Gross Weight and Center-of-Gravity Estimation System for the V-22

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Abstract

An evaluation of a combination Artificial Neural Network and Kalman filter system to estimate gross weight and center of gravity for the V-22 is presented. A sampling of V-22 flight test data is used to develop the estimation models, and typical event-driven recorded flight data is used to test the performance of the estimation method. Estimation results of airplane mode gross weight using the combined methods indicate an improvement over using a neural network method alone. The estimated gross weight is able to follow the recorded data without being subject to large gaps or spikes in the event-driven recorded data, as would be the case using a neural network method alone with this type of data. Results of airplane mode CG, helicopter mode GW, and helicopter mode CG estimation are also presented, but using a neural network only at this time. These estimation results match the recorded data well and will provide a good starting estimation for use in a Kalman filter in future efforts.

Introduction

Airframe life estimates are highly dependent on accurate knowledge of the gross weight and center-of-gravity (GW/CG) of an aircraft because airframe loads, and ultimately component fatigue lives, are directly related to GW/CG. Accurate knowledge of the GW/CG of an aircraft can be challenging, especially when cargo, troops, and sling loads are carried within any given flight. Even at operating empty weight, assumptions are still made about the GW of the aircraft, and unless the aircraft is weighed prior to flight, the assumed GW could be substantially in error. In addition, poor record keeping might leave the aircraft with no record of weight for any particular flight. Because these hand methods of recording initial GW/CG are not directly derived from the dynamics of the aircraft while in flight, current recording methods of recording GW/CG for any particular flight may not be appropriate when used for airframe life estimates.

Previous work has been completed which relates aircraft state measurements to the GW/CG of an aircraft. An artificial neural network (ANN) is one approach that has been shown to have promise. References [1] and [2] specifically address this problem with the formulation of an ANN for the V-22, where actual data similar to that used in this project were used, and for the XV-15 tilt rotor aircraft, although simulated data was used to provide the training and test data set. The challenges for developing an ANN using test data are greater than when using simulation data due to data non-linearities, measurement noise, unsteady atmospheric phenomena, and data recording dropouts. A technique for aircraft GW/CG estimation using an ANN plus a simplified aerodynamics model is also described in Reference [3].

The GW/CG estimation of an aircraft using a Kalman filter has been investigated previously [4], although the measurement data used was created by a rotorcraft simulator and lacks the irregularities present in flight test measured data as described above.

The goal of this current methodology is to use a realistic set of operationally recorded flight data to drive an ANN/Kalman filter estimation method for GW/CG. Combining these two methods will overcome issues using either method independently. Even though this methodology is being developed for the V-22, the characteristics of this system can be applied to other aircraft. This technology will allow for greater accuracy of recorded GW/CG data, reducing errors in the data which may be caused by faulty fuel gauges, incorrect or missing weight entries, incorrect assumptions about weight sources including pallets, equipment, and crew, or incorrect empty gross weight assumptions. Eliminating the effect of these errors in GW/CG recording will lead to better airframe life estimates.

In addition, as a result of the Kalman filter process, recorded and unknown aircraft states can be estimated using data from multiple sources. Therefore, greater accuracy of the measured states can be achieved as a result of the parameter estimation process, which can also be used to highlight a possible faulty sensor if the estimated state differs greatly from the measured state.

Data Selection

Flight data used to develop the models is Computer Aided Flight Test Analysis (CAFTA) data from V-22 test aircraft #7 and #8. Flights were selected based upon a.
number of factors including flight test recorded GW/CG range, types of maneuvers performed, nacelle angle, and specific parts of the flight envelope covered.

Figure 1 shows the range of data selected in this development. These data points were intended to cover the forward flight operational range of the V-22 at all nacelle angles. Each data point represents the mean value of a flight test time history. Hovering flight was not currently investigated due to the majority of the V-22 flight time being in forward flight mode, however, this regime is an important one from an operational and structural fatigue standpoint and will be investigated in future efforts.

Data Characteristics

Vibration, Structural Life, and Engine Diagnostics (VSLED) data was used to test the GW/CG estimation system. Using VSLED data creates a challenge in developing a successful process to estimate GW/CG, but is necessary to prove the practical usage of an ANN/Kalman filter system on a flight-by-flight basis. VSLED data is not recorded in sequential time history format, as flight test data is typically collected, making the parameter estimation process more complicated. It is an event-driven system that will record events when certain thresholds are exceeded. These events include peaks and valleys detected in sling load, elevator actuator position, stick position, attitudes, and several others. Certain events do trigger a ten second burst of high sample rate time history data, although the proportion of the flight where high sample rate data is collected versus the single event data collection points is very low. In addition, a single data point will be recorded if none has been recorded in 60 seconds. The lack of a consistent, finely sampled recording of data necessitates a change to the modelling of the state equations for the Kalman filter, as will be described later.

An example of VSLED data recorded during an entire V-22 flight is shown in Figure 2. As can be seen, each data point represents a snapshot of data, so the behavior of the aircraft can be determined on a macro scale, but the details of the dynamic response is missing because of the relatively sparse data set.

**Figure 1. V-22 Flight Test Aircraft Weight and Balance Data Points for ANN Training**

**Figure 2. Sample VSLED Data**
Estimation Models and Process

Artificial Neural Network

An ANN can be used to map a complex underlying relationship within any given set of data. In this application, V-22 flight test data (CAFTA) was used to map a set of input parameters to GW and CG. After the ANN is trained with a “training” set of data, the ANN essentially performs pattern recognition on the input data set, and provides the output which best matches the input. Figure 3 shows this process.

![Figure 3. ANN Learning Process Schematic](image)

The neural network paradigm chosen initially is a back-propagation network (BPN). More sophisticated ANN formulations have been used in the past, such as the Radial Basis Function (RBF) network [1]; however, due to prior experience with the BPN and the scope of this effort, it was decided to maintain the BPN approach while concurrently developing an RBF network for future use. The selected input parameters for the ANN in airplane mode are shown in Table 1.

<table>
<thead>
<tr>
<th>Measured Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>KCAS</td>
</tr>
<tr>
<td>Density Altitude</td>
</tr>
<tr>
<td>Pitch Attitude</td>
</tr>
<tr>
<td>Average Rotor RPM</td>
</tr>
<tr>
<td>Average Rotor Torque</td>
</tr>
<tr>
<td>Average Symmetric Flaperon Position</td>
</tr>
<tr>
<td>Nz</td>
</tr>
</tbody>
</table>

Originally the neural network was developed by combining all airplane mode quasi-steady wings level flight test data points into a single training set. The results showed that there were discrepancies in some of the regions of the envelope that required greater scrutiny. After reviewing the input data, it was decided to develop three separate neural networks dependent on the average flaperon setting.

Figure 4. ANN Test Set Results

Out of the entire CAFTA data set, 10% of the flight test data was used as test inputs to assess the quality of the ANN training. The results are shown in Figure 4. A perfectly trained neural network should result in the output parameters equal to the input parameters, meaning all data points would lie on the solid line shown in Figure 4. The total RMS error was examined by using Eq. (1) below.

\[
RMS \ Error = \sqrt{\frac{\sum_{i=1}^{n}(e_i - m_i)^2}{n}} \tag{1}
\]

For the test set, the percent RMS error for all three ANNs was 3.49%. This error may be improved upon in several ways. The first is that the ANN may be changed from the back-propagation network selected to a radial basis function (RBF) network as described in Reference [1], which was shown to perform better in this task. Second, is the training and test sets could be selected differently to reduce the clustering of the data points seen in Figure 4, which can make the network sensitive to over-training. The third is to further extract data from the flight test data set to develop a more comprehensive training set, thereby reducing the error when the network is forced to perform estimation near the edge of the training set.

Kalman Filter

The Kalman filter is an efficient recursive means to estimate the state of a process, in a way that minimizes the mean of the squared error. It supports estimations of past, present, and future states and it can do so even when the precise nature of the modeled system is unknown [5].

The Kalman filter uses a form of feedback control. Initially the state is estimated via a model of the system, contained in the A and B matrices of the linear time invariant (LTI) system shown in Eq. (2). After the state is estimated, the filter obtains feedback in the form of a noisy measurement shown in Eq. (5). Thus Eqs. (1) and (2) can be
described as the time update equations and Eqs. (4), (5), and (6) the measurement update equations. A simplified version of the Kalman filter equations is presented below. A more general form is contained in Reference [5].

Estimated state propagation:
\[ \dot{x} = Ax + Bu \]  
(2)

Error covariance estimate propagation:
\[ \dot{P} = APA^{-1} + Q \]  
(3)

where Q is the noise associated with the uncertainty of the model and P is the error covariance.

Kalman gain calculation:
\[ K = \dot{P} (\dot{P} + R)^{-1} \]  
(4)

where R is the measurement noise matrix and K is the Kalman gain.

State estimate correction:
\[ x = \dot{x} + K (z - \dot{x}) \]  
(5)

where z is the measurement vector.

Error covariance correction:
\[ P = (I - K) \dot{P} \]  
(6)

In Eq. (4), the Kalman gain is computed. This matrix contains the information required to weight the measurement and estimated states according to their relative uncertainties. For instance, if the noise of the measurement of a particular state is high compared to the uncertainty of the state based upon the model, the Kalman gain will tend to apply more weight to the output of the system model for this state. The converse is also true, if there is little confidence in the model, the Kalman gain matrix will weigh the measurement more heavily.

The model noise matrix used is given by:
\[ Q = \begin{bmatrix} 1.5E^{-3} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 10 & 0 \\ 0 & 0 & 0 & 1E^{-3} \end{bmatrix} \]  
(7)

The measurement noise matrix used is given by:
\[ R = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1E^{-2} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 5.6E^6 \end{bmatrix} \]  
(8)

The values chosen in the model noise matrix, Eq. (7), and the measurement noise matrix, Eq. (8), are based on trial and error. Initially, the error covariance matrix, P, was set equal to the initial model noise. This matrix changes with each iteration of the Kalman filter based upon the state transition matrix A, the model noise Q, and the Kalman gain K. A description of the elements of the error covariance matrix, P, is given in Table 2.

### Table 2. Kalman Filter Error Covariance Matrix, P, Description

<table>
<thead>
<tr>
<th>Mean square ( \alpha ) error</th>
<th>Cross-correlation of ( \alpha ) and ( \theta ) errors</th>
<th>Cross-correlation of ( \theta ) and VV errors</th>
<th>Cross-correlation of ( \alpha ) and GW errors</th>
</tr>
</thead>
<tbody>
<tr>
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<td>Cross-correlation of ( \theta ) and VV errors</td>
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<td>Cross-correlation of VV and GW errors</td>
</tr>
<tr>
<td>Mean square VV error</td>
<td>Cross-correlation of ( \alpha ) and GW errors</td>
<td>Mean square GW error</td>
<td>Cross-correlation of GW and GW errors</td>
</tr>
</tbody>
</table>

The measurement vector, Eq. (9), is generated at every time step from the VSLED data with the exception of the last element of the measurement vector, the GW, which is obtained from the output of the ANN.

\[ z = \begin{bmatrix} \alpha_{meas} \\ \theta_{meas} \\ VV_{meas} \\ GW_{ANN} \end{bmatrix} \]  
(9)

**Aerodynamic Model**

The Kalman filter requires a linear model of the system for the estimated state propagation in the first step of the filter. A simple aerodynamic model of the V-22 in forward flight was created for this purpose using quasi-steady data from both CAFTA flight test data and VSLED flight data. The model is a function of basic aerodynamic properties derived from the average of test data time histories, including lift coefficient and pitching relationships with vertical velocity. State equations, which are required for the Kalman filter, were derived based on basic principles using these aerodynamic properties.

The derived state equations used in the development of the Kalman filter are:

\[ \alpha_2 = \theta_1 + C1VV_1 - C2 \]  
(10)

\[ \theta_2 = -C1VV_1 + \frac{n_s GWW_1}{C_{Lq} \bar{q}S} - \frac{C_{L\alpha}}{C_{Lq}} \frac{T \sin \theta_1}{C_{Lq} \bar{q}S} + C2 \]  
(11)
\[ VV_2 = VV_1 \]  
\[ GW_2 = \frac{C_{L\alpha} \alpha_1 \bar{q}S + C_{L0} \bar{q}S + T(\sin \theta_1)}{n_z} \]

Where \( VV \) is the vertical velocity, \( T \) is the total thrust, \( C_{L\alpha} \) is the lift curve slope, and \( C_{L0} \) is the lift at zero angle of attack. Subscripts 1 and 2 refer to initial state and propagated state estimate, respectively. \( C1 \) and \( C2 \) are empirically derived constants based on flight data.

The state equations used for the development of the Kalman filter are a departure from the previous methods used to determine the aircraft GW/CG, where the differential equations of flight were solved and GW/CG fell out of the analysis. The reason that a different formulation had to be used was the nature of VSLED data; because it is recorded by event-driven “snapshots” and not continuously at high rate (as in a typical system dynamics analysis), the standard formulation would fail. The structure of the state equations used here allows for the states to be propagated at the individual event-driven time points.

The formulation of the linear time invariant system is defined below:

\[ \dot{x} = Ax + Bu \]  

Converting the state equations presented earlier into state space form yields:

\[
\begin{bmatrix}
\alpha_2 \\
\theta_2 \\
VV_2 \\
GW_2
\end{bmatrix} = \begin{bmatrix}
0 & 1 & C1 & 0 \\
0 & 0 & -C1 & \frac{n_z}{C_{L0} \bar{q}S} \\
C_{L0} \bar{q}S & 0 & 0 & 0 \\
\frac{n_z}{C_{L0} \bar{q}S} & 0 & 0 & 0
\end{bmatrix} \begin{bmatrix}
\alpha_1 \\
\theta_1 \\
VV_1 \\
GW_1
\end{bmatrix} + \begin{bmatrix}
-C2 \\
C2 - \frac{C_{L0}}{C_{L\alpha}} \\
0
\end{bmatrix} \begin{bmatrix}
\frac{C_{L0} \bar{q}S + T(\sin \theta_1)}{n_z}
\end{bmatrix}
\]  

(15)

Parameter Estimation Process

The process, shown in Figure 5, to combine the ANN with the Kalman filter to estimate GW/CG begins with the input of VSLED data, on a flight by flight basis, into both the ANN and Kalman filter. The first estimate of the GW/CG, which gets passed to the measurement matrix in the Kalman filter along with aircraft state parameters, is based upon the flight test data developed ANN. The measurements are then used to correct the state estimates (including GW/CG) determined by the V-22 aerodynamic model. After these two data sources get fused together by the Kalman gain, the GW/CG estimate is complete and the Kalman filter then performs its next iteration on the next set of measurements.

GW/CG Estimation Results

The results that are contained in this section show how well combining the ANN and KF works for airplane mode even with a very simplified aerodynamic model that was developed from a set of flight data. It is anticipated that with a more refined aerodynamic model, the results will improve substantially. In addition, increasing the accuracy of the ANN through an expansion of the data sets used for training will provide additional accuracy gains in this application.

Format of Results

The results presented are given in the domain of “VSLED Sample Number.” There are two reasons for this. The first is that the VSLED data is not sampled continuously, so if the data was plotted as a function of time, there would be gaps in the data. In addition, these gaps would be exacerbated by the fact that only quasi-steady wings level data was used. This is shown in the following chart, Figure 6, of VSLED recorded angle-of-attack as a function of time.
Each dot in Figure 6 represents a VSLED snapshot. As can be seen, there is a large gap in the data between roughly 4,000 and 5,200 seconds. The data is plotted as discrete dots to avoid the assumption of data where there is none if the data were plotted as a continuous line. To avoid these gaps, the data is used as a function of sample number rather than time. This has no effect on the results presented because the formulation of the Kalman filter used in this report does not require discrete time to be sampled continuously at high sample rates as is the case with previous work done in this area [4]. A chart showing the same angle of attack time history as a function of VSLED sample number is shown in Figure 7. To assist the reader with determining how much time has elapsed for a given chart, a “Total Elapsed Time” is included in the chart.

Airplane Mode GW Estimation Results

As will be seen in the airplane mode GW estimation results (Figure 8 through Figure 12), the Kalman filter works as designed. It is able to distinguish between the ANN estimate of GW that is beneficial to providing the correct value of GW, thereby weighting it more heavily, and able to reject it and go with the internal aerodynamic model of the V-22 when it is detrimental to use the ANN data.

The deterministic model shown in Figure 8 is defined by the standard equation which is adjusted based upon the symmetric setting of the flaperons:

\[ GW = \frac{C_{\lambda}}{\sqrt{S}} \]  \hspace{1cm} (16)

Because it is deterministic, it will provide an output of gross weight for every value of angle of attack regardless of whether it is wildly incorrect or not. This is seen in VSLED data where there are temporary dropouts in angle of attack measurement. In these cases the gross weight would be projected as zero, which is obviously not the case. This deterministic data, which is similar to the case of a flight simulator model fed VSLED data, is used to provide a comparison with the Kalman filter/ANN combination and the stand-alone ANN data.

Figure 8 shows the results over a span of 3.1 hours during a V-22 flight. The red line is the recorded GW from VSLED, the black line is the output from the ANN, the green line is the deterministic model of GW, and the blue line is the output from the Kalman filter/ANN fusion. As can be clearly seen, the Kalman filter/ANN fused output dominates the stand-alone ANN as well as the deterministic model in terms of accuracy against the recorded VSLED data, even tightly following the increases in GW due to what is assumed to be aerial refueling operations.

The fluctuations in the state parameters shown in Figure 9 illustrate how the Kalman filter/ANN estimation performs well under fluctuations and dropouts in angle of attack, rotor torque, KCAS, dynamic pressure, and flaperon angle. The state of the aircraft is continually changing during the flight; however, as shown in Figure 8, the GW is consistently estimated and follows the fuel burn characteristics of the aircraft.
Figure 8. Kalman Filter/ANN GW Estimation Overlaid on VSLED Output (VSLED File #1), Airplane Mode

Figure 9. Operational V-22 Aircraft State Data from VSLED File #1, Airplane Mode
The results in Figure 10 show how the deterministic model over-predicts and the ANN under-predicts the recorded GW. Approximately midway through the flight, the Kalman filter/ANN estimate begins to drift downwards (lighter GW); however, it then corrects itself and begins trending heavier along with the deterministic model and stand-alone ANN.

The result shown in Figure 11 is interesting in that there is a good match between the stand-alone ANN, deterministic solution, and the Kalman filter/ANN; however, the VSLED data is noisy with drop outs. Upon review of the actual VSLED file, it appeared that the sling load measurement was dramatically fluctuating, thus influencing the recorded GW from VSLED. As can be seen at about sample 400, the VSLED GW jumps resulting in an instantaneous error of approximately -10% with the Kalman filter/ANN, but the Kalman filter soon re-acquires the solution and reduces the error to about zero at sample 440. This jump could either be the result of aerial refueling or the V-22 picking up a sling load or other cargo midway through the VSLED time history.

The result in Figure 12 shows that the Kalman filter/ANN solution follows the VSLED recorded data very well during this long flight, where it appears that aerial refueling occurred. Even though both the ANN and deterministic solution showed that the GW was higher than the VSLED records at the early portion of the time history, the Kalman filter/ANN solution drops to a lower weight and follows along with the fuel burn of the V-22. Two anomalies occur at about sample 1,000 and at the end of the time history, which is due to a configuration change and rapid descent which was not accounted for in the simplified modelling developed for the Kalman filter in this application.

Figure 10. GW Estimation and Error for VSLED File #2, Airplane Mode
Figure 11. GW Estimation and Error for VSLED File #3, Airplane Mode

Figure 12. GW Estimation and Error for VSLED File #1 (expanded), Airplane Mode
Airplane Mode CG Estimation Results

The CG implementation of the Kalman filter has not yet been completed for airplane mode, but estimations using only an ANN have been completed and show promising results for use with a Kalman filter. The CG estimation results for five different airplane mode sample flights are shown in Figure 13. ANN results are shown in the standard time domain and at the data snapshot time points.

Figure 13. CG Estimation with ANN Only, Airplane Mode
Helicopter Mode GW/CG Estimation Results

The GW/CG implementation of the Kalman filter has not yet been completed for helicopter mode, but estimations using only an ANN have been completed and show promising results for use with a Kalman filter. The GW/CG estimation results for four different helicopter mode sample flights are shown in Figure 14 and Figure 15. ANN results are shown in the standard time domain and at the data snapshot time points.

Figure 14. Gross Weight Estimation with ANN Only, Helicopter Mode

Figure 15. CG Estimation with ANN Only, Helicopter Mode
Concluding Remarks

The capability of a combination Kalman filter and Artificial Neural Network method to estimate gross weight and center of gravity was evaluated for use with the V-22. To evaluate the estimation capability in a real world usage scenario, V-22 VSLED data was used, which is a non-continuous and small snapshot (event driven) type of data collection method. Results of the combination Kalman filter/ANN for gross weight estimation were shown for several airplane mode cases. Overall, the GW estimation was found to improve upon the ANN estimation method alone, which can be subject to large errors as a result of spikes or dropouts in the recorded data.

The primary focus of this effort has been on reducing the airplane mode GW estimation error of the V-22 by using a Kalman filter/ANN combination, where the ANN provides an initial estimate of the aircraft GW that is then fed into the Kalman filter. This allows the mechanism for the proper use of the Kalman filter/ANN combination to be more easily refined. A more robust aerodynamic model will be needed for development of the process for conversion or helicopter mode and hover. However, positive results were shown for GW/CG estimation in airplane and helicopter mode using only an ANN, which creates confidence that combining this with a Kalman filter will yield similar results to what has been shown for airplane mode GW estimation.

In addition, using the Kalman filter formulation has the advantage of providing a check of the recorded aircraft state data through the use of the system dynamics model, allowing an aircraft kinematic consistency check in addition to GW/CG estimation. This will reduce errors associated with operational data collection sensors that are out of tolerance. In addition, because the ANN estimates the GW/CG with only the recorded aircraft states, the Kalman filter, in this application, can be used even with a low confidence in the recorded GW/CG or an absence of this information. By accurately and automatically estimating the GW/CG of an aircraft based on operationally recorded aircraft state data, it can have a profound impact on current aircraft lifing practices which develop structural damage estimates based upon the recorded data from on-board recording devices.

References


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