give the engineer the insight to enable understanding of how great a difference should be tolerated for this experiment and for these instruments.

Even with the errors plotted and the uncertainty available, the process of analyzing data over a flight test on a rapid schedule is cumbersome upon the test engineers. Compound the problem with experiments utilizing hundreds of parameters, and the ability to examine all data for failures becomes limited. Therefore the fault detection methods presented are offered as a means of not just relating uncertainty in instruments but of automating the process of fault detection for the engineer. The example in this paper was used to illustrate an automated approach to fault detection for the problem specified.

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