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Online parameter estimation applied to mixed conduction/radiation

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ABSTRACT

This paper describes online parameter estimation and modeling applied to a mixed conduction/radiation heat transfer as is the case often witnessed in Space Hardware Qualification. We investigate several recent techniques such as the Extended Kalman Filter and the Unscented Kalman Filter. Results show that EKF fails in parameter estimation in cases where tests featured strong non linearities. UKF was found to perform well in all the experimental test conditions.

Keywords: Non linear Kalman Filter, Conduction, Radiation, Heat Transfer, Parameter Estimation, Dual Estimation

1. NOMENCLATURE

Control Inputs

q_3 : Heat load on lens Vacuum chamber.

q_4 : Heat load on Power board.

T_1 : Boundary node Temperature.

State Variables

T_2 : Starnav I chassis temperature

T_3 : Invar Tube Temperature

T_4 : Vacuum Chamber Temperature

T_5 : Power Board Temperature

Model Parameters

k_1 : Conductance between T_2 and T_1

k_2 : Conductance between T_2 and T_3

k_3 : Conductance between T_3 and T_4

k_4 : Conductance between T_4 and T_2

k_5 : Conductance between T_2 and T_5

H_0 : Linearized Radiative heat transfer coefficient

m_1 : Thermal mass of Starnav I Box

m_2 : Thermal mass of Invar Tube

m_3 : Thermal mass of Lens Vacuum Chamber

m_4 : Thermal mass of Power Board

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2. INTRODUCTION

The objective often is to obtain model parameters from experimental data. We present online state and parameter estimation applied to temperature data from different environmental test on a payload (StarNav I). A five node simplified model is built to understand the dynamics of the system. A state space model is then built from the nodal equations of this model. The parameters (like conductance or thermal masses) are first estimated from the observations from four thermal tests performed on the ground, using initial guesses obtained of the CAD model built in Thermal Desktop©[9] . Using this data, a new estimation can then be performed on the data obtained during flight for parameters which could not be obtained on the ground (environmental heat loads).

Two methods are used to estimate the model parameters, the Extended Kalman Filter(EKF) and Unscented Kalman Filter(UKF). Both of these methods are described briefly below.

3. KALMAN FILTER

The Kalman filter provides a recursive solution to the linear optimal filtering problem. The solution is recursive in that each updated estimate of the state is computed from the previous estimate and the new input data, so only the previous estimate requires storage. The Kalman filter is computationally more efficient than computing the estimate directly form the entire past observed data at each step of the filtering process. Most of the following information on Kalman filtering is obtained from "Kalman Filtering and Neural Networks" by S. Haykin.[1]

The Kalman filter is based on the following two equations:

1. Process equation:

$$x_{k+1} \;=\; F_{k+1,k}x_k \;+\; w_k \tag{1}$$

where $F_{k+1,k}$ is the transition matrix taking the state x_k from time k to time k+1. The process noise w_k is assumed to be white and Gaussian, with zero mean and with the covariance matrix defined by

$$E[w_n w_n^T] = \left\{ \begin{array}{ll} Q_k & \text{for } n = k \\ 0 & \text{for } n \neq k \end{array} \right\} \tag{2}$$

where the superscript T denotes transposition. The dimension of the state space is denoted by M.

2. Measurement equation:

$$y_k = H_k x_k + v_k \tag{3}$$

where y_k is the observation vector at time k and H_k is the measurement matrix. The measurement noise v_k is assumed to be additive, white, and Gaussian, with zero mean and with the covariance matrix defined by

$$E[v_n v_n^T] = \left\{ \begin{array}{ll} R_k & \text{for } n = k \\ 0 & \text{for } n \neq k \end{array} \right\} \tag{4}$$

In equations (1) and (3) , the measurement noise v_k is uncorrelated with the process noise w_k. The dimension of the measurement space is denoted by N. The Kalman filtering process is the solving of the process and measurement equations for the unknown state in an optimum manner. It uses the entire observed data $y_1, y_2, \cdots y_k$ to find for each k ≥ 1 the minimum mean square error estimate of the state x_i.

4. EXTENDED KALMAN FILTER

The Kalman filter only addresses the estimation of a state vector in a linear model. If the model is nonlinear, the Kalman filter can be extended through a linearization procedure yielding the Extended Kalman Filter (EKF). This extension is feasible because the Kalman filter is described in terms of difference equations in the case of discrete-time systems. Consider a nonlinear dynamical system described by the following state-space model:

$$x_{k+1} \;=\; f(k, x_k) \;+\; w_k \tag{5}$$

$$y_k = h(k, x_k) + v_k \tag{6}$$

where w_k and v_k are independent zero-mean white Gaussian noise processes with covariance matrices R_k and Q_k, respectively. The functional f(k, x_k) denotes a nonlinear transition matrix function that is possibly time-variant. The functional h(k, x_k) denotes a nonlinear measurement matrix that also may be time-variant.

The idea of the extended Kalman filter is to linearize the state space model at each time instant around the most recent state estimate, which is taken to be either the current estimate x_k or the prior estimate x_k^-, depending on which particular functional is being considered. After linearizing the model, the standard Kalman filter equations can be applied. This is done in two stages:

Stage 1:

$$F_{k+1,k} = \frac{\partial f(k,x)}{\partial x}_{x=x_k} \tag{7}$$

$$H_k = \frac{\partial h(k,x_k)}{\partial x}_{x=x_k^-} \tag{8}$$

The ij-th entry of $F_{k+1,k}$ is equal to the partial derivative of the i-th component of $F(k,x)$ with respect to the j-th component of x. The ij-th component of H_k is equal to the partial derivative of the i-th component of $H(k,x)$ with respect to the j-th component of x.

Stage 2:

Once the matrices $F_{k+1,k}$ and H_k are evaluated, they are used in the first-order Taylor approximation of the nonlinear functions F(k, x_k) and H(k, x_k) around x_k and x_k^-.

$$F(k,x_k) \approx F(x,x_k) + F_{k+1,k}(x,x_k) \tag{9}$$

$$H(k,x_k) \approx H(x,x_k) + H_{k+1,k}(x,x_k^-) \tag{10}$$

hence the non linear state equations are given as

$$x_{k+1} \approx F_{k+1,k}x_k + w_k + d_k \tag{11}$$

$$\overline{y}_k \approx H_k x_k + v_k \tag{12}$$

where

$$\overline{y}_k = y_k - h(x, x_k^-) - H_k x_k^- \tag{13}$$

$$d_k = f(x, x_k) - F_{k+1,k}x_k \tag{14}$$

5. UNSCENTED KALMAN FILTER

Because EKF relies on a linear approximation of the non linear functions F and H, it has shown to fail in instances of strong non linearities. The Unscented Kalman filter addresses this approximation issue with UKF. The distribution of the state variable is represented by a Gaussian random variable, and is specified using a minimal set of carefully chosen sample points. The sample points capture the mean and covariance of the Gaussian random variable[1234] .

Unscented Transformation

The Unscented Transformation is a method for calculating the statistics of a random variable which undergoes a nonlinear transformation. For more information refer.[1]

Unscented Kalman Filter

The Unscented Kalman filter is an extension of the Unscented Transformation. No explicit calculations or Jacobians or Hessians are necessary to implement this algorithm.

6. APPLICATION TO STARNAV I

StarNav I is an advanced star tracker designed and built by the Spacecraft Technology Center and the Aerospace Engineering Department at Texas A&M University, It flew during the STS-107 mission aboard the Space Shuttle Columbia. Its objective was to validate the Lost in space algorithm (LISA) developed by Dr. Junkins for determining precise spacecraft attitude without prior knowledge of position.[6] In order to successfully pass safety reviews, the StarNav I payload went through different thermal vacuum tests. The goal of this paper is to show how the thermal model of the payload was estimated through the course of the various thermal tests.

6.1. Starnav Simplified Thermal Model

The Thermal Desktop©[9]/SINDA conductance model of StarNav I must be reduced in order to be able to compare temperature data provided by the experimental tests. A simplified thermal model of 5 nodes was devised -see Figure 1. Each node represents different interconnected parts of the instrument.

The equations used to derive the state model from this simplified model are given below:

Node 1: Boundary node (Describes the temperature of the environment)

Node 2: Starnav I box

$$m_1 \frac{d}{dT} T_2 = k_2(T_3 - T_2) + k_4(T_4 - T_2) + k_5(T_5 - T_2) - K_1(T_2 - T_1) - H_0(T_2 - T_1) \tag{15}$$

Node 3: Invar Tube (containing optics)

$$m_2 \frac{d}{dT} T_3 = k_3(T_4 - T_3) - k_2(T_3 - T_2) \tag{16}$$

Node 4: Vacuum Chamber

$$m_3 \frac{d}{dT} T_4 = q_3 - k_3(T_4 - T_3) - k_4(T_4 - T_2) \tag{17}$$

Node 5: Power Board

$$m_4 \frac{d}{dT} T_5 = q_4 - k_6(T_5 - T_1) - k_5(T_5 - T_2) \tag{18}$$

Writing this system of equations in state form we obtain:

$$\frac{d}{dT}\begin{bmatrix} T_2 \\ T_3 \\ T_4 \\ T_5 \end{bmatrix} = \begin{bmatrix} -\frac{(k1+k2+k4+k5+H_0)}{m_1} & \frac{k_2}{m_1} & \frac{k_4}{m_1} & \frac{k_5}{m_1} \\ \frac{k_2}{m_2} & -\frac{k_2+k_3}{m_2} & \frac{k3}{m_2} & 0 \\ \frac{k4}{m_3} & \frac{k_3}{m_3} & -\frac{k_3+k_4}{m_3} & 0 \\ \frac{k_5}{m_4} & 0 & 0 & -\frac{k_5+k_6}{m_4} \end{bmatrix} \begin{bmatrix} T_2 \\ T_3 \\ T_4 \\ T_5 \end{bmatrix} + \begin{bmatrix} 0 & 0 & \frac{k_1+H_0}{m_1} \\ 0 & 0 & 0 \\ \frac{1}{m_3} & 0 & 0 \\ 0 & \frac{1}{m_4} & 0 \end{bmatrix} \begin{bmatrix} q_3 \\ q_4 \\ T_1 \end{bmatrix} \tag{19}$$

Initial guesses of the different conductances of the model were devised through conductance computation of the CAD model of StarNav I in Thermal Desktop©.[9] As mentioned earlier, four thermal tests were conducted on the ground on StarNav I and the data from these tests is used as observations to estimate the model parameters using both Extended Kalman Filter and Square root Unscented Kalman Filter. The dual estimation using these methods is performed with the help of a tool called REBEL which stands for Recursive Bayesian Estimation Toolkit and was developed by Rudolph van der Merwe and Eric A. Wan[8]

7. GROUND TEST DESCRIPTION AND RESULTS

The results obtained from the test data parameter estimation process are described below.

For Figures 3 to 12, it can can be observed that the estimated states (temperatures of the invar tube-T3, the vacuum chamber-T4, and the power board-T5) are correlating with the observation (top section of the figure) and that the estimated parameters (bottom section) are converging toward a asymptotic value quickly. The initial discrepancy between state and observation is due to the parameter estimation.

Test-A1 This test was conducted in thermal vacuum at 290K. The results from the test and parameter estimation subroutines are presented in Figures 3 and 4. Figure 3 presents estimation using the Square Root Unscented Kalman Filter. The bottom part presents the estimation of $\frac{1}{m_4}$ and $\frac{k_4}{m_3}$, where m4 is the thermal mass of the power board, m3 the thermal mass of vacuum chamber, and k4 the conductance between T4 and T2. Figure 4 presents the results obtained using the Extended Kalman Filter. These results are essentially the same as the ones presented in Figure 3 using UKF.

Test-A2 This test was conducted in thermal vacuum at 290K. The results from the test and parameter estimation subroutines are presented in Figures 5 and 6. Figure 5 presents estimation using the Square Root Unscented Kalman Filter. The bottom part presents the estimation of $\frac{1}{m_3}$ and $\frac{k_5}{m_4}$, where m3 is the thermal mass of the vacuum chamber, m4 the thermal mass of the power board, and k5 the conductance between T2 and T5. Figure 6 presents the results obtained using the Extended Kalman Filter. These results are essentially the same as the ones presented in Figure 5 using UKF.

Test-A3 This test was conducted in thermal vacuum at 290K. The results from the test and parameter estimation subroutines are presented in Figures 7 and 8. Figure 7 presents estimation using the Square Root Unscented Kalman Filter. The bottom part presents the estimation of $\frac{k_2}{m_2}$ and $\frac{k_3}{m_3}$, where m2 is the thermal mass of the invar tube, m3 the thermal mass of the vacuum chamber, k2 the conductance between T2 and T3, and k3 the conductance between T3 and T4. Figure 8 presents the results obtained using the Extended Kalman Filter. These results are essentially the same as the ones presented in Figure 7 using UKF.

Test-A4 This test was a thermal cycling test conducted in vacuum from +40C to -20C. The results from the test and parameter estimation subroutines are presented in Figures 9. This figure presents estimation using the Square Root Unscented Kalman Filter. The bottom part presents the estimation of $\frac{k_2}{m_1}$ and $\frac{k_3}{m_2}$, where m1 is the thermal mass of the StarNav I chassis, m2 the thermal mass of the invar tube, k2 the conductance between T2 and T3, and k3 the conductance between T3 and T4. For this test the Extended Kalman Filter failed. This could be due to the fact that non linearities are much stronger in this test (T^4 variations) due to large variation of the environmental temperatures.

Test-A5 This test was done at Kennedy Space Center. The primary objective of this test was to estimate the contact conductance from the startracker to the Spacehab module in the shuttle bay. The results from the test and parameter estimation subroutines are presented in Figures 10 and 11. Figure 10 presents estimation using the Square Root Unscented Kalman Filter. The bottom part presents the estimation of $\frac{k_1}{m_1}$, where m1 is the thermal mass of the StarNav I chassis, and k1 the conductance between T2 and T1. Figure 11 presents the results obtained using the Extended Kalman Filter. These results are essentially the same as the ones presented in Figure 10 using UKF.

The final values of the estimated parameters are:

$k_1 = 0.79$ W/C

$k_2 = 0.40$ W/C

$k_3 = 0.21$ W/C

$k_4 = 0.47$ W/C

$k_5 = 1.65$ W/C

$m_1 = 3371.8$ J/C

$m_2 = 185.96$ J/C

$m_3 = 255.42$ J/C

$m_4 = 277.9$ J/C

8. FLIGHT DATA

Estimation of on orbit environmental heat loads is the last step of this study. Five sets of Data called 'alpha', 'gamma', 'delta', 'epsilon' and 'tau' were collected during the mission. Estimations of these heat loads were performed and estimated. Figures 12 to 20 show initial results for the state and parameter estimations obtained.

9. CONCLUSIONS

The concept of online parameter estimation using both Extended and Unscented Kalman Filtering techniques has been presented and successfully applied to test data from ground testing of a star tracker in vacuum. These parameters were conductance values as well as thermal mass values. It has been observed that the Extended Kalman Filter does not perform well with significantly varying environmental temperatures. We believe this is due to the strong non linearities induced by the T^4 terms in the dual estimation problem.

ACKNOWLEDGMENTS

The authors wish to thank Rudolph van der Merwe and Eric A. Wan for providing the REBEL[8] toolkit.

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9. http://crtech.com

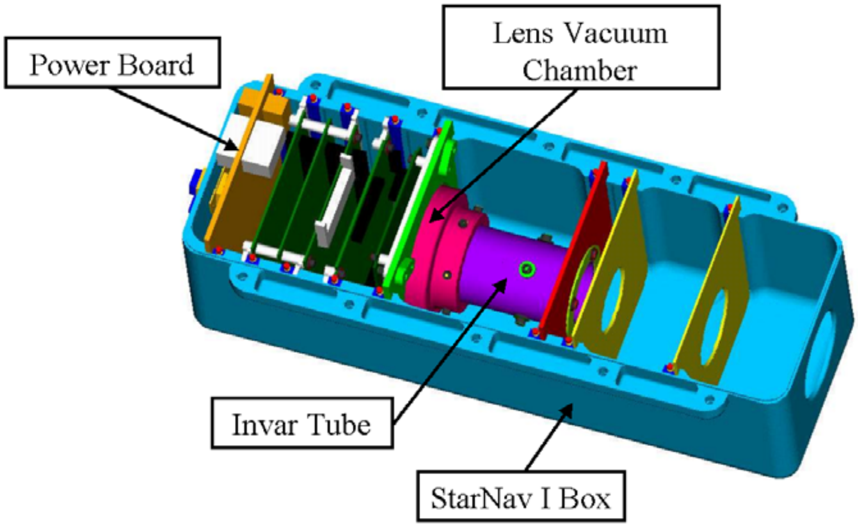

Figure 1: StarNav I design

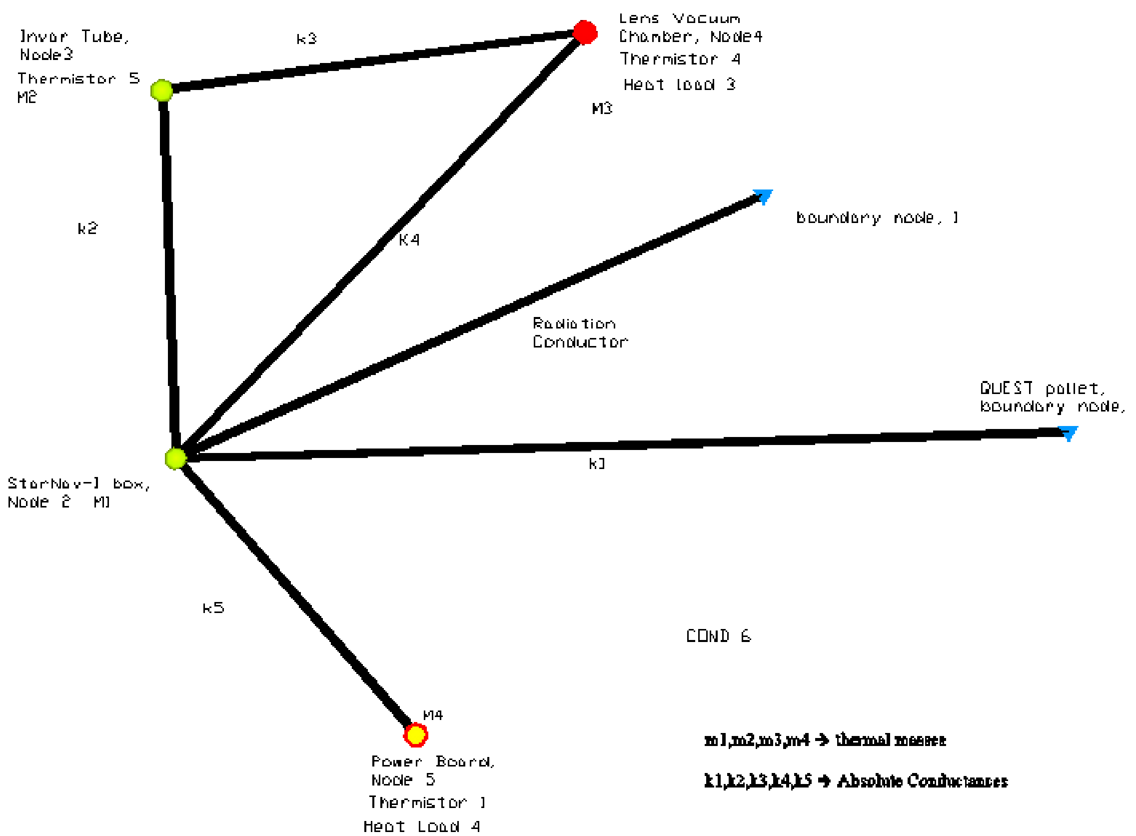

Figure 2: Starnav I simplified thermal model

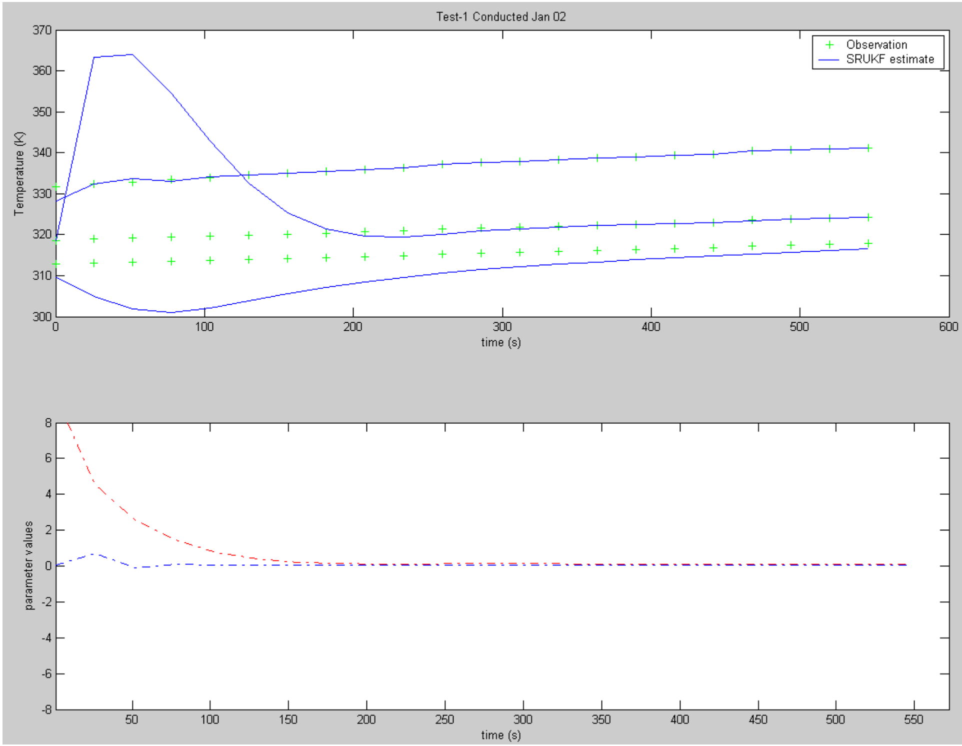

Figure 3: Ground Test 1 Estimation using SRUKF

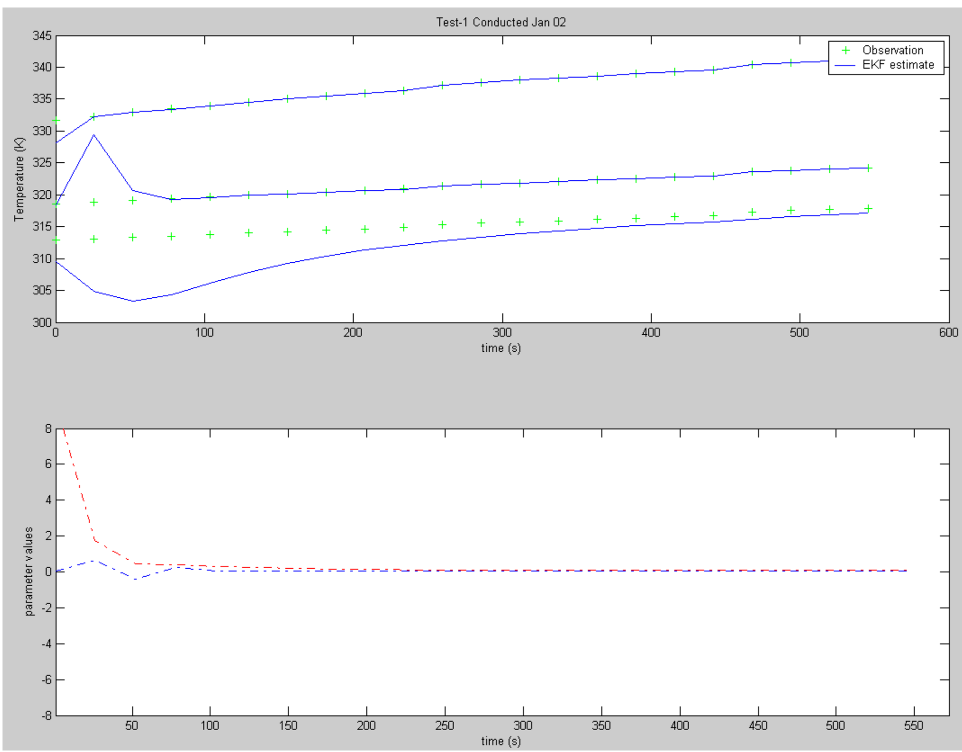

Figure 4: Ground Test 1 Estimation using EKF

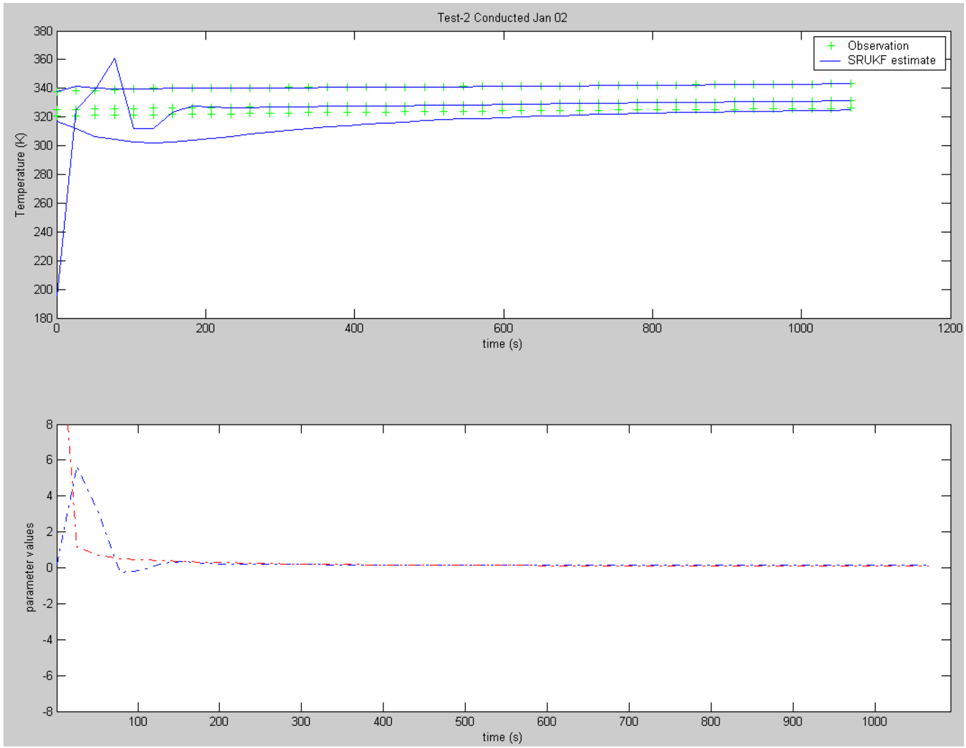

Figure 5: Ground Test 2 Estimation using SRUKF

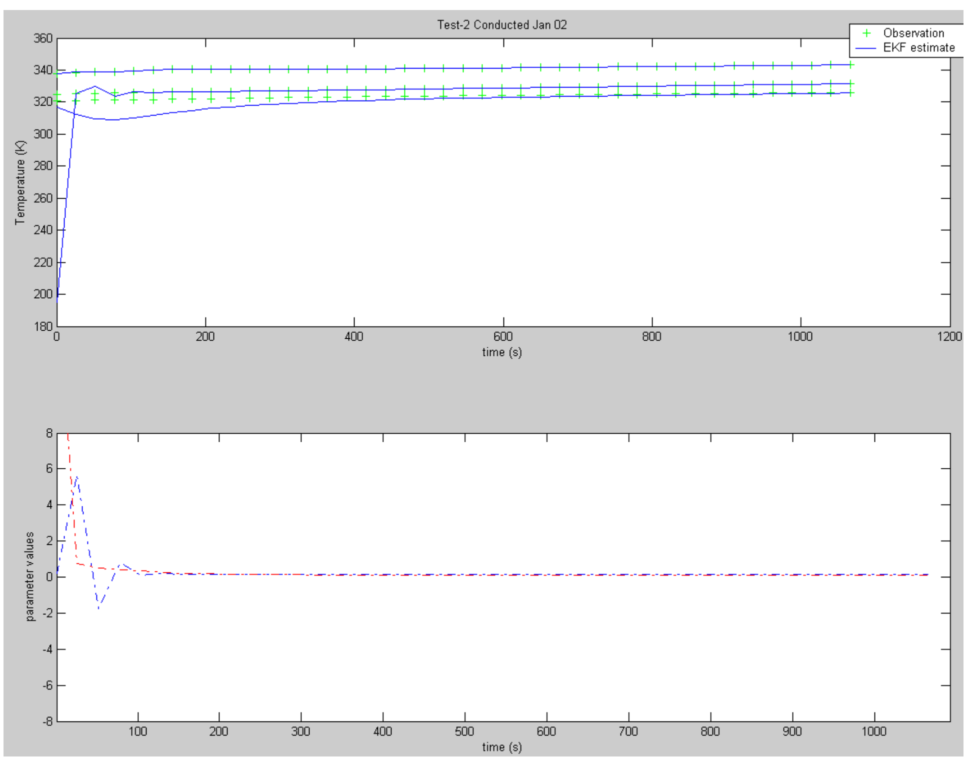

Figure 6: Ground Test 2 Estimation using EKF

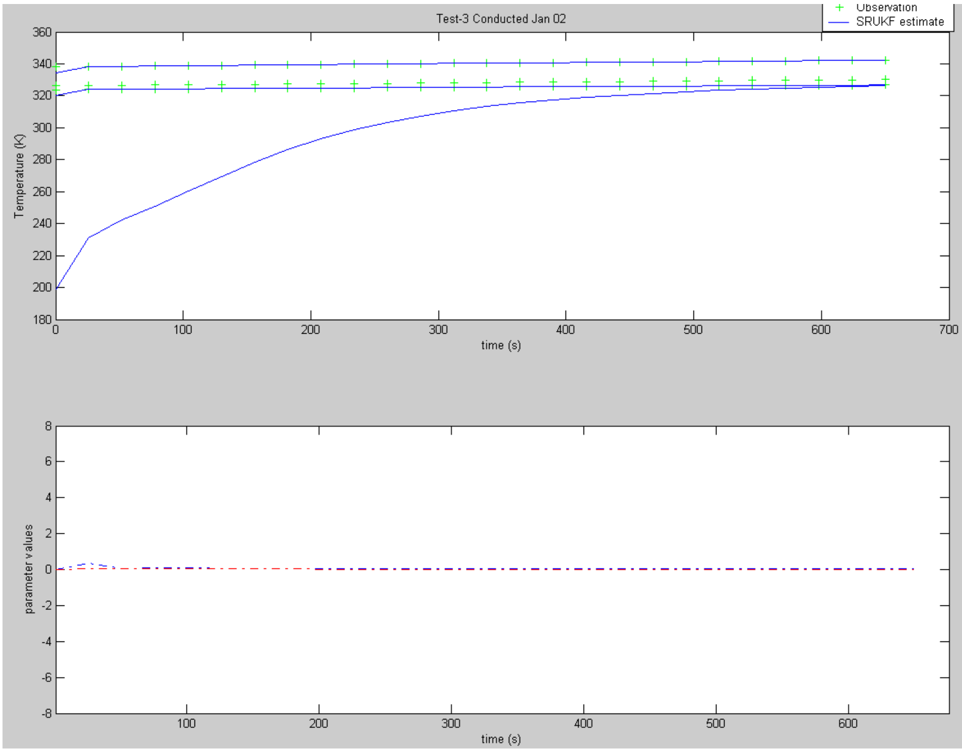

Figure 7: Ground Test 3 Estimation using SRUKF

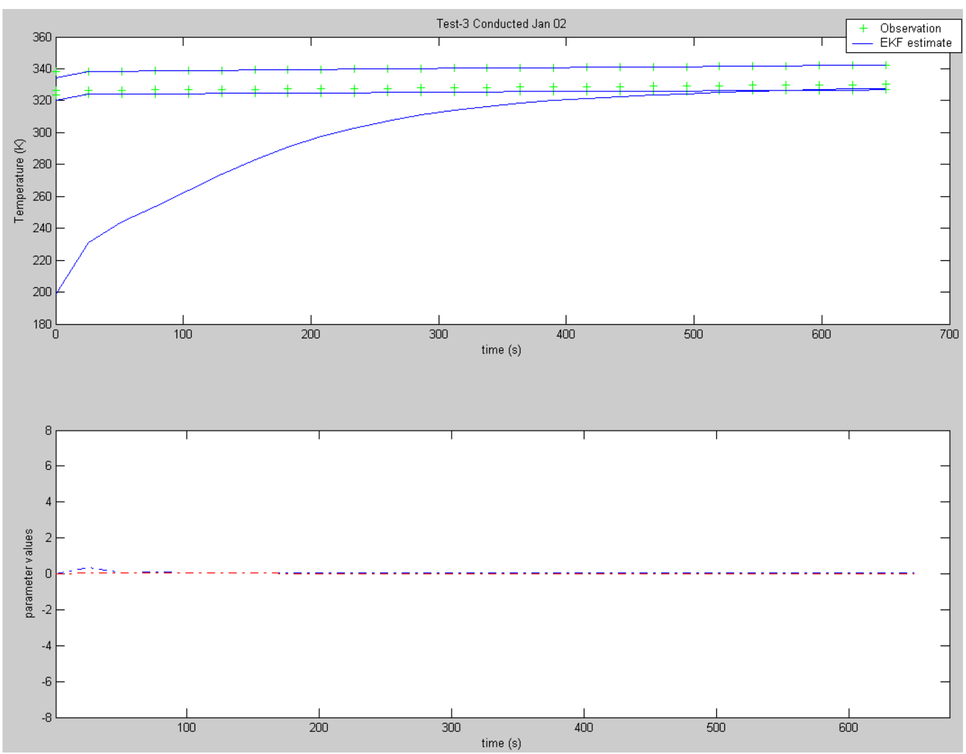

Figure 8: Ground Test 3 Estimation using EKF

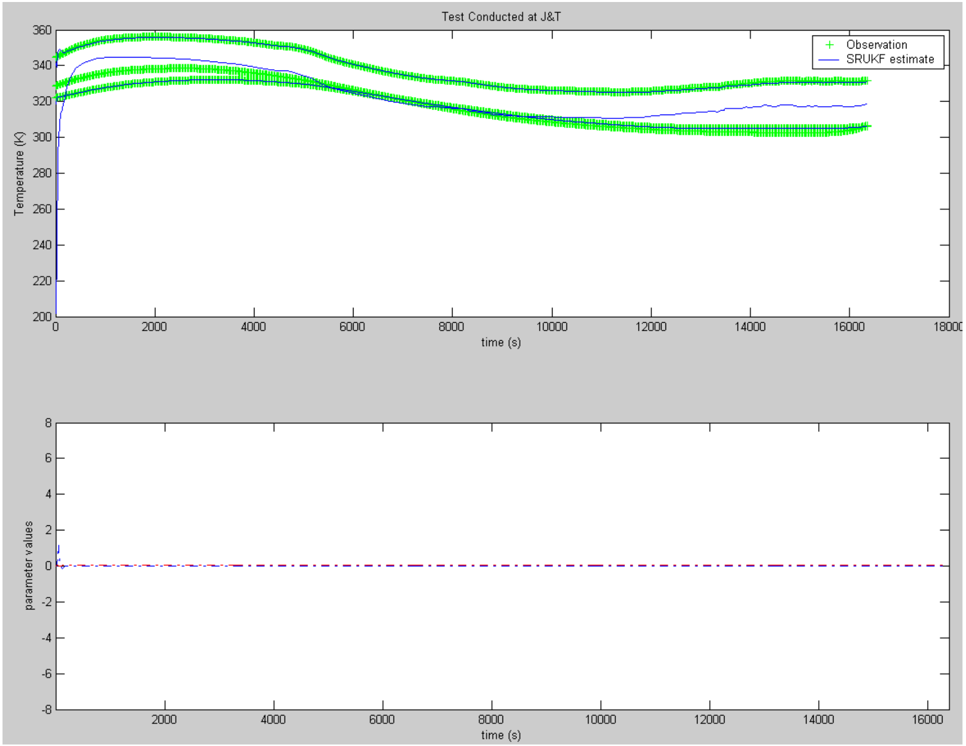

Figure 9: Ground Test 4 Estimation using SRUKF

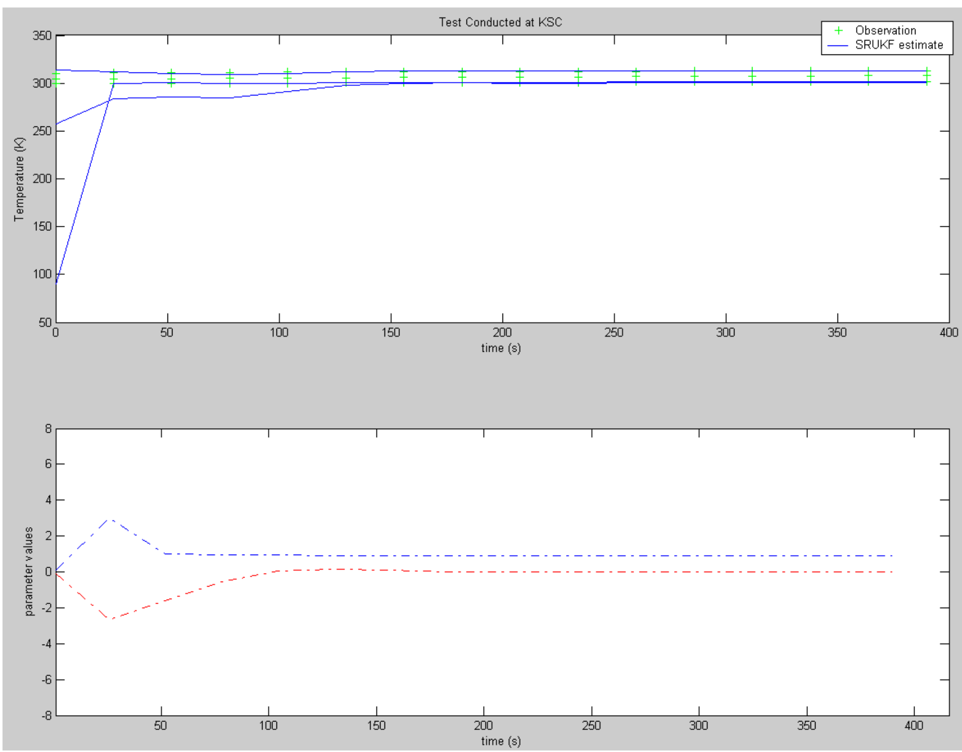

Figure 10: Ground Test 5 Estimation using SRUKF

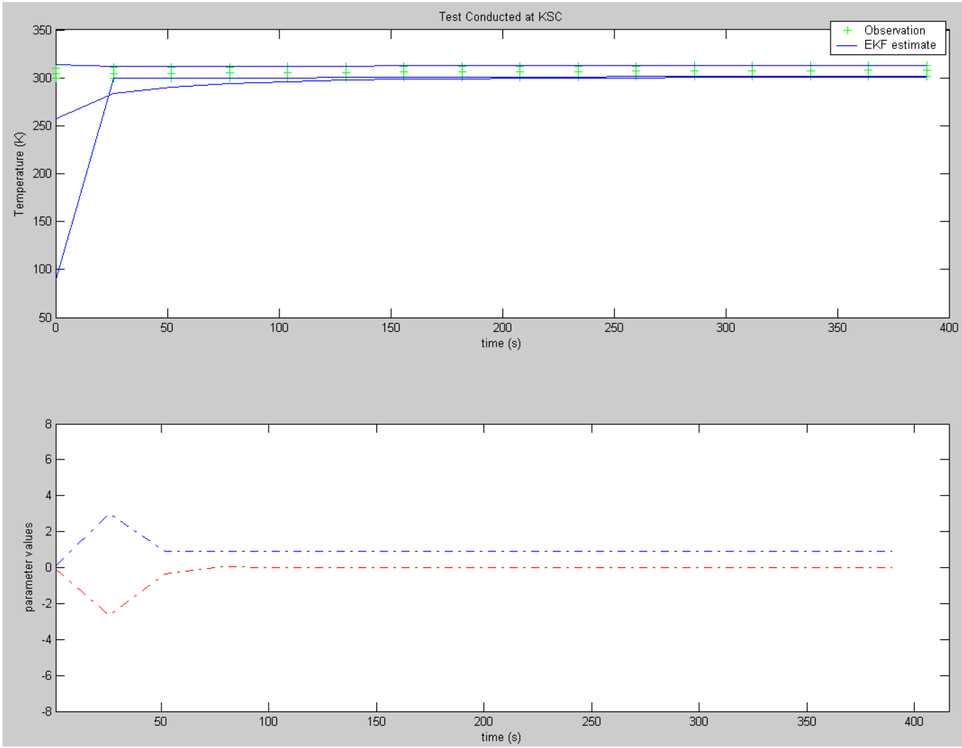

Figure 11: Ground Test 5 Estimation using EKF

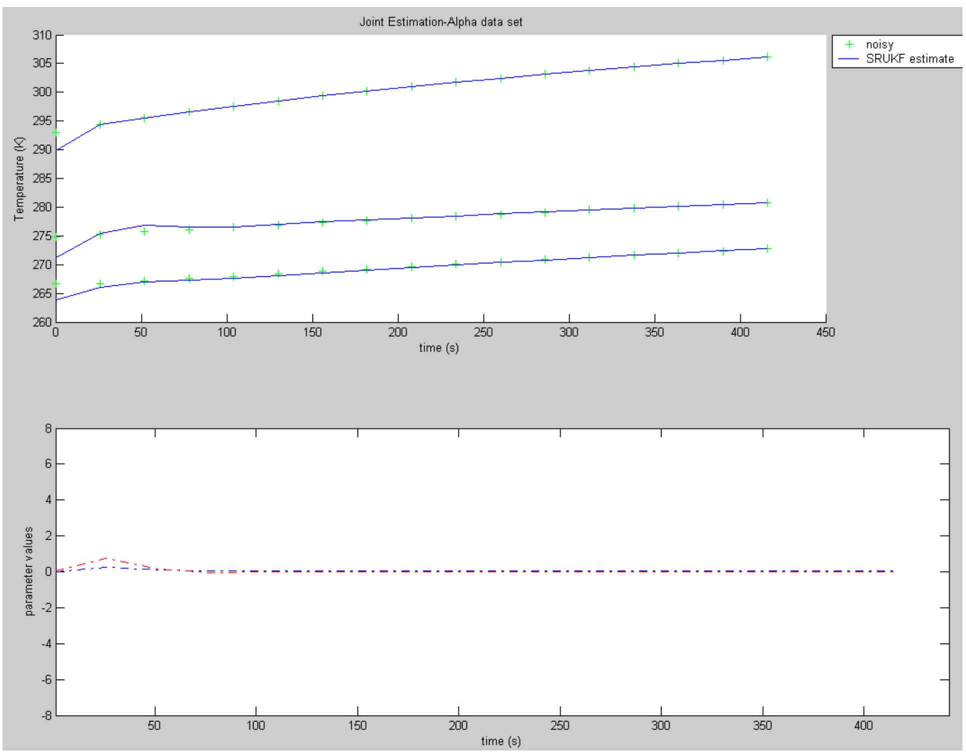

Figure 12: Flight Results 'alpha' using SRUKF

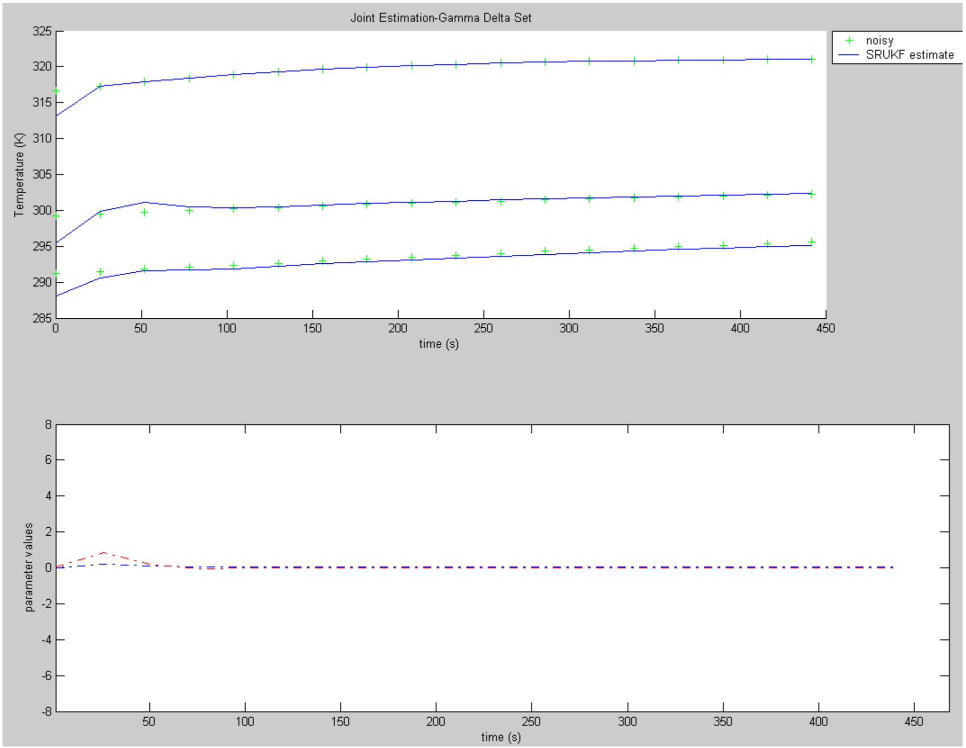

Figure 13: Flight Results 'gamma' using SRUKF

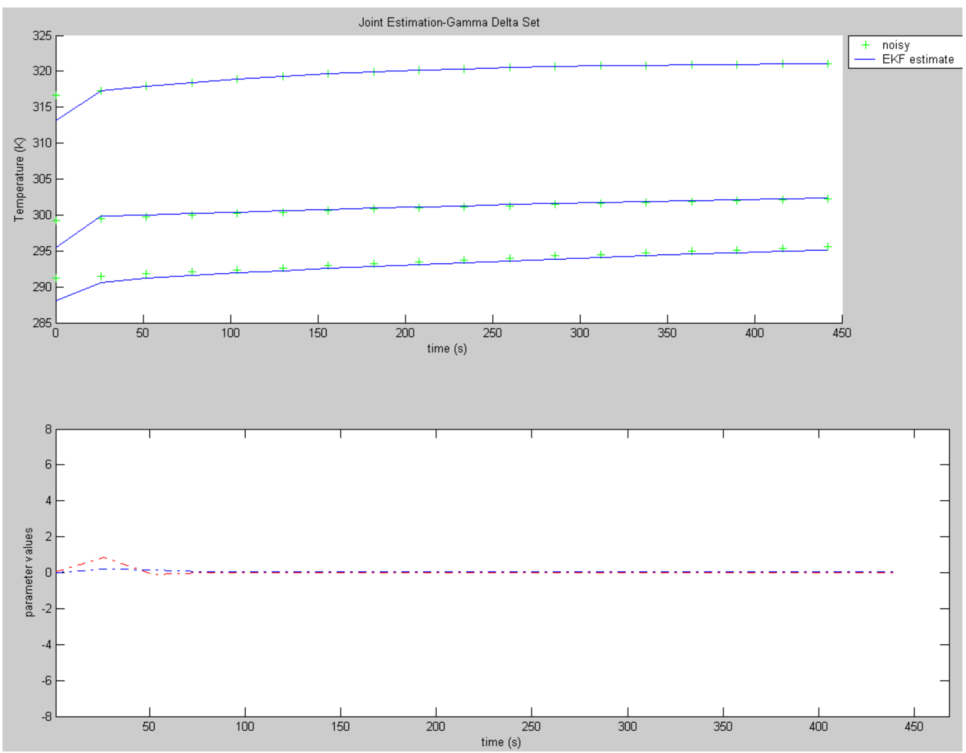

Figure 14: Flight Results 'gamma' using EKF

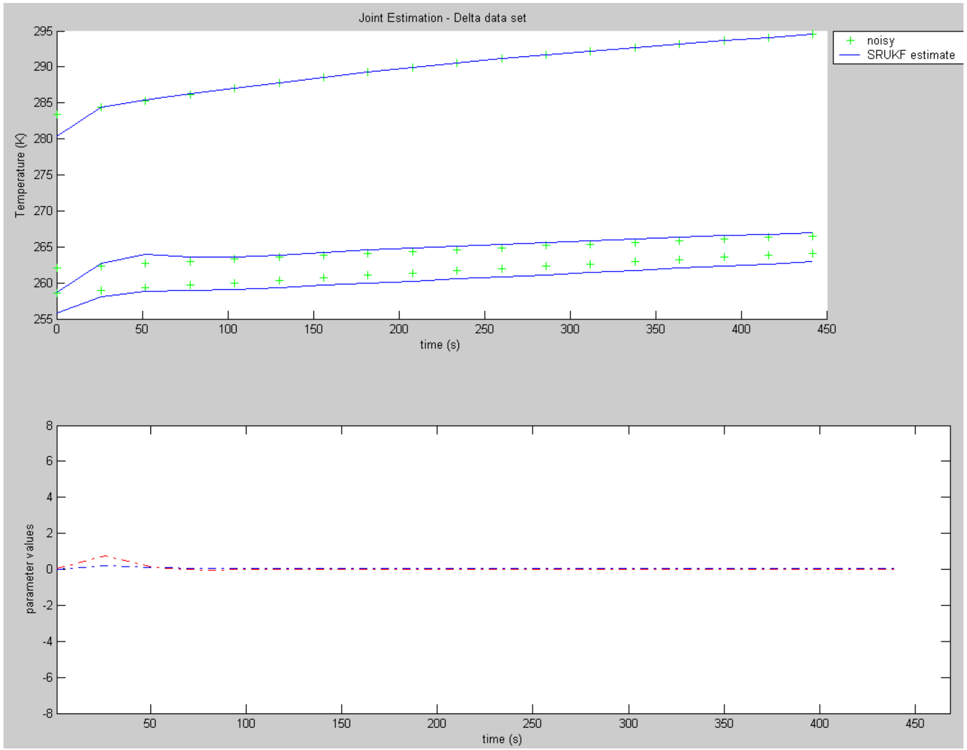

Figure 15: Flight Results ‘delta’ using SRUKF

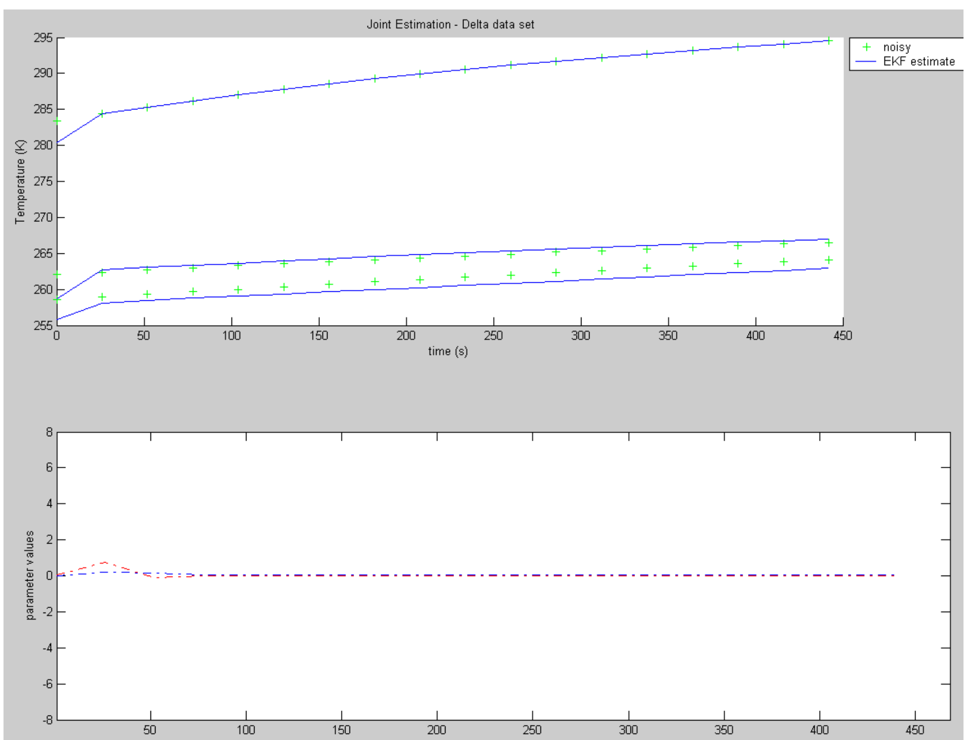

Figure 16: Flight Results ‘delta’ using EKF

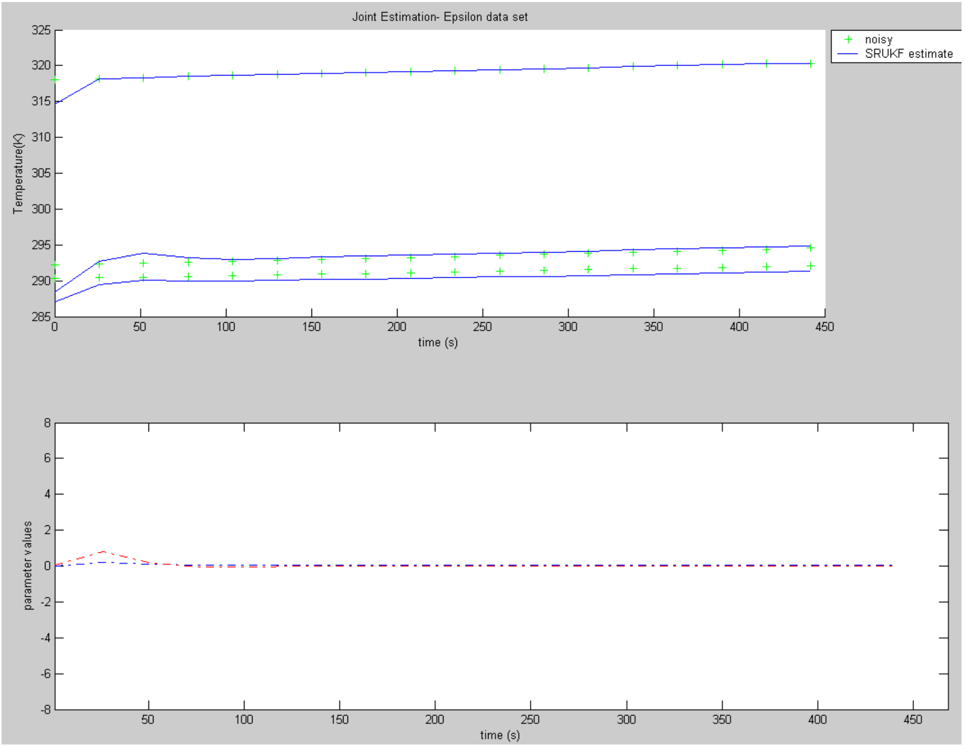

Figure 17: Flight Results ‘epsilon’ using SRUKF

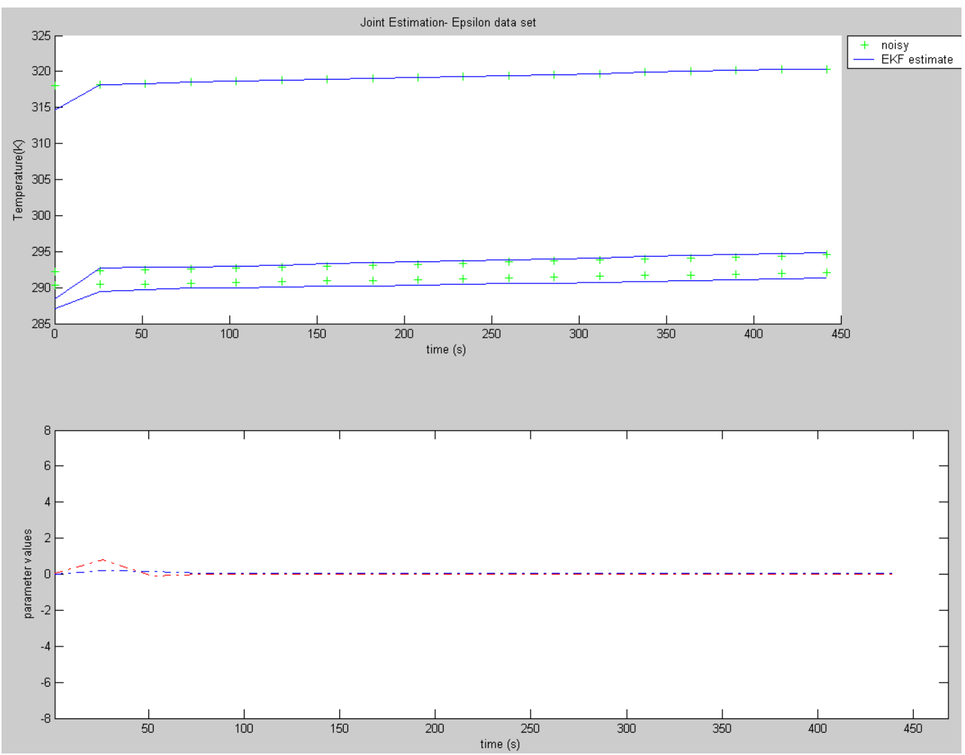

Figure 18: Flight Results ‘epsilon’ using EKF

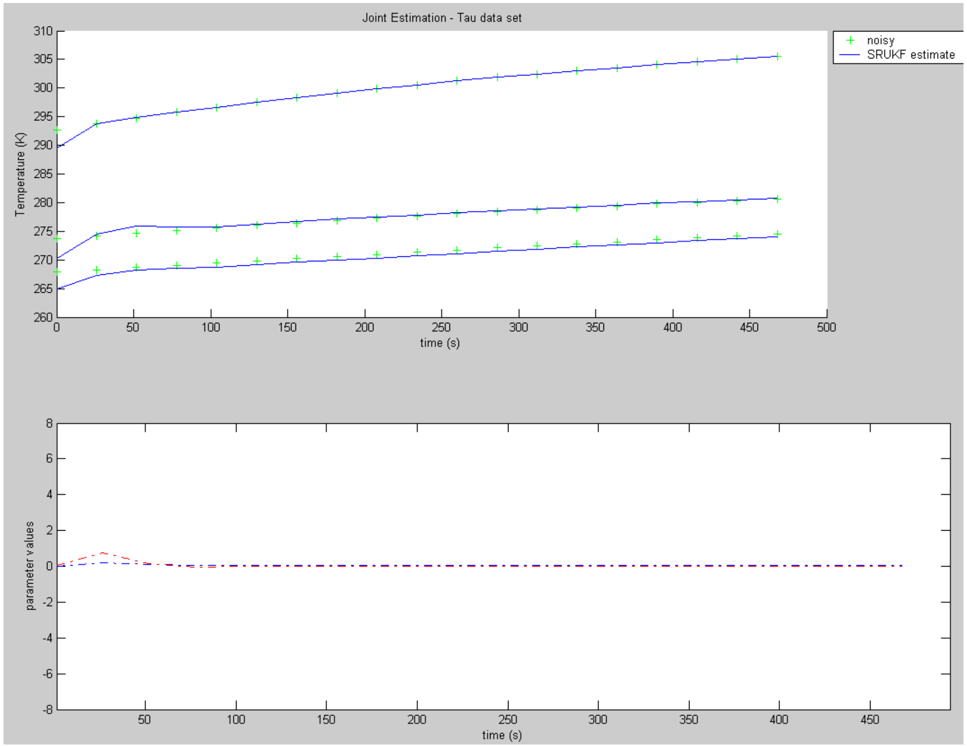

Figure 19: Flight Results 'tau' using SRUKF

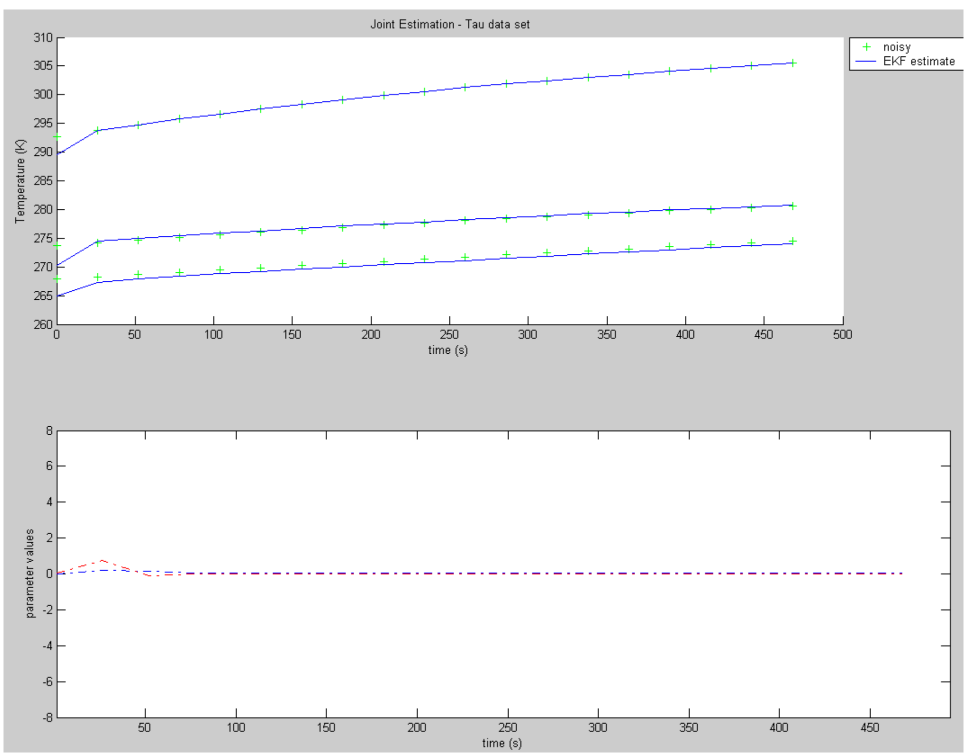

Figure 20: Flight Results 'tau' using EKF